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Aims and Scope: *Financial Services Review* is the official publication of the Academy of Financial Services. The purpose of this refereed academic journal is to encourage rigorous empirical research that examines **individual behavior** in terms of financial planning and services. In contrast to the many corporate or institutional journals that are available in finance, the focus of this journal is on individual financial issues. The Journal provides a forum for those who are interested in the individual perspective on issues in the areas of Financial Services, Employee Benefits, Estate and Tax Planning, Financial Counseling, Financial Planning, Insurance, Investments, Mutual Funds, Pension and Retirement Planning, and Real Estate.

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REVIEW

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From the Editor

This issue contains **Issue 4 of Volume 26** of *Financial Services Review* (*FSR*). I would like to thank the board and members of the Academy of Financial Services for their continued support. I continue to work in broadening the scope of articles, while still focusing on individual financial management and personal financial planning. I encourage authors to reach out when discussing implications of their findings in a more comprehensive way. As such, all articles in the Journal more appropriately relate to financial planning issues.

The lead article "Does Financial Risk Tolerance Change Over Time? A Test of the Role Macroeconomic, Biopsychosocial and Environmental, and Social Support Factors Play in Shaping Changes in Risk Attitudes" is coauthored by Stephen Kuzniak and John E. Grable, both at University of Georgia. In this paper, the authors address the need that financial planners, as well as regulators, require evidence documenting to what extent risk tolerance changes over time, and if changes do occur, the variables associated with variability. Based on a model that included macroeconomic indicators, biopsychosocial and environmental factors, and measures of social support, they find that risk-tolerance attitudes are remain generally stable over time. Additionally, there are groups of test takers that exhibit significant shifts in risk tolerance. They also describe some of the variables associated with these score changes, as well as provide financial planning professionals with guidance on how to identify clients who may be prone to shifting their tolerance for financial risk.

The second article "Which Measures Predict Risk Taking in a Multi-stage Controlled Investment Decision Process?" is coauthored by Kremena Bachmann, Thorsten Hens, and Remo Stössel, all at the University of Zurich. The authors assess the ability of different risk profiling measures to predict risk taking along a multi-stage process that reflects individuals' willingness to take risks. They find that the individual willingness to take risks varies along the process, but its level is always related to a composite measure of the individual risk tolerance. Assessment of the risk tolerance cannot be substituted by a simulated experience, although the latter can improve the perception of the risk and reward potential of the investment and motivate higher risk taking. The risk tolerance measure addresses different notions of risk, but they found that individual loss aversion is the most powerful predictor of risk taking at all stages of the discovery process. By contrast, they found that neither the self-assessed risk tolerance measures nor investment experience are suitable for consistently predicting risk taking at different stages of the process.

The third article, "Evaluating the relationship between IFA remuneration and advice quality: an empirical study" is coauthored by Jiří Sindelar and Petr Budinsky, both at the University of Finance and Administration Prague. The authors investigate the interaction between commission remuneration of independent financial advisers and selected sales factors, including the quality of advice. Utilizing data on investment transactions and a linear model with mixed effects, they found that the link between commission and quality of the subsequent recommendation is not homogeneous, and advice-bias potential is present only in a limited range of organizational environments, connected mainly to the flat-structure business model. Alternatively, they found that arbitrage between different product classes creates a biasing potential across almost all types of firms, creating potential for market systemic risk.

The fourth article, "Portfolio insurance using leveraged ETFs" is coauthored by Jeffrey George and William J. Trainor Jr., both at East Tennessee State University. The authors examine the use of leveraged exchange traded funds (LETFs) within a constant proportional portfolio insurance (CPPI) strategy. They state that the advantage of using LETFs in such a strategy is that it allows a greater percentage of the portfolio to be invested in the risk-free rate relative to a traditional CPPI. They indicate that where a standard CPPI strategy may require 50% of the portfolio to be invested in equities, using a 2x LETF only requires 25%, and a 3x LETF only requires 16.7% to attain the same effective exposure to equities. Their results show that when the risk-free asset is yielding at least 3% or the 1 year minus 90-day Treasury exceeds 1%, the use of LETFs within a CPPI framework results in annual returns approximately 1–2% higher with better Sharpe, Sortino, Omega, and Cumulative Prospect Values, while reducing Value at Risk (VaR) and Excess Shortfall (ES) below VaR.

The final article, "Who Seeks Financial Advice?" is coauthored by Maher H. Alyousif and Charlene M. Kalenkoski, both at Texas Tech University. The authors examine the determinants of seeking five types of financial advice and find consistency across different types of advice. Additionally, they observe no significant differences among subsamples defined by gender, age, and financial literacy. They show that income and risk tolerance are related positively to the demand for financial advice and affect the probability of seeking advice more than other variables. They also indicate that a low perception of financial knowledge, which can be a proxy for self-confidence, and financial fragility decrease the probability of seeking financial advice.

Thanks to those who make the journal possible, especially the referees and contributing authors. Over the past year, the following reviewers provided excellent reviews of the articles you enjoyed within the pages of Financial Services Review. I would like to send a special thank you to the many reviewers that have significantly contributed to the quality of our journal by providing timely and thorough reviews of the submissions to our journal.

Please consider submission to the Financial Services Review and rely on the style information provided to ease readability and streamline the review process. The Journal welcomes articles over the range of areas that comprise personal financial planning. While

Aamer Sheikh	Quinnipiac University	KC Ma	Stetson University
Abigail B. Sussman	University of Chicago	Kenneth N. Ryack	Quinnipiac University
Andy Terry	University of Arkansas at Little Rock	Kenneth White	University of Georgia
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Kathleen M. Rehl	Rehl Wealth Mgt	Wade Pfau	The American College
		William Jennings	US Air Force Academy

FSR articles are certainly diverse in terms of topic, data, and method, they are focused in terms of motivation. FSR exists to produce research that addresses issues that matter to individuals. I remain committed to the goal of making Financial Services Review the best academic journal in individual financial management and personal financial planning.

Best regards,
Stuart Michelson
Editor *Financial Services Review*

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FINANCIAL SERVICES REVIEW

Does financial risk tolerance change over time? A test of the role macroeconomic, biopsychosocial and environmental, and social support factors play in shaping changes in risk attitudes

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Abstract

Financial planners work in an environment that requires the documentation of a client's financial attitudes and preferences. Financial risk tolerance is one such attitudinal construct that is generally required by regulators to be evaluated. While there are numerous commercial and academic products used to assess client risk attitudes, questions have been raised over the past several decades regarding the stability of scores from risk-tolerance tools. Specifically, financial planners, as well as regulators, require evidence documenting to what extent risk tolerance changes over time, and if changes do occur, the variables associated with variability. The purpose of this study was to address these needs. Based on a model that included macroeconomic indicators, biopsychosocial and environmental factors, and measures of social support, it was determined that risk-tolerance attitudes remain generally stable over time. However, there are groups of test takers that exhibit significant shifts in risk tolerance. This article describes some of the variables associated with these score changes, as well as providing financial planning professionals with guidance on how to identify clients who may be prone to shifting their tolerance for financial risk.

Keywords: Financial risk tolerance; Macroeconomic indicators; Social support; Change in risk tolerance

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1. Introduction

Understanding appropriate investment options and recommending a suitable allocation of a client's assets is a key component of a well-drafted comprehensive financial plan. Accurate assessment of financial risk tolerance, as an element of the asset allocation process, is generally accepted as an essential condition to developing a suitable and quality financial plan for individuals (CFP Board, 2015). For those working as a financial planner, financial risk tolerance (FRT) can be defined parsimoniously as an individual's willingness to take risk (Dalton and Dalton, 2004). In the information and data gathering stage of client work, a suitable risk assessment is generally required to be used to meet regulatory requirements, as well as to formulate the best plan for an individual (Roszkowski and Davey, 2010). Understanding how a person's FRT influences decision making and behavior is becoming an increasingly important aspect of how financial planners formulate and execute recommendations. For researchers, practitioners, policy makers, economists, and financial professionals, understanding the role of risk and FRT is closely linked to better understanding the mechanics that combine to influence an individual's behavior (Xiao, 2008).

FRT assessment serves as a foundation for nearly all financial planning models, frameworks, and recommendations. A well-designed FRT assessment is a tool that can be used to anticipate an individual's decisions, determine optimal financial choices, and maximize utility under the constraint of imperfect knowledge. One question related to the study of FRT is of particular importance, specifically: Does FRT change over time? The concept of FRT "traitedness" is gaining traction as a way to answer the question of how much an individual's FRT deviates over time (Roszkowski, Delaney, and Cordell, 2009). The extent to which people will exhibit a personality trait in behaviors across different situations and contexts defines traitedness (Baumeister and Tice, 1988). For financial planners, policy makers, and researchers, answering the question of how much an individual's FRT changes (if at all) across time is needed to fully understand how clients will react in a variety of situations and within the context of changing macroeconomic environments.

The purpose of this study was to document changes in FRT across time. An important aspect of the study was to test whether macroeconomic variables and social support, as indicated by country of residence, were associated with changes in FRT at the individual/household level. Results from this study help expand the existing literature on the degree to which FRT changes over time. Furthermore, results provide an insight into the role macroeconomic and household level variables play in shaping changes in FRT.

2. Research framework

If the assumption that FRT is an essential element in the development of an accurate and acceptable comprehensive financial plan is true, it then follows that understanding its malleability over time is an important aspect to consider in the financial planning process. Roszkowski and Davey (2010) delved deeply into how major events, like the global financial crisis, can affect an individual's measured FRT. They noted that some view FRT as a completely stable characteristic (trait), while others view FRT as something that varies

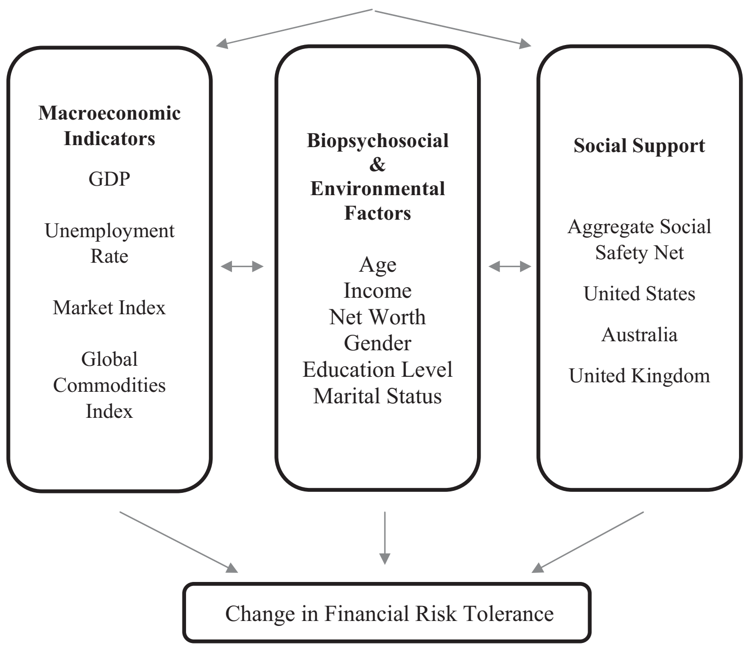

Fig. 1. The financial risk tolerance (FRT) model based on changes in FRT.

depending on the mood or environment of the test taker (state). However, they concluded, based on a review of the literature and their own experience, that FRT is relatively stable over time but somewhat susceptible to situational influences and life circumstances. The implications of this insight are important for financial planners to contemplate, especially considering the unique nature of the field in which multidecade relationships are common.

To fully understand the impact different variable relationships have on an individual's willingness to take risk, a model was developed specifically for this study. This model uniquely includes propositions about the associations between and among macroeconomic variables, demographic factors, and social support and FRT. The model is shown in Fig. 1.

The model was developed using concepts from three frameworks of risk taking: macroeconomic theory, the cushion hypothesis, and a model of the determinants of risk taking developed by Irwin (1993). It was hypothesized in this study that the macroeconomic condition of any nation may be associated with changes in FRT. Macroeconomic conditions are complex, with codependent activities that combine to produce and consume resources. Macroeconomic factors may influence the willingness of individuals to take risk in two ways. First, negative events may reduce financial capacity, leading to a negative shift in FRT. Second, perceptions of conditions, rather than the actual impact of macroeconomic events, could shape someone's willingness to take financial risk. Four variables were used in this study to test the impact of macroeconomic conditions on changes in FRT: country level gross domestic product (GDP), national unemployment rates, stock market conditions, and global commodity prices.

The second element of the framework was based on Irwin's (1993) model of risk taking. Irwin surmised that different predisposing factors affect an individual's risk-tolerance attitude. Biopsychosocial and environmental were two concepts Irwin used as classifying factors that influence FRT. Biopsychosocial factors include variables such as age and gender while environmental factors include income, net worth, education, and marital status, among other factors. Taken together, the combination of these factors and characteristics are expected to have a meaningful influence on an individual's risk-tolerance attitude. Imbedded within Irwin's (1993) model are variables related to cultural experiences and socialization.

As shown in Fig. 1, social support was also included in the model. The choice of this variable was based on the cushion hypothesis. This hypothesis states that individuals who live in collectivist cultures generally have a greater social support system that "cushions" downside risks when making risky decisions (Hsee and Weber, 1999; Weber and Hsee, 1998). In theory, when personal risk is minimized, individuals are allowed to try new things, start small businesses, or invest in potentially riskier opportunities that promise a higher return. In other words, the hypothesis posits that as social support increases, so does the willingness to take financial risk at the household level. It is important to note, however, that it can also be hypothesized that the opposite may be true. It may be that risk is often taken because of the necessity of making progress or achieving financial goals. Statman (2008) noted that individuals often pay with risk for a chance to move up in life and that in many countries, individuals are willing to take greater risks for potentially higher rewards, even when familial and national support is low.

3. Literature review

Hallahan, Faff, and McKenzie (2004) noted the following: "Despite its importance in the financial services industry, there remain some unresolved questions with respect to the 'determinants of financial risk tolerance'" (p. 58). By determinants, Hallahan et al. meant the identification of factors or variables that reveal a systematic association with FRT. Over the years, varied factors have been proposed and tested but the results have been inconsistent. This review highlights literature that has tested some of these factors.

3.1. Macroeconomic factors

Many individuals who were economically active or invested in the markets during the global financial crisis intuitively know that the overall economy likely has some effect on how individuals make decisions. The extent to which economic forces impact individuals and investment markets has been studied by Chen, Roll, and Ross (1986). The results of their research suggested that from the perspective of efficient market theory, asset prices are influenced, to some degree, by macroeconomic factors. In addition, Chen et al. concluded that stock returns are exposed to systematic economic news, and assets are priced in relation to this exposure. Their study documented an important link in the relationship between the macro economy and the way individuals make investing decisions involving risk.

Reinhart and Borensztein (1994) took a unique approach to measuring the macroeconomic determinants of commodity prices. In their research, they focused on determining real commodity prices beyond that of looking exclusively at demand factors. Their research examined international developments across Eastern Europe and the Soviet Union to help understand the connection between the macro economy and commodity prices. Their results, however, were unable to explain the marked and sustained historical commodity price trends throughout the 1980s and 1990s. Popular press articles often discuss the relationships between well-known commodities, such as oil and gold, and the association they have with markets and overall economic conditions. While it is possible to see commodity prices as drivers of the economy, nearly all market pundits address commodity issues by looking at the effect market conditions have on investable commodity markets (Motley Fool, n.d.). In addition to commodity investment markets, countries around the world have varying levels of structural macroeconomic exposure to commodity prices. For several Middle Eastern economies, for example, commodity prices (including oil) make up disproportionally large components of total revenue and output (World Bank, n.d.).

West and Worthington (2014) examined the relationship between macroeconomic conditions and financial risk attitudes. Based in Australia, their study relied on surveys of approximately 6,800 households. They noted, consistent with past literature, that demographic characteristics—especially age—had a strong relationship with changes in FRT over time. They also noted that macroeconomic conditions were jointly significant in shaping risk attitudes. Several of the variables studied were found to be significantly associated with the risk attitudes of individuals.

Unemployment rates and domestic stock market returns were discussed by Yao, Hanna, and Lindamood (2004). In their work, Yao et al. looked at changes in FRT during the period 1983–2001. Based on the Survey of Consumer Finances, FRT exhibited significant increases from 1995 to 1998 during a period of strong stock growth and large drops in unemployment. Yao and her associates also noted that poor global economic conditions in Asia and Russia had a seemingly negligible effect on domestic FRT.

Market conditions have been hypothesized to influence FRT. Rabbani, Grable, Heo, Nobre, and Kuzniak (2017), for example, noted that daily market volatility exhibited a positive association with FRT scores in their study, although the relationship was not strong enough to generally warrant a change in portfolio holdings. A similar finding was reported by Zeisberger, Vrecko, and Langer (2010). Santacruz (2009) looked at general economic mood and its influence on FRT scores. He concluded that there is limited need to make major adjustments to current models. It was noted, however, that financial planners should recognize the herding behavior that can result in investors' perceptions of recent salient macroeconomic events. In general, however, there continues to be a paucity of research that deals with this topic, and as such, the relationship is still subject to debate.

To address this apparent gap in the literature, the relationship between global macroeconomic variables and an individual's FRT was examined in this study using macroeconomic variables, including unemployment rates, national production (GDP), commodity prices, and market pricing. One of the most difficult aspects of examining macroeconomic variables is the interdependent relationship among economic indicators. Therefore, one essential step to evaluating the usefulness of economic variables in future studies will be determining which variables are independently related to FRT.

3.2. Biopsychosocial and environmental factors

Age, income, education, and wealth have all been shown to be significantly associated with an individual's FRT (Bajtelsmit, Bernasek, and Jianakoplos, 1999; Grable and Lytton, 1999; Pålsson, 1996), but the explanatory power and magnitude of their effects have been disputed (Gollier and Zeckhauser, 2002; Hariharan, Chapman, and Domian, 2000). In general, young men and those with more income and wealth are thought to be more risk tolerant compared with older individuals and those with fewer resources. The role of household size in shaping risk attitudes has also been explored. Most often, large households tend to exhibit relative risk aversion. This may result from a lack of risk capacity or a preference to be conservative with household resources. Similarly, variables associated with human capital have been found to be positively associated with FRT. Higher attained education, for example, is generally thought to be associated with elevated levels of FRT.

Baker and Haslem (1974) showed that some socioeconomic characteristics have a more profound influence in shaping the risk and return preferences of individual investors. Among the most important factors are age, gender, marital status, education, and income. The implications of their findings were that a person's demographic profile can have a strong influence on perceptions of risk and ultimately FRT.

In 1997, Wang and Hanna (1997) studied the association between age and FRT. Based on data from the Survey of Consumer Finances, they tested the life-cycle investment theory. Wang and Hanna measured FRT as the amount of risky assets held as a percentage of total wealth. They concluded that FRT increased with age, controlling for other important variables. Dahlbäck (1991) found that the propensity to take risks was influenced by saving decisions. Individuals who are willing to save more may have the ability to invest more aggressively. This implies that older investors—typically those with more wealth—may be more willing to take more risk. This relationship, however, is out of step with what financial planners typically assume. Nearly all financial planners, and some individual investors, simply use heuristics or rules such "Age = Percent Allocated to Bonds" to estimate the appropriate risk level within a given portfolio allocation (Benartzi and Thaler, 2007). However, the effect may not always be related to biological age but instead age acting as a proxy for an investor's time horizon or risk capacity. By default, as someone ages they lose time to recoup potential losses. As such, there may be no real age effect.

A 1996 study by Sung and Hanna (1996) investigated several factors that are generally thought to have a positive association with a household's willingness to take a financial risk. Based on data from the 1992 Survey of Consumer Finances, they concluded that education, age, and net worth (including liquidity) were positively correlated with a household's willingness to take some level of risk. It was also shown that female headed households were less likely to be risk tolerant compared with similar male headed or married households.

Grable (2000) measured risk taking in everyday money matters and the relationships among demographic, socioeconomic, and attitude characteristics both in individuals and groups. His results showed that a higher FRT was associated with being male, older, married, professionally employed with higher income, and more education, among other factors. Morin and Suarez (1983) examined the empirical evidence of the effects of wealth on relative risk aversion. Their work investigated a household's demand for risky investments using a dataset of asset holdings based in Canada. The results of their study showed a diverging relative risk aversion when housing was excluded from the definition of wealth (or investments) or treated as a riskless asset. In addition, they noted that an investor's stage in the life cycle and age were uniformly increasing over time with tolerance for risk.

Bakshi and Chen (1994) tested how changes in demographic variables influence investments in capital markets. The life-cycle investment hypothesis suggests that at an early stage an investor will allocate more wealth to housing and then allocate a higher proportion of resources to financial assets at later life stages. Using the Euler Equation, Bakshi and Chen provided baseline estimates for determining how risk aversion and investor "consumption-portfolios" can be measured for individuals of all ages and across diverse cultural environments. They noted that when the population ages, aggregate demand for financial investments rise and demand for housing declines. One conclusion from their work was that changes in someone's demographic profile can bring about fluctuations in asset demand.

3.3. Social support and country of origin factors

Cross-cultural FRT has emerged over the last 20 years as a niche area of interest among those who study FRT. Bontempo, Bottom, and Weber (1997) observed patterns across four different countries. They concluded that uncertainty avoidance in a country may influence risk perceptions. Many other studies using international comparisons have observed differences between the United States (or Western Europe) and Asian countries, notably China (Fan and Xiao, 2005; Hsee and Weber, 1999; Tan, 2011; Wang and Fischbeck, 2004). Findings from these studies have generally indicated that the Chinese are more risk seeking in financial arenas but not necessarily across other domains of risk. Kim, Chatterjee, and Cho (2012) looked at the differences in asset ownership of Asian immigrants from many different countries including China. They found a strong relationship between country of origin and the holdings of different asset classes, including homeownership, equities, and business ownership.

Rieger, Wang, and Hens (2014) presented a comprehensive evaluation of international risk taking in their article. Rieger et al. documented the risk preferences of individuals in 53 countries. They reported that individuals across cultures are, on average, risk averse regarding gains and risk seeking with losses. This finding was in line with the propositions found in prospect theory (Kahneman and Tversky, 1979). Rieger et al. also noted that risk preferences appear to be dependent on economic conditions and cultural factors. It was suggested that their results may serve "as an interesting starting point for further research on cultural differences in behavioral economics" (p. 637).

Two other large-scale international assessments of FRT were conducted by Statman (2008) and Vieider, Chmura, and Martinsson (2012). Studying 22 and 30 countries, respectively, the findings from these studies showed that those from wealthy countries tend to be more risk averse in financial domains. Statman explained that, "People in low income countries have high aspiration relative to their current income" and they "pay with risk for a chance to move up in life" (p. 44). The findings of Vieider et al. showed a unique relationship between international socioeconomic variables and risk-seeking behavior. They reported a strong negative correlation between FRT and personal income. They explained the phenomenon by suggesting that risk attitudes act as a transmission mechanism for growth by encouraging entrepreneurial activities throughout the world.

When viewed from the perspective of the cushion hypothesis, country of origin variables become important because each country has a unique social support policy. It is possible that countries with generous social support systems create a ‘cushion’ for risk takers who fail in the markets. If true, this ought to increase the willingness of those in these countries to take risk. On the other hand, a robust social support system may dampen FRT based on signals that country residents need not take risk to gain financial stability. At this point, neither hypothesis has been fully explored in the literature.

3.4. Stability of FRT

One of the least discussed notions within the FRT literature is the likeliness and degree to which risk attitudes change over time (Zeisberger et al., 2010). In this regard, Roszkowski and his associates (Roszkowski et al., 2009) concluded that intrapersonal consistency was stable over time but greater variability was associated with higher risk-tolerance scores. What remains to be discovered are the unique characteristics of individuals who show inconsistency in their FRT scores across multiple assessments.

The consistency of individual FRT over time can be assessed and split into four distinct categories: (1) stability over time, (2) reactions to market conditions, (3) consistency across different dimensions of FRT, and (4) consistency across different types of questionnaires (Roszkowski et al., 2009). When looking at FRT change over time, Yao et al. (2004) surmised that if significant time trends are evident after controlling for biopsychosocial and environmental factors, the changes over time can be interpreted to be related to changes in attitudes toward risk, not changes because of other factors. Yook and Everett (2003), Grable and Lytton (2001), and Yang (2004) each looked at the consistency of different risk questionnaires across time. In generally, they found that psychometrically valid assessment tools with published reliability estimates tend to, on average, generate repeatable scores, but that even with the most reliable instrument, changes in FRT scores do occur among some test takers. The general theme of research regarding the intrapersonal consistency of FRT across time is that the construct of FRT is relatively stable but does show some fluctuation based on environmental factors. For example, Zeisberger et al. (2010) noted that risk parameters appear quite stable for the majority of investors, but that it is possible for one-third of investors to exhibit significant instability over time.

4. Methodology

In an attempt to test the FRT model (Fig. 1), this study used a secondary dataset made available by FinaMetrica Pty Ltd. The risk profiling database included information collected in the United States (US), United Kingdom (UK), and Australia (AUS). The choice to retain data from each country was based on two factors. First, it was thought that the risk tolerance exhibited by citizens of each country might differ based on the macroeconomic conditions present in each locale. Second, the use of multicountry data allowed for a test of the cushion hypothesis. The data contained biopsychosocial and environmental information, as well as composite FRT scores for individuals who completed multiple risk assessments. Data collection began in January of 2010 and ended in December of 2014. The mean and median time period between tests was 805 and 763 days, respectively ($SD = 388.74$) or slightly more than two years. The time span provided a unique perspective on the global trends and distinctive macroeconomic environments that existed in the post global financial crisis period. Table 1 shows the demographic profile of the sample based on age, education, income, household size, net worth, and gender. Keep in mind that education, income, and net worth were measured using ordinal variables (variable coding is discussed later in this section). The sample size used in the regression ($n = 4{,}983$) was reduced because of missing data and modeling delimitations.

With an average age of 57, the sample population was older than the mean global population, but this was not surprising based on the fact the sample was drawn from individuals seeking financial or investment guidance. Average income fell into the $50,000 to $100,000 range, whereas the average net worth for respondents fell into the $250,000 to $500,000 range. The mean education level was the Some College or Trade School category. The sample was skewed slightly toward males who made up almost 55% of the sample.

A unique feature of the dataset was that all respondents took multiple assessments over the course of several months or years. This unique aspect of the dataset allowed for a comparison of respondents at different points in time, which made possible the identification of unique attributes of respondents who exhibited a notable change in their risk-tolerance score (RTS). The sample was delimited to include only those respondents who completed multiple assessments. Table 2 shows the distribution of risk scores based on the initial risk-tolerance score (RTS_1) and the follow up risk-tolerance score (RTS_2) test dates. The variables were also coded by country (AUS, UK, US).

The FinaMetrica scale was utilized across each of the three countries in the sample to create consistency and comparability across countries. Because of a common language, translation and semantic issues represented less of a methodological issue in this study compared with other research projects measuring global risk attitudes where survey tools have been translated into multiple languages. Minor adjustments to reflect regional dialects may have been used, but inconsistency across differing country boundaries was expected to be minor. The validity and reliability of the assessment tool has been verified in previous studies that have used the FinaMetrica dataset. For example, when testing the validity of the measure, Gilliam, Chatterjee, and Zhu (2010) reported a Cronbach's alpha of 0.89, suggesting a high degree of reliability for the assessment tool. An example of two of the questions used in the assessment includes:

Compared with others, how do you rate your willingness to take financial risk?

1. Extremely low risk taker
2. Very low risk taker
3. Low risk taker
4. Average risk taker
5. High risk taker
6. Very high risk taker

Table 1 Demographic profile of sample

Variable	*N*	Percent of sample
Gender		
Males	5,285	54.6%
Females	4,392	45.4%
Age		
18–34	1,930	25.0%
35–54	1,930	25.0%
55–65	1,930	25.0%
65+	1,930	25.0%
Education		
Did not complete high school	832	13.7%
Completed high school	707	11.6%
Trade or diploma	1,246	20.5%
University degree or higher	3,298	54.2%
Marital status		
Married (or in a de facto relationship)	5,174	83.2%
Unmarried	1,046	16.8%
Income (income from all sources)		
Under $30,000	625	10.2%
$30,000-$50,000	1,177	19.2%
$50,000-$100,000	2,133	34.7%
$100,000-$200,000	1,295	21.1%
$200,000-$300,000	672	10.9%
Over $300,000	241	3.9%
Household size		
0	2,180	36.2%
1	1,957	32.5%
2	859	14.3%
3	661	11.0%
4+	366	6.1%
Net worth		
Under $10,000	46	0.8%
$10,000-$25,000	31	0.5%
$25,000-$50,000	55	0.9%
$50,000-$100,000	116	1.9%
$100,000-$150,000	297	4.9%
$150,000-$250,000	966	15.9%
$250,000-$500,000	2,055	33.8%
$500,000-$1,000,000	1,460	24.0%
$1,000,000-$2,500,000	735	12.1%
Over $2,500,000	322	5.3%
Country		
Australia	1,762	18.2%
United States	6,269	64.7%
United Kingdom	4,564	17.1%

7. Extremely high risk taker

How easily do you adapt when things go wrong financially?

1. Very uneasily
2. Somewhat uneasily
3. Somewhat easily

Table 2 Demographic profile of the sample based on financial risk tolerance (FRT) scores

FRT scores	*N*	%	Mean	Standard deviation	Min	Max
RTS_1	9,692	100.0%	47.40	9.51	14	93
RTS_2	9,692	100.0%	48.00	9.61	15	95
AUS_RTS_1	1,762	18.1%	48.72	9.63	18	86
AUS_RTS_2	1,763	18.1%	48.92	9.49	16	87
UK_RTS_1	6,269	64.3%	46.61	9.56	14	93
UK_RTS_2	6,270	64.3%	47.38	9.69	15	95
US_RTS_1	1,661	17.0%	49.18	8.81	18	83
US_RTS_2	1,662	17.0%	49.73	9.15	21	84

RTS = risk-tolerance score; AUS = Australia; UK = United Kingdom; US = United States.

4. Very easily

Some of the advantages associated with the use of the FinaMetrica system include the academic and theoretical manner in which the scale was conceptualized, wide professional and individual use, and simple to understand interpretations that help financial planners know how to allocate their client's investments (FinaMetrica, n.d.).

4.1. Dependent variable

4.1.1. Change in FRT score

FRT, as defined by each respondent's RTS, was the primary outcome variable of interest. The assessment score was based on a 25-item scale that was aggregated to compute a composite risk score. Ranging from 1 to 100, higher scores were indicative of having a higher FRT. The mean and standard deviation of the initial test (RTS_1) for the sample was 47.40 and 9.51, respectively. In addition to measuring overall composite FRT scores, another aspect of the sample were matching data pertaining to changes in FRT scores across time by individual respondent. The dataset contained an additional score for each respondent (RTS_2). The mean and standard deviation for the RTS_2 score was 48.10 and 9.61, respectively. Overall, FRT scores increased less than one point (0.63; *SD* = 6.13) from the initial test.

With such a large sample, one would expect to see a selection of individuals who exhibited both extreme consistency in FRT and others who had major fluctuations in their FRT scores. The following mean deviation technique, as outlined by Roszkowski and Spreat (2010), was used to estimate large fluctuations as a way to isolate those with significant changes in FRT:

1. Subtract the reliability coefficient from 1.0.
   a. $1.0-0.89 = 0.11$
2. Calculate the square root of the estimate.
   a. $\mathrm{SQRT}(0.11) = 0.33$
3. Multiply the square root outcome by the test's standard deviation to estimate the standard error of measurement (SE_M).

a. 0.33 * 9.51 = 3.14

4. Estimate the 95% confidence interval by multiplying the SE_M by 1.96 (this is the approximate z score associated with 95% coverage within a normal distribution).

a. 3.14 * 1.96 = 6.15

5. Based on the test mean of 47.40, any test taker with a RTS_2 score between 41.25 to 53.55 (41 to 54 rounded) was considered *RTS_Stable*.

This methodological approach, based on the standard error of the mean, provided an estimate of how much variation was needed to confidently conclude that a significant change in a RTS had occurred. If the difference in test scores between *RTS_1* and *RTS_2* dropped below the defined confidence interval, the respondent was placed into the *RTS_Decrease* category. If the difference in test scores between *RTS_1* and *RTS_2* rose above the defined confidence interval, the respondent was placed into the *RTS_Increase* category. Again, by measuring respondents at two separate times, with months and/or years in between, and by combing information about time periods, biopsychosocial and environmental variables, macroeconomic factors, and social support, it was possible to draw conclusions about the unique properties of respondents who exhibited variability in their risk attitude.

4.2. Independent variables

Six biopsychosocial and environmental variables were also recorded at the time of each initial test: age, income, net worth, gender, education level, and marital status. Country of origin, time and date of initial response, and the date of the follow up survey were also measured. In addition to the information in the dataset, macroeconomic indicator variables were combined with each sampling unit based on the date of the initial survey. In an effort to understand what, if any, macroeconomic variables might influence an individual's willingness to take risk, the combined dataset allowed for tests of the significance of global macroeconomic factors. Three macroeconomic variables were included for each country: unemployment rate, quarterly GDP, and stock market performance. A fourth macroeconomic variable was included to account for global commodity prices. In addition to country specific macroeconomic variables, all countries were also combined to examine the broad global trends. A set of global variables were then used to measure overall and interaction effects on FRT. Although survey responses were collected daily, some of the global macroeconomic variables were released monthly or quarterly; therefore, the tests focused on these broader macroeconomic data points by matching data based on the date of the initial assessment.

The macroeconomic variables were operationalized as follows:

- *United States Gross Domestic Product (GDP)*: Reported quarterly, the range of US GDP was measured using data from the Bureau of Economic Analysis. The range of GDP from 2010 to 2015 was \$14.7 trillion to \$18.1 trillion, with a mean of \$16.4 trillion.
- *Australia GDP*: Measured in millions of US dollars, the total annual GDP ranged from

$1.34 trillion ($1.43 trillion AUD) to $1.55 trillion ($1.65 trillion AUD) with a mean of $1.45 trillion ($1.54 trillion AUD).

- *United Kingdom GDP*: Measured in US dollars, the chained volume measures were reported in trillions. The annual range of GDP from 2010 to 2015 was $2.53 trillion (£1.60 trillion) to $2.83 trillion (£1.79 trillion), with a mean of $2.67 trillion (£1.69 trillion).
- *United States Unemployment Rate*: The US Bureau of Labor statistics produces a monthly account of individuals defined as the percentage of the labor force that is unemployed but actively seeking and willing to work. The estimate was used in this study.
- *Australia Unemployment Rate*: Data from the Australian Bureau of Statistics evaluating the monthly unemployment rate was used. The Australian unemployment rate measures the number of people actively looking for a job as a percentage of the labor force.
- *United Kingdom Unemployment Rate*: Data from the United Kingdom Office for National Statistics were used based on the monthly unemployment rate (seasonally adjusted for all). The United Kingdom unemployment rate is defined as individuals currently unemployed, but have actively been seeking work in the past four weeks and are available to begin a job within the next two weeks.
- *US Stock Market Index*: To obtain an idea of general equity market conditions, the composite Standard & Poor's (S&P) 500 was used in this study. The S&P 500 is a market capitalization based index of the 500 largest companies listed on the New York Stock Exchange (NYSE) or NASDAQ.
- *Australia Stock Market Index*: In April of 2000, the ASX 200 became the primary investment benchmark for the Australian market. The ASX accounts for 70% of the equity market. The index contains the top 200 listed companies by way of float-adjusted market capitalism. The ASX 200 index was used to measure the Australia equity market (denominated in Australian dollars).
- *United Kingdom Stock Market Index*: The FTSE 350 index is a market capitalization weighted stock market index composed of the largest 350 companies whose primary listing is based on the London Stock Exchange. The FTSE 350 index was used to measure the UK equity market (denominated in British pounds).
- *Global Commodities Index*: Although given less attention than equity markets, commodity markets are aggressively traded internationally and many countries (e.g., Australia, Saudi Arabia, Russia, and Brazil) have commodity intensive domestic markets. The Green Haven Continuous Commodity Index (CCI) fund provides a broad based, diversified commodity basket that can be used as a proxy for commodity performance. The CCI uses an index of 17 commodity groups including grains, energy, precious metals, cash, and government treasury securities. The trajectory of the global index was used as an indicator for the general supply, demand, and pricing of global commodity markets. Although traded daily, a month average was calculated and matched with test score dates to provide a measure of commodity market activity.
- *Composite Gross Domestic Product:* To obtain a global perspective on domestic productions' relationship to FRT, a weighted composite model was developed. Using

weighted averages from the three countries represented in the sample, a Global GDP variable was created. The formula below was used for the calculation:

$$\mathrm{GDP} = \frac{US\_GDP}{US\_GDP \times UK\_GDP \times AU\_GDP} \times US_{GDP} + \frac{UK_{GDP}}{US_{GDP} \times UK_{GDP} \times AU_{GDP}} \times UK_{GDP} + \frac{AU\_GDP}{US\_GDP \times UK\_GDP \times AU\_GDP} \times AUS\_GDP$$

- *Composite Stock Market Index:* In addition to a composite GDP measure, a global stock market index variable was created using combined market information from Australia, United Kingdom, and the United States.

These data were matched, by date of the initial test, to each respondent's data profile. These data, rather than a change variable, were used in subsequent analyses.

Other variables were also included in the analysis. To test the effects of initial outliers, a variable was created that separated individuals into categories based on their RTS_1. If someone scored extremely low they were coded as Low Initial score, and if they scored extremely high they were given a High Initial score notation.

Biopsychosocial and environmental factors were also included in the analysis. It is well known that many professional financial planners use biopsychosocial and environmental variables to predict and assess the FRT of their clients (Spitzer and Singh, 2008). Previous research has done a relatively thorough job describing the most popular biopsychosocial and environmental variables used by financial planners (Grable, 1997; Grable and Joo, 1998; Sung and Hanna, 1996) that appear to be associated with financial risk tolerance. Some of the most important of these factors were included in this study. Each was measured as follows:

- *Age*: Age was calculated using year of birth at the initial survey date.
- *Income*: Income was measured using five categories: (1) Under $30,000; (2) $30,000-$50,000; (3) $50,000-$100,000; (4) $100,000-$200,000; and (5) Over $200,000.
- *Net Worth*: The data for net worth were coded using 10 distinct categories as follows: (1) Under $10,000; (2) $10,000-$25,000; (3) $25,000-$50,000; (4) $50,000-$100,000; (5) $100,000-$150,000; (6) $150,000-$250,000; (7) $250,000-$500,000; (8) $500,000-$1,000,000; (9) $1,000,000-$2,500,000; and (10) Over $2,500,000.
- *Gender*: Males were coded 1; females were coded 2.
- *Education Level*: Four levels of education were used to measure attained academic achievement: (1) Less than High School; (2) Completed High School; (3) Trade School or Some College; and (4) University Degree or Higher.
- *Household Size*: Household size was the count of all members (including children) in the household.
- *Marital Status*: Marital status was coded dichotomously. those who were married were coded 1, otherwise 0.

Table 3 Social support by country

Country	Social support (% GDP)
United Kingdom	21.7%
United States	19.2%
Australia	19.0%

GDP = gross domestic product.

A measure of social support was included in the study. Social support is a broad term that describes the aggregate level of transfers from government to individuals. Social support can be measured many ways with differing levels of comparability. Simply equating absolute numbers does not make sense globally when production, income, and consumption differ widely across regions. Social support can comprise many different concepts or programs, including, but not limited to, socialized healthcare, secondary and/or university education, unemployment insurance, and supplemental retirement income. Government transfers, as a percentage of GDP, produces a percentage statistic that allows for comparison across any set of countries worldwide. Adding the social support variable in this study was done to provide a test of the cushion hypothesis. For the scope of this study, social support was measured by percentage of GDP based on the US OECDs index, as shown in Table 3.

Table 4 provides a descriptive summary of the dependent and independent variables used in this study (data for social support are shown in Table 3). A mean value is shown when the data were recorded at the interval level. A median score is shown for categorical variables.

4.3. Data analysis methodology

The following statistical techniques were used in this study: correlation, probability distribution, and logistic regression analyses. After testing the individual variables for normality and potential multicollinearity, a multinomial logistic regression analysis was used to examine the relationships among the independent variables and changes in FRT. Specifically, the conceptual model was tested using a multinomial logistic linear regression with the dependent variable separated into three different binary categories: Decrease in Risk Score, Stable Risk Score, and Increase in Risk Score. The model was used to evaluate the change of those whose RTS decreased and those whose RTS increased across time relative to respondents with stable scores. The results provided clarity to which, if any, variables uniquely influenced a respondent's change in FRT across time.

5. Results

The first step in the analysis involved testing for possible multicollinearity among the independent variables. This test was conducted using a correlation analysis. The associations between and among the biopsychosocial and environmental factors were not particularly

Table 4 Descriptive summary of the independent variables

Variable	N	Mean/median	Standard deviation	Min	Max
RTS_1	9,692	47.4	9.51	14	93
RTS_2	9,692	48.1	9.61	15	95
Δ in RTS	9,692	.63	6.13	−36	48
Days between tests	9,692	805.0	388.70	0	1985
Education	6,113	3.1	1.09	1	4
Income	6,143	3.2	1.26	1	6
Household size	6,023	1.2	1.28	1	9
Net worth	6,083	7.2	1.49	1	10
Age	7,722	57.8	11.30	18	93
Gender	9,692				
Male	5,285	54.6	n.a.	0	1
Female	4,407	45.4	n.a.	0	2
Marital status	9,692				
Married	5,174	83.2	n.a.	0	1
US GDP	9,692	$15,741.6	657.23	$14,681	$17,914
AUS GDP	9,692	$ 1,392.1	44.96	$ 1,326	$ 1,522
UK GDP	9,692	$ 2,611.8	53.11	$ 2,528	$ 2,823
US commodity	9,692	29.9	3.37	21	36
US market	9,692	$ 1,339.8	203.99	$ 1,031	$ 2,107
UK market	9,692	£3,079.3	258.18	£2,598	£3,862
AUS market	9,692	AUS$4,596.8	355.29	AUS$4,009	AUS$5,929
US unemployment	9,692	8.6%	0.89	5%	10%
UK unemployment	9,692	7.9%	0.40	6%	9%
AUS unemployment	9,692	5.2%	0.27	5%	6%

RTS = risk-tolerance score; GDP = gross domestic product; US = United States; AUS = Australia; UK = United Kingdom.

high. On the other hand, the correlations among some of the macroeconomic variables were quite high, as shown in Table 5.

As shown in Table 5, worldwide GDP and investment markets were highly correlated during the period of analysis. The correlation between US GDP and UK and AU GDP was 0.98 and 1.00, respectively. Given the high correlations among these variables, composite variables based on each country's data were created. The correlations among these new variables are show in Table 6.

Unemployment and gross domestic product were correlated at almost –1.00. Overall, the high degree of correlation, as defined as a coefficient over 0.70 (Tabachnick, Fidell, and Osterlind, 2007) indicated a potential multicollinearity issue. Because GDP tends to be the primary indicator of economic activity, this variable was chosen to be included in the model.

To build the multinomial logistic model, study participants were split into three unique groups. The first split included respondents who exhibited a significant decrease in their RTS (N = 938). The second split was based on respondents who exhibited a significant increase in their RTS (N = 1,355). The third group included those with a nonsignificant change in their RTS (N = 7,399). After separating out the groups, specific factors were identified to examine the differences associated with changes in FRT, using the stable group as the reference category.

Table 5 Macroeconomic variables correlation table

	US GDP	UK GDP	AUS GDP	US market	UK market	AUS market	Commodity index	US unemployment	AUS unemployment	UK unemployment
US GDP	1.00	0.98	1.00	0.91	0.75	0.35	−0.12	−0.98	0.65	−0.45
UK GDP		1.00	0.97	0.93	0.80	0.44	−0.1	−0.97	0.70	−0.53
AUS GDP			1.00	0.89	0.72	0.31	−0.14	−0.98	0.65	−0.41
US market				1.00	0.93	0.66	−0.07	−0.93	0.71	−0.66
UK market					1.00	0.81	0.04	−0.77	0.60	−0.65
AUS market						1.00	−0.17	−0.41	0.60	−0.80
Commodity index							1.00	0.16	−.060	0.33
US unemployment								1.00	−0.69	0.54
AUS unemployment									1.00	−0.65
UK unemployment										1.00

US = United States; UK = United Kingdom; AUS = Australia; GDP = gross domestic product.

Table 6 Simplified macroeconomic variables correlation table

	Avg. GDP	Avg. MKT	Avg. COMMODITY	Avg. UNEMP
Avg. GDP	1.00	0.66	−0.12	−0.97
Avg. MKT		1.00	−0.09	−0.73
Avg. COMMODITY			1.00	0.17
Avg. UNEMP				1.00

GDP = gross domestic product; MKT = market; COMMODITY = commodity index; UNEMP = unemployment.

Table 7 compares the differences in scores between the respondents from RTS_1 to RTS_2. The overall distribution of changes in risk scores appeared normal.

A correlation estimation was made between change in RTS and days between tests. The test was conducted to evaluate if a longer (or shorter) time horizon between tests might have explained the likelihood of a shifting RTS. The mean score change was 0.63, whereas the mean period between tests was 805 days. A small positive association was noted between the two variables ($r = 0.02$); however, the effect size was very small, with much of the association resulting from the large sample size. The result of the test confirmed that test scores generally increased over the period of analysis, but that the time gap between tests was not a particularly important variable in explaining this shift.

Table 8 show the results of splitting respondents into distinct categories based on a meaningful change between RTS_1 and RTS_2. Respondents that had a significant decrease or increase in score over time, as measured by the standard error of mean technique, were separated from respondents who exhibited stable scores across assessments. Almost 25% of respondents had a significant change in their RTS. In addition, respondents who exhibited significant decreases consistently scored above the mean on the initial assessment, whereas respondents who had significant increases in FRT had initial lower than average scores.

The results of the multinomial logistical model are shown in Table 9. The second and third columns of Table 9 show the model comparing those with a decrease in FRT to those whose score was stable. The last two columns in Table 9 show the model comparing those with an increase in FRT to those whose score remained stable.

The results from the test provide insights into the change some individuals exhibited in their FRT over time. Relative to those whose RTS did not change:

Table 7 Comparison of initial and follow-up scores

Variable	Mean	Standard deviation	Standard error mean	Upper 95%	Lower 95%
Initial average score RTS1	47.01	6.29	0.07	47.15	46.87
Initial average score RTS2	47.61	7.59	0.09	47.77	47.44
Initial low score RTS1	29.83	3.85	0.14	30.11	29.56
Initial low score RTS2	34.64	7.38	0.27	35.17	34.11
Initial high score RTS1	64.82	4.72	0.15	65.11	64.52
Initial high score RTS2	62.38	7.72	0.25	62.87	61.89

RTS = risk-tolerance score.

Table 8 Description of RTS by change across time (N = 9,692)

Variable	Mean	Standard deviation	Standard error mean	Upper 95%	Lower 95%	% of sample
RTS total						
Test 1	47.44	9.51	0.10	47.63	47.25	100.0%
Test 2	48.06	9.61	0.10	48.26	47.87	100.0%
RTS stable						
Test 1	47.66	8.98	0.10	47.87	47.46	76.3%
Test 2	47.81	9.02	0.10	48.01	47.60	76.3%
RTS increase						
Test 1	42.55	9.93	0.27	43.08	42.02	14.0%
Test 2	53.33	10.13	0.28	53.87	52.79	14.0%
RTS decrease						
Test 1	52.73	9.72	0.32	53.35	52.10	9.7%
Test 2	42.50	9.63	0.31	43.11	41.88	9.7%

RTS = risk-tolerance score.

- Older respondents were more likely to be in the decrease category.
- Older respondents were less likely to be in the increase category.
- Those with more education were less likely to be in the decrease category.
- Those who lived in a country with high social support were less likely to be in the decrease category.
- Those who lived in a country with high social support were less likely to be in the increase category.
- Those who lived in a country with a high GDP were less likely to be in the decrease category.
- Those who lived in a country with a high GDP were more likely to be in the increase category.
- When the market was initially high, respondents were more likely to be in the decrease category.
- Those with a low RTS_1 score were more likely to be in the decrease category.
- Those with a low RTS_1 score were less likely to be in the increase category.
- Those with a high RTS_1 score were less likely to be in the decrease category.
- Those with a high RTS_1 score were more likely to be in the increase category.
- An interaction between GDP and social support was noted for those in the decrease category.
- An interaction between GDP and gender was present for those not in the increase category.
- An interaction between market and age was noted for those in the increase category.
- An interaction between market and gender was present for those in the increase category.

To summarize, the regression results provide insights into the unique attributes of individuals who exhibited a change in their FRT across time. The following individuals were more likely to show a decrease in their FRT: older respondents with less education, who lived in a country with lower social support and GDP with initially high market values. They were also more likely to have a lower initial RTS_1 score. Among those showing an increase in FRT were younger respondents who lived in a country with lower social support and a higher GDP. They also had a higher initial RTS_1 score. Although not unexpected, it is noteworthy

Table 9 Multinomial logistic model comparing RTS decrease/increase to RTS stable

Variable	Decrease in score		Increase in score	
	Increase *B*	*p*-value	Increase *B*	*p*-value
Intercept	6.189	0.000	0.194	0.888
Age	0.010	0.043***	−0.018	0.000***
Education level	−0.090	0.046***	−0.048	0.204
Income	−0.073	0.128	0.033	0.394
Household size	−0.062	0.176	0.035	0.300
Net worth	−0.057	0.117	−0.017	0.573
Social support	−0.105	0.005***	−0.069	0.031***
Commodity index	−0.010	0.464	−0.014	0.249
GDP	−0.001	0.000***	0.000	0.061***
Market	0.001	0.014***	0.000	0.143
Gender	−0.110	0.292	0.082	0.348
Married	−0.103	0.423	0.025	0.824
Low initial score	0.719	0.009***	−1.344	0.000***
High initial score	−1.185	0.000***	0.898	0.000***
GDP × Age	0.000	0.961	0.000	0.993
GDP × Gender	0.000	0.451	−0.001	0.015***
GDP × Education	0.000	0.541	0.000	0.597
GDP × Income	0.000	0.378	0.000	0.783
GDP × Married	0.000	0.920	0.000	0.655
GDP × Household size	0.000	0.969	0.000	0.906
GDP × Net worth	0.000	0.380	0.000	0.429
GDP × Social support	0.000	0.039***	0.000	0.290
Market × Age	0.000	0.166	0.000	0.080***
Market × Gender	0.001	0.106	0.001	0.021***
Market × Ed	0.000	0.393	0.000	0.972
Market × Income	0.000	0.535	0.000	0.582
Market × Married	−0.001	0.338	−0.001	0.366
Market × Household size	0.000	0.572	0.000	0.460
Market × Net worth	0.000	0.562	0.000	0.349
Market × Social support	0.000	0.364	0.000	0.510
Commodity × Age	−0.002	0.229	0.001	0.277
Commodity × Gender	0.037	0.187	0.044	0.101
Commodity × Education	0.011	0.377	0.006	0.617
Commodity × Income	−0.007	0.598	0.010	0.411
Commodity × Married	−0.041	0.271	0.013	0.713
Commodity × Household size	−0.003	0.772	0.006	0.587
Commodity × Net worth	−0.004	0.654	−0.011	0.258
Commodity × Social support	0.002	0.837	0.006	0.516

GDP = gross domestic product. N = 4,983: Cox and Snell (1989) for first model: 0.07; Cox and Snell (1989) for second model: 0.07.

that the direction of the effects for each of the independent variables (excluding social support) between respondents who exhibited a RTS decrease and a RTS increase showed an almost complete inverse relationship. It is worth noting that tests of those respondents who originally had an extremely low RTS_1 score tended to report a higher RTS_2 score relative to respondents who had stable scores on both tests. Likewise, respondents who originally had an extremely high RTS_1 score tended to exhibit a decrease in their RTS_2 score relative to respondents who had a stable score on both tests.

6. Discussion

The principal purpose of this study was to identify biopsychosocial, environmental, macroeconomic, and social support variables associated with changes in FRT across time. Several noteworthy findings emerged from the analysis. In general, those who were older at the initial test date were more likely to exhibit a significant decline in their risk score. A similar result was noted for those with less formal education. An interesting find was that living in a country with high social support tended to reduce the migration towards either a decrease or increase on FRT scores. Living in a country with a high GDP was indicative of exhibiting an increase in FRT scores. High market values at the initial assessment was predictive of a decrease in FRT.

The findings from this study can be incorporated into the practice of financial planning. One of the challenges many financial professionals face is the need to gain an understanding of a client's feelings and attitudes validly and quickly during the data gathering phase of the financial planning process. Rapport is often built over time, which makes it difficult to gain a full picture of an individual after a short introductory meeting or two. Trying to assess different personality traits or tendencies is often accomplished through various assessments and, for better or worse, financial planner intuition. Risk capacity is often examined once all relevant documents (e.g., cash flow, net worth, and insurance forms) have been reviewed, but accurately assessing personality attitudes and traits in a brief period of time is also necessary and, if accurate, helpful for both the client and the financial planner. To help a client allocate their investments, some form of FRT assessment is needed. In addition to a basic risk assessment, financial planners also need to know if the information gathered will be relevant now and in the future. It is customary to have a client complete a FRT assessment during the data intake process. Other than an initial assessment, there are no rules that require any follow-up evaluations. Being able to identify clients who are likely to show a FRT change can be helpful for both financial planners and individuals assessing their own allocation decisions. Findings from this study help financial planners determine approximately how "traited" FRT is and what the characteristics are of individuals who may change over time.

As shown here, individuals tend to exhibit generally stable FRT scores, but as most financial planners know, household dynamics do change over time, which may cause this financial planning data input to change. In general, FRT scores increased across the sample, but not enough to warrant a change in portfolio or other financial recommendations. Among some respondents, a marked decrease or increase in FRT scores was noted. The age of the test taker was an important predictor of change. Older respondents were more likely to exhibit a decrease in their RTS, whereas younger respondents were more likely to report a higher RTS at a later date.

Another insight is that initial test scores were predictive of future scores. A RTS outside the typical range provides an indication that a client may exhibit a meaningful change in his or her FRT at some point in the future. If a client initially scores extremely high or extremely low, it may be useful to monitor that individual closely across time. In addition, any major changes to macroeconomic conditions may be an indicator that FRT should be reassessed to ensure that portfolio recommendations still match a client's needs and willingness to take risk. It should also be noted that any major, or potentially major, changes in social policy around social retirement plans or national health insurance may influence the way an individual perceives risk.

Does FRT change over time? That was, and still, remains one of the most important questions asked by financial planners, researchers, and policy makers. Overall, FRT, in this study, was relatively stable. FRT did show some deviation across time, but for the majority of respondents, the initial RTS changed very little. However, even if only a small portion of clients exhibit inconsistent FRT scores, this can cause a problem in practice. In this study, approximatively 75% of individuals exhibited consistent scores across two assessments. So, hypothetically extrapolated, for a midsized firm with 200 clients over a five-year period, almost 50 clients could have significant changes in their FRT scores. Macroeconomic variables at the time of initial assessment, initial test scores, and social support all had a significant role to play in describing who was likely to exhibit significant a decrease or increase in their FRT across two assessments.

When interpreting the results from this study it is important to keep in mind that the macroeconomic, stock market, and commodity index variables were based on values when the first test was taken. A few studies have used change in market conditions or domestic production variables to forecast variations in FRT scores, but this study used a baseline metric of the conditions present during the initial test. This methodological approach was applied for two reasons. First, the period in which the study was performed was a relatively stable period with generally favorable market conditions occurring after the global financial crisis. Second, the applied nature of the study drove the decision. Financial planners, when working with clients in developing investment recommendations within a financial plan, must use data at hand. They do not have access to pre- and postperiod macroeconomic data. The ability to describe potential variations in client FRT requires the use of baseline inputs. Even so, comparing the results presented here with future studies that use macroeconomic, biopsychosocial, and social support change data would be useful.

It is also worth noting that while the results from this study are valuable in establishing baseline metrics for predicting changes in FRT, the overall amount of explained variation in the dependent variable was relatively small. Although different than residuals in a traditional linear model, Cox and Snell (1989) developed a methodology for determining the amount of explanation in a given logistic model. For the model tested in this study, the Cox and Snell coefficient was 0.071. This means the model explained about 7% of the effect for changes in FRT scores over time. Although not extremely large, the ability to show significant effects for different unique variables is a starting point to begin the discussion for future research about the exact reasons individuals change their willingness to take risk across time.

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Which measures predict risk taking in a multi-stage controlled investment decision process?

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Abstract

We assess the ability of different risk profiling measures to predict risk taking along a multistage process that reflects individuals' discovery of their willingness to take risks. We find that the individual willingness to take risks varies along the process, but its level is always related to a composite measure of the individual risk tolerance. Assessment of the risk tolerance cannot be substituted by a simulated experience, although the latter can improve the perception of the risk and reward potential of the investment and motivate higher risk taking. The risk tolerance measure addresses different notions of risk, but we found that the individual loss aversion is the most powerful predictor of risk taking at all stages of the discovery process. By contrast, we found that neither the self-assessed risk tolerance measures nor the investment experience are suitable for consistently predicting risk taking at different stages of the process. © 2017 Academy of Financial Services. All rights reserved.

JEL classification: D81; G11

Keywords: Risk profiling; Risk tolerance; Risk attitude; Risk preferences; Risk taking; Experience sampling

1. Introduction

An essential task in investment management is determining the amount of risk an investor should take. In principle, investors can identify their willingness to bear risks through investment in the financial market, but this approach is costly because a considerable amount

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of wealth can be lost because of inconsistent decisions during the learning process. To assist investors and justify their recommendations as required by regulators, financial professionals use various techniques to determine the level of risk that their clients should take.

In this study, we evaluate the suitability of such risk profiling techniques based on their power to explain and predict individual risk-taking behavior. More important, we believe that the relationship between the assessed risk profile and the subsequent risk taking may not be stable if individuals are still in the process of identifying their willingness to take risks. The involvement in such a process is likely because individuals are not always able to correctly anticipate their emotional reactions to possible outcomes (Kahneman, 2009).

To shed some light on this issue, we conduct an experimental study on whether an individual's risk taking changes over different stages of a process along which private investors are expected to correct misperceptions and discover their true willingness to take risks. We then analyze how the predictability of risk profiling questions varies over the stages of such a process. The goal of the study is to identify risk profiling measures that consistently explain and predict risk taking at all stages of the discovery process. This consistency is important because investment advisors usually do not know which stages of the process their clients have completed. Using a risk profiler that is suitable only if clients have completed certain stages of the discovery process can lead to inappropriate advice being given.

To determine the relevant stages of the discovery process, we consider evidence from previous studies reporting that individual risk taking varies with certain characteristics of the decision setting, such as ambiguity, personal experience, and feedback. We use these features to design a multistage discovery process that reflects the investment experience of a typical private investor. For simplicity, investors only decide between one risky asset and cash. At the beginning of this process, it is assumed that investors decide within an ambiguous situation, that is, they know the return of holding cash, but they do not know anything about the return distribution of the risky asset. Afterwards, the ambiguity is revealed while investors can choose its presentation format. In the third stage, the investors are asked to answer some risk profiling questions. In the next stage of the process, they experience the risk-return characteristics of different asset allocations based on simulations. In the fifth stage, the investors learn which return they have made, and in the last stage, they are able to reconsider their investment decision using a three-day break. We analyze whether individual risk taking changes over the different stages of the process, that is, whether investors are involved in a process of discovering their willingness to take risks. We then analyze the ability of different risk profiling questions to consistently predict risk taking over the different stages of the process.

Nobre and Grable (2015) suggest that risk profiling questions should consist of questions assessing the risk need (the amount of risk required to meet a particular financial goal), the risk capacity (the client's ability to absorb a possible financial loss resulting from the financial risk taken) and the financial risk tolerance (an individual's willingness to accept uncertainty related to the outcome of a financial decision). Carr (2014) analyses the optimal weighting of these dimensions. In this study, we focus on the assessment of the investors' risk tolerance, which is a psychological concept. The assessment of the risk need and the risk capacity are purely financial issues that can be managed with financial planning tools. In our study, we use a broad definition of risk tolerance that refers to losses as an additional notion of risk. Moreover, we use different formats to state the questions, that is, some questions use lotteries and others use verbal alternatives; we also consider questions based on a self-assessment. Additionally, we consider other factors that may affect risk taking, such as investment experience outside of the study and the investors' risk awareness as reflected in the misperception of the true risk-reward profile of their investments. We also analyze whether simulated experience can substitute for risk profiling based on questions.

We find that some aspects of an individual's risk tolerance explain risk taking at all stages of the decision process, while the risk awareness and the self-stated investment experience cannot. Moreover, although simulated experience improves risk awareness and supports risk taking, it cannot be used as a substitute for the assessment of individual risk tolerance when explaining and predicting risk taking. While risk tolerance can be measured in many ways, we find that the individuals' loss aversion is the most suitable measure because it most accurately predicts the risk-taking behavior of investors involved in a process of discovering their willingness to take risks. Of interest, we find that self-assessed risk tolerance measures are not suitable for predicting risk taking at any stage of the decision process. If individuals' risk tolerance cannot be assessed and one must rely on socioeconomic characteristics, then only gender can be used as a predictor of risk taking.

The results of our study have important policy implications. Regulators in most developed countries acknowledge the importance of using risk profilers, and professional advisors use various risk profiling methods to justify their recommendations. However, it is not clear whether the risk profilers used in practice are suitable for determining the optimal level of risk taking (Brayman, Finke, Grable, and Griffin, 2017). Their external validity is sometimes tested based on real asset allocation decisions (Corter and Chen, 2006; Gilliam, Chatterjee, and Grable, 2010; Grable and Lytton, 2003; M. Guillemette, Finke, and Gilliam, 2012; Wärneryd, 1996). However, it is unclear whether an asset allocation at a certain point of time is a good assessment criterion because clients may still be involved in the process of discovering their willingness to take risks. Our analysis explicitly considers the impact of this discovery process on the suitability of different risk profiling measures. We identify measures that consistently predict risk taking at every stage of the process. This is important for advisors because they usually do not know which stages of the discovery process their clients have already passed. Using questions that consistently predict risk taking at all stages of the discovering process increases the probability that clients remain satisfied with the recommendations. At the same time, making recommendations based on questions that consistently predict risk taking at all stages of the discovery process should support the advisors' confidence that these recommendations match the clients' risk tolerance and do not encourage misperceptions that are corrected over time.

2. Literature review and research hypotheses

Using different measures of individual risk tolerance, previous studies have found that these measures are related to individual investment risk taking. For example, Barsky and Juster (1997) find that risk tolerance revealed in a hypothetical choice between uncertain income streams predict stock ownership. Yook and Everett (2003) find a significant positive correlation between the total score of several risk tolerance measures and the percentage of actual stock holdings in portfolios. Corter and Chen (2006) propose another risk tolerance measure and show that it is positively correlated with the riskiness of the actual investment portfolios chosen. Wärneryd (1996) finds a significant relationship between the individual investment attitude based on risk-return considerations and the risk in portfolios of Dutch households. Gilliam et al. (2010) find a significant positive association between broadly used risk tolerance measures and equity ownership.

While these studies show that the evaluation of the individual risk tolerance is important for explaining investment risk taking, it remains unclear whether the explanatory power remains stable over time because individuals change their risk-taking behavior. For this reason, we designed a controlled laboratory experiment that stays close to the advisory processes found in praxis so that the setting is not too artificial.

We also consider information- and experience-driven changes in investment risk taking. At the beginning, investors are expected to make investment decisions under ambiguity, that is, they may not know the exact risk-return characteristics of the alternatives that they consider for investment. Frisch and Baron (1988) argue that ambiguity arises from the perception of missing information relevant for a probability judgment, which supports the normative status of utility theory. From a theoretical perspective, ambiguity is important because it motivates lower stock market participation compared with the basic expected utility model (see, e.g., Epstein and Schneider, 2010 among others). Antoniou et al. (2015) confirm the prediction of the theoretical ambiguity literature. In particular, they find that an increase in ambiguity is associated with reductions in capital flows into equity mutual funds. Hence, providing information that makes probability judgments easier can increase risk taking. Based on this literature, we conjecture that our participants take less risk under ambiguity, that is, in the first stage, than in later stages of our experiment.

In the second stage of our experiment, the participants can acquire three different descriptions of the returns of the risky asset. Previous studies have shown that even if individuals are provided with identical information, the presentation format can influence the utilization of information. In a classic demonstration of this phenomenon, Slovic et al. (1978) observe that the presentation of formally equivalent statistics influences risk-taking behavior. Similar types of framing effects have been reported in the literature on decision-making (Tversky and Kahneman, 1981). Framing effects have been extensively used to modify risk-relevant behavior, facilitate cooperative conflict resolutions and advance knowledge or attitudes (see Rohrmann, 1992 for an overview). We focus on the last aspect and hypothesize that individuals have different abilities to utilize information in different formats, which may influence their risk-taking behavior.

In the third stage of our experiment, the participants are asked to answer questions regarding their risk tolerance and investment experience. The effect, wherein individuals change their behavior in response to being monitored, has been widely discussed in health economics (Parsons, 1974) and consumer behavior research (Fitzsimons and Williams, 2000). In our study, we consider the existence of assessment effects in the context of investment risk taking.

In the fourth stage of our experiment, the participants can experience the return distribution by drawing samples from it before they can decide how to invest. Converging findings show that there are systematic differences between decisions based on experience and decisions based on description (Hertwig and Erev, 2009), particularly in the context of decisions involving rare events (Hertwig et al., 2004). Kaufmann et al. (2013) show that communicating risk with the help of experience sampling and graphical displays leads to higher risk taking. Goldstein et al. (2008) suggest that using interactive methods allowing individuals to explore the probability distributions of potential outcomes can be beneficial for inferring preferences and predicting subsequent risk-taking behavior. In line with this research, we hypothesize that experience sampling influences risk taking. In particular, we analyze whether experience sampling can substitute the assessment of individual risk tolerance in explaining and predicting risk-taking behavior.

In the next stage of our experiment, the participants have a break of three days in which they can carefully study the design of the experiment and what they have done so far. Previous research suggests that decision-makers switch to simpler strategies if decisions have to be made under time pressure, which can explain preference reversals (Ordonez and Benson, 1997). In negotiations, for example, individuals appear to reach higher-quality agreement after a break because the latter allows them to assess strategies and behavior (Harinck and De Dreu, 2008). We hypothesize that giving individuals time to re-evaluate the decision problem may have an impact on their subsequent risk taking.

In the last stage of our experiment, the participants learn the outcomes of their previous investments and decide for the last time whether and how to revise them. Given that all relevant information is available before a decision is made, the outcome of a decision should not be used to improve subsequent decisions. However, Fischhoff (1975) demonstrates the existence of a hindsight bias, an effect of the outcome information on the judged probability for different outcomes. His explanation for observing this bias is that outcome information calls attention to information that would make a decision good or bad. For example, bad outcomes call attention to the risks associated with the decision as an argument against taking the decision. We hypothesize that the information on the outcomes of previous decisions may affect the subsequent risk taking and take the effect into account when assessing the suitability of risk profiling questions.

3. Survey design

Our study consists of six stages, which differ either in the information that individuals receive or in the tasks they have been asked to perform. Table 1 provides an overview of all stages. It specifies the information that is also provided at every stage and the tasks that the individuals were asked to perform after receiving the new information.

A common task at every stage is an investment decision. At each stage, individuals were given financial wealth expressed in Experimental Currency Units (ECU) and asked to split the wealth between a risky and a riskless asset. The amount in ECU varied between individuals dependent on their true financial situation, which was assessed in advance

Table 1 Survey structure

	New information provided	Tasks after receiving new information
Stage 1: Ambiguity	Information on the return of the riskless asset	Make an investment decision
Stage 2: Return information	Return distribution of the risky asset (described by graphics, scenarios, and statistics)	Make an investment decision
Stage 3: Profile estimation		1. Answer questions assessing risk tolerance, financial knowledge, and experience 2. Make an investment decision 3. Answer risk awareness questions (1st time)
Stage 4: Simulated experience	Experience the risk-return profile of different asset allocations through simulations	1. Answer risk awareness questions (2nd time) 2. Make an investment decision
Stage 5: Time break	Three days break	Make an investment decision
Stage 6: Feedback	Receive report of returns with all previous investment decisions	1. State satisfaction/expectations 2. Make an investment decision

together with other demographic and socio-economic characteristics. The monetary value of all ECU endowments was 10 Euros. The investment decisions between stages were independent. The individuals were informed that one of their investment decisions would be relevant for their final payment and that the relevant decision would be determined randomly at the end.

In the first stage, individuals were asked to make an investment decision under ambiguity, that is, the individuals knew only the return of the riskless asset but did not have any information about the return distribution of the risky asset. The latter was provided in the second stage using different formats. The graphical format used histograms, the verbal format was based on scenarios, and the statistical format used descriptive statistics (see Appendix D). The individuals could use the format that they considered most helpful. Acquiring information was not mandatory. Subsequently, individuals were asked to make an investment decision for a second time. In the next stage, no new information was provided. Instead, individuals were asked questions about their risk tolerance, financial knowledge and investment experience. Because asking such questions may change the individual risk-taking behavior, we asked individuals to make a third investment decision. Afterwards, individuals were asked questions assessing their risk awareness, that is, their understanding of the risks and rewards associated with different investment decisions.

In the fourth stage, individuals received the opportunity to experience the risk of investment in the risky asset. Our experience sampling tool is based on the same idea as the tool used by Kaufmann et al. (2013), that is, individuals draw different scenarios on the realization of the risky asset and observe how the return distribution of different asset allocations emerge. To make asset allocations comparable, we allowed individuals to simultaneously observe the final outcomes of two different asset allocations side-by-side (see Figure A-1 in the Appendix). Both asset allocations use the same return realization of the risky asset and the same investment horizon of 1 year. The simulations were restarted with every change in the asset allocation. To avoid framing effects, both return distributions were scaled in the same way. After observing the final outcomes of at least two hundred scenarios (this required at least 10 drawings), the individuals were asked to answer our risk awareness questions for the second time and to make an investment decision. The payoff of the participants depended on this investment decision but not on the decisions made while drawing outcomes of different asset allocations.

In the fifth stage, the individuals were informed that they would have a three-day break. In reality, the clients received factsheets with investment information. Similarly, individuals were given the option to download the description of the assets for further reference. After a three-day break, the individuals were asked to make their fifth investment decision. They were also asked to state which investment decision they consider the best one, that is, which investment decision they would consider relevant for their payment.

In the sixth stage, individuals received a report on the realized returns with each of their five investment decisions. For each decision, the individuals were asked to state to what degree they are satisfied and to what degree they are positively or negatively surprised. Afterwards, the individuals were asked to make a final investment choice.

3.1. Incentives

The participants received a base payment of 13.25 Euros and a payoff based on one of the five investment decisions. The relevant decision was selected randomly. The payoff in the selected decisions depended on the preferred exposure to the risky asset and the return of the risky asset, which was drawn from the previously communicated distribution of the risky asset. Additionally, the participants could gain or lose 2% (20 cents) of their initial endowment with every correct (incorrect) answer to the risk awareness questions. All questions that were relevant for the final payment were marked in red, and the instructions stated that this indicates payoff relevance. The median completion time was 27 min, excluding the three-day break. The total payments varied between 21.75 and 27.65 Euros with an average of 26.20 Euros.

3.2. Participants

The survey was conducted online[1] in January 2014 with 439 Germans aged between 18 and 65. The sample was provided by a professional market research agency and included individuals from a national panel of over 200,000 Germans. Socioeconomic questions were used to apply a quota sampling procedure for selecting participants from the general population to ensure the representativeness of the sample.

We used the time those individuals took to read the instructions and answer the questions to exclude those that are most likely to provide random answers.[2] The filtered sample includes 320 individuals. A summary of their socioeconomic profiles is provided in Table B-1 in the Appendix. Most of the individuals have no children, have a high school degree, work as employees without supervisory responsibilities, have a monthly net income between 1,300 to 2,600 Euros and have a financial wealth of between 2,500 to 10,000 Euros.

3.3. Definitions

The *risk profiler* is a composite of several measures that predicts investment risk taking. Nobre and Grable (2015) suggest that risk profiling questions should consist of questions assessing the risk need (the amount of risk required to meet a particular financial goal), the risk capacity (the client's ability to absorb a possible financial loss resulting from the financial risk taken) and the financial risk tolerance (the individual's willingness to accept uncertainty related to the outcome of a financial decision). We focus on the assessment of the risk tolerance since the first two concepts are purely financial issues that can be managed with financial planning tools. In our setting, the investor's *risk tolerance* is a multidimensional construct that reflects an investor's attitude toward risk. We use different notions of risk that refer to the uncertainty of payoffs and to payoffs below a certain reference point. The attitude toward uncertainty is usually called risk aversion. The attitude toward payoffs below a certain reference point is called loss aversion. We consider the investor's *risk awareness* as an additional driver of risk taking. It measures the discrepancy between the perceived and the true risk-reward characteristics of the chosen investment.

3.4. Questions design

The questions used in our survey assess an individual's risk tolerance, risk awareness and investment experience, along with socio-economic and demographic characteristics as potential drivers of financial risk taking. The questions are provided in the Appendix.

The questions assessing an investor's risk tolerance address different notions of risk. In line with the results of Morrison and Oxoby (2014), who find that loss aversion influences decisions involving risk beyond the effects of risk aversion, we assess risk aversion and loss aversion as separate descriptions of an individual's risk tolerance. The estimation of individual's risk aversion is based on self-assessments. An individual's loss aversion is estimated with a price table task, which is similar to the one used by Holt and Laury (2002). In this task, the individuals were asked to make eight binary comparisons. In each comparison, they were asked to select either the safe option or the risky option. A control question describing the individual's choice asks individuals to confirm or revise their decision.

The question assessing individual risk awareness aimed to evaluate an investor's understanding of the return distribution of the risky asset. We used multiple choice questions with individually randomized answers. In addition to answering the questions, we asked individuals to state their confidence in the correctness of their answers.

To compare the different question types, we apply the same seven-point Likert scale to all questions.[3] For three questions, it was not appropriate to use a Likert scale. In these cases, we ensured that the questions had seven answer options with equal psychological distance, that is, we used numbers such as years for the financial experience questions, which precisely defined the steps between the answers. In the empirical analysis, we treated the answers as an interval-based numerical dataset.[4]

Table 2 Risk taking revisions

	Percentage of individuals changing risk taking	Risk taking revisions			
		Mean (in%)	SD (in%)	Min (in%)	Max (in%)
Stage2-Stage1 (after ambiguity reduction)	55.9%	−0.067	14.43	−57	50
Stage3-Stage2 (after risk profiling questions)	46.3%	0.214	12.39	−55	55
Stage4-Stage3 (after experience sampling)	61.3%	4.019	16.07	−90	65
Stage5-Stage4 (after break)	54.1%	−1.299	13.09	−60	50
Stage6-Stage5 (after outcome feedback)	56.2%	0.189	12.87	−50	55

4. Results

4.1. Risk taking along the discovery process

Our experimental design is based on the idea that individuals facing investment decisions are involved in a process of discovery of their willingness to take risks. To test this conjecture, we first consider the individual changes in risk taking between two subsequent stages of the decision process. Because participants had to allocate their wealth between a risky and a risk-free asset, we take the percentage allocated in the risky asset as the measure of risk taking. The summary statistics reported in Table 2 suggest that at all stages, about half of all individuals change their risk-taking behavior. Except in the stage after the experience sampling, where individuals increase their risk taking by 4% on average, risk-taking revisions do not have a clear direction.

Next, we test whether the risk-taking revisions are associated with individual characteristics observable in the corresponding stages. The relevant characteristics of the stages that differ among individuals are linked to (1) the demand for information on the risky asset, (2) an improvement in the risk awareness after the experience sampling, and (3) the average portfolio return with past investment decisions, expectations and satisfaction with these returns. Table 3 reports summary statistics on risk-taking revisions between two subsequent decisions. It also includes the results of independent tests on the association of individual characteristics observed in different stages of the decision process and the risk-taking revisions.

We observe that individuals acquiring information on the risky asset are more likely to change their risk taking. Additional Kruskal-Wallis tests, which are not reported here, suggest that the description type (verbal, graphical, and statistical) is not associated with either the risk-taking revisions or with the level of risk taking in the second stage. Furthermore, we observe that individuals who improve their awareness of extreme outcomes and extreme positive outcomes after the experience sampling take more risks on average. Finally, we observe that individuals change risk taking after receiving information on the outcomes of previous decisions. In particular, individuals who receive a bad (nonpositive) outcome on average reduce their risk taking, while individuals who receive a good (positive) outcome with previous decisions take more risks on average. Significantly more individuals change their risk taking after bad outcomes than individuals who change their risk taking after good

Table 3 Risk taking revisions and individual characteristics

	Level of risk taking revisions						
	Mean (in%)	SD (in%)	Min (in%)	Max (in%)	Kruskal-Wallis Test (p-value)	Individuals changing risk taking	Pearson χ^2-Test (p-value)
Acquire information							
No	−0.48	14.56	−50	50		0.47	
Yes	0.08	14.42	−57	50	0.510	0.59	0.036
Risk awareness							
q1 (extreme returns)							
Deterioration	−2.78	17.06	−48	30		0.65	
No change	4.03	16.22	−90	65		0.62	
Improvement	6.33	14.75	−30	53	0.070	0.57	0.665
q2 (low returns)							
Deterioration	4.53	13.72	−20	30		0.68	
No change	4.10	15.95	−90	65		0.61	
Improvement	3.19	18.28	−48	65	0.872	0.62	0.790
q3 (extreme low returns)							
Deterioration	4.05	12.61	−30	35		0.59	
No change	4.82	15.59	−40	65		0.61	
Improvement	−6.95	24.41	−90	10	0.351	0.63	0.959
q4 (extreme high returns)							
Deterioration	6.60	15.05	−20	50		0.76	
No change	3.16	15.68	−90	65		0.59	
Improvement	9.26	19.24	−30	65	0.068	0.65	0.249
q5 (volatility)							
Deterioration	4.32	14.60	−48	35		0.66	
No change	4.21	16.08	−90	65		0.61	
Improvement	2.41	17.96	−40	60	0.420	0.56	0.690
q6 (average return)							
Deterioration	8.27	16.39	−15	63		0.63	
No change	3.73	16.32	−90	65		0.61	
Improvement	2.57	11.69	−30	35	0.464	0.65	0.874
Average outcome							
Non-positive	−17.94	14.52	−50	0		0.89	
Positive	1.27	11.95	−50	55	0.000	0.54	0.003
Expectations							
Comforted	1.61	11.24	−50	45		0.52	
Disappointed	−2.68	15.30	−50	55	0.001	0.65	0.016
Satisfaction							
Comforted	1.58	12.60	−50	55		0.54	
Disappointed	−3.22	12.94	−48	30	0.002	0.61	0.149

The table presents summary statistics of risk taking revisions as well as the percentage of individuals changing risk taking over two subsequent decisions. It also reports the results of independent tests on the association between risk taking revisions and individuals' characteristics in different stages. In the case of variables with two categories, the Pearson χ^2-Test is equivalent to the one-sides Fisher exact test.

outcomes. Similarly, individuals disappointed by their previous returns tend to reduce their risk taking, while individuals pleased with their previous returns tend to increase their risk taking.

So far, we find that the stages of the decision process under consideration are associated with significant changes in individual risk taking. However, do individuals learn something about their willingness to take risks by going through the various stages? To answer this question, we asked individuals to state which investment decision they consider the best one. To avoid outcome bias, we asked this question just before the outcomes of their investment decisions were revealed to them. Approximately 30% of the participants who revised their risk taking stated that their best decision was the last one. Moreover, the association between risk-taking revisions and choosing the last decision as the best one is statistically significant (Fisher exact test, p value: 0.02). We conclude that the provided decision stages were helpful for participants involved in a process of discovering their willingness to take risks.

Overall, we find that individual risk taking changes significantly after receiving information on the risky asset, while the direction of risk taking depends on individual risk tolerance. Moreover, the individual risk taking increases significantly after improving risk awareness in the experience sampling task. Although the outcome of previous decisions should not change risk taking because outcomes cannot be accumulated over stages, there are significant differences in the risk-taking revisions of individuals experiencing good or bad outcomes on average with their previous decisions. Finally, we find that individuals involved in discovering their willingness to take risks learn successfully over the different stages of the decision process.

4.2. Explaining risk taking

In this section, we analyze the importance of individual risk tolerance, risk awareness and financial experience as drivers of investment risk taking. The evaluation of these factors is based on a factor analysis. The analysis shows that the answers to the twenty questions evaluating individuals' risk tolerance, risk awareness and financial experience can be summarized by three different factors, which are not correlated with each other (see Appendix C for more details).

In the following, we use these factors in ordinary least square regressions to test whether they can explain risk taking as expressed by the amount of wealth that individuals invest in the risky asset at each stage. Previous research suggests that demographic and socioeconomic characteristics influence an individual's risk tolerance and risk taking (see, e.g., Grable and Lytton, 2003; Sundén and Surette, 1998; Xiao, 1996). To take this into account, we use age, gender, number of children, education, job position, income, and wealth as controls in each regression. As an additional independent variable, we include an indicator variable that captures whether the individual acquires information on the risky asset. In the last decision, we include the average return of the previous investment decisions as a further independent variable. The estimation results are reported in Table 4.

We observe that among the three factors capturing the individuals' risk tolerance, risk awareness and financial experience, only the risk tolerance factor explains risk-taking

Table 4 Risk taking drivers

	Investment in the risky asset (0–100)							
Decision 1								
Risk tolerance	8.628***	9.651***					8.623***	9.622***
	(1.198204)	(1.095)					(1.209)	(1.098)
Risk awareness			−1.166	0.514			−0.396	0.759
			(1.492)	(1.434)			(1.384)	(1.289)
Financial experience					−0.451	1.555	0.347	0.985
					(1.6044)	(1.331)	(1.486)	(1.201)
Acquire	9.159***	10.201***	9.652***	9.761***	8.849**	10.349***	9.486***	9.738***
Information	(2.490)	(2.304)	(2.839)	(2.796)	(2.743)	(2.570)	(2.652)	(2.519)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
Adjusted R^2	0.2506	0.2297	0.1166	0.04133	0.115	0.04505	0.2457	0.2274
Decision 2								
Risk tolerance	9.353***	10.228***					9.464***	10.218***
	(1.2338)	(1.137)					(1.244)	(1.139)
Risk awareness			−0.1056	1.349			0.759	1.612
			(1.551)	(1.494)			(1.4244)	(1.337)
Financial experience					0.04716	1.651	0.971	1.005
					(1.665)	(1.388)	(1.529)	(1.245)
Acquire	10.295***	10.761***	10.157***	9.676**	10.108***	10.919***	10.127***	9.645***
Information	(2.564)	(2.392)	(2.951)	(2.913)	(2.848)	(2.680)	(2.728)	(2.611)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
Adjusted R^2	0.27	0.2368	0.1234	0.04445	0.1234	0.04625	0.2666	0.2373
Decision 3								
Risk tolerance	9.398***	10.172***					9.402***	10.196***
	(1.2339)	(1.140)					(1.245)	(1.145)
Risk awareness			−1.138	0.231			−0.298	0.565
			(1.5512)	(1.497)			(1.425)	(1.344)
Financial experience					−0.487	0.344	0.389	−0.247
					(1.667)	(1.392)	(1.531)	(1.252)
Acquire	10.7677***	10.739***	11.2282***	10.515***	10.430***	10.735***	11.049***	10.273***
Information	(2.565)	(2.398)	(2.951)	(2.920)	(2.850)	(2.687)	(2.731)	(2.626)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
Adjusted R^2	0.271	0.2341	0.1248	0.04179	0.1234	0.0419	0.2662	0.2297
Decision 4								
Risk tolerance	9.635***	10.719***					9.857***	10.67***
	(1.3872)	(1.248)					(1.3926)	(1.245)

(continued on next page)

Table 4 (Continued)

	Investment in the risky asset (0–100)							
Risk awareness			1.283	2.741			2.0013	2.686
			(1.680)	(1.600)			(1.5607)	(1.443)
Financial experience					0.7789	1.722	1.9091	1.146
					(1.8448)	(1.504)	(1.7153)	(1.354)
Acquire	12.646***	13.157***	11.31***	10.772***	12.154***	12.677***	12.137***	11.559***
Information	(2.882)	(2.628)	(3.224)	(3.076)	(3.1483)	(2.914)	(3.0074)	(2.778)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
Adjusted R^2	0.2279	0.2284	0.09951	0.05763	0.09824	0.05283	0.2298	0.2339
Decision 5								
Risk tolerance	9.176***	10.137***					9.087***	10.153***
	(1.262)	(1.144)					(1.272)	(1.147)
Risk awareness			−0.993	0.880			−0.503	0.873
			(1.5404)	(1.4811)			(1.426)	(1.330)
Financial experience					−1.837	0.093	−0.974	−0.41
					(1.687)	(1.389)	(1.567)	(1.248)
Acquire	10.414***	11.54***	10.258***	10.371***	9.291**	10.938***	10.414***	10.947***
Information	(2.623)	(2.408)	(2.9557)	(2.847)	(2.880)	(2.692)	(2.747)	(2.561)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
Adjusted R^2	0.2431	0.2335	0.1046	0.04461	0.107	0.04356	0.2391	0.2299
Decision 6								
Risk tolerance	9.4223***	10.143***					9.3997***	10.1586***
	(1.3302)	(1.184)					(1.341)	(1.186)
Risk awareness			−0.099	1.437			0.428	1.430
			(1.617)	(1.522)			(1.502)	(1.375)
Financial experience					−1.625	0.076	−0.660	−0.441
					(1.772)	(1.428)	(1.651)	(1.2905)
Acquire	9.992***	10.346***	9.368**	8.824**	8.905**	9.743***	9.607**	9.397***
Information	(2.763)	(2.492)	(3.103)	(2.925)	(3.024)	(2.768)	(2.896)	(2.647)
Average return	2.862***	2.911***	3.215***	3.371***	3.204***	3.379***	2.869***	2.899***
	(0.352)	(0.331)	(0.374)	(0.356)	(0.373)	(0.355)	(0.354)	(0.333)
Controls	Yes	No	Yes	No	Yes	No	Yes	No
Adjusted R^2	0.1957	0.2137	0.0545	0.0342	0.0573	0.0315	0.1908	0.2116

The table reports the estimation results of ordinary least square regressions with the percentage of wealth invested in the risky asset (0–100) as a dependent variable in each regression. Standards errors are given in parentheses. Age, gender, number of children, education, job position, income, and wealth are used as controls. ***, **, and *indicate significance levels of 1%, 5%, and 10%, respectively.

behavior at each stage. Its impact on risk taking is stable over different decision modes and is robust to demographic and socio-economic characteristics used as controls. The influence of the factors capturing individuals' risk awareness and financial experience on risk taking is statistically not significant. Interestingly, we observe significant and robust differences in the risk taking associated with the demand for information on the risky asset. Individuals who acquire information on the risky assets invest approximately 10% more in the risky asset than individuals who do not acquire information on the risky asset. Although individuals cannot accumulate returns of subsequent investment decisions, their risk taking in the last stage changes with the average outcome of their previous investment decisions.

4.3. Predicting risk taking

In the following, we analyze which combination of single questions has the strongest predictive power for risk-taking behavior. We apply a cross-validation analysis.[5] Table 5 reports the estimated coefficients of the variables with significant predicting power. The risk awareness assessed before (after) the experience sampling is used to predict the first (last) three investment decisions. The average return on past investment decisions is used only in the prediction of the last decision.

We observe that risk taking at all stages is best predicted by individuals' loss aversion. Its assessment is, however, critical. While a general loss aversion formulation is not helpful in predicting risk taking, a verbal question specifying returns and a quantitative version based on a lottery question are able to predict risk taking in all decision modes. By contrast, risk aversion measures based on self-assessment cannot be used to predict risk taking. Another important predictor of risk taking is the returns of past decisions. Although the odds of the outcomes do not change over time and returns cannot be accumulated, the participants take significantly more (less) risks after observing positive (negative) average returns with their past investment decisions.

In the context of the assessed risk tolerance, demographic and socio-economic characteristics have limited predictive power. To shed some light on them, we repeat the cross-validation analysis while excluding the risk tolerance and the investment experience questions. Table 6 reports the estimation results.

We observe that among the demographic and socioeconomic characteristics, gender is the most reliable variable in predicting risk taking. Females are less willing to take risks. As in the previous analysis, age can be a good predictor of risk taking but only in certain situations, while income loses predicting power. The effect of previous returns on subsequent risk-taking remains strong.

We conclude that assessed individuals' loss aversion is the most powerful predictor of risk taking at all stages and in the context of all other questions that we use with a potential impact on risk taking. We find that self-assessed knowledge, experience, and risk aversion are not useful in predicting individual risk taking. Finally, recommending less risky investment can be optimal for female individuals if there is no option to assess their risk tolerance.

Table 5 Predicting power of single questions

	Decision 1	Decision 2	Decision 3	Decision 4	Decision 5	Decision 6
General risk taking						3.5532* (1.3725)
General financial risk taking						
Current financial risk taking						
Past financial risk taking						
General financial loss aversion						
Verbal financial loss aversion	6.525*** (1.082)	6.438*** (1.115)	6.375*** (1.102)	7.537*** (1.204)	8.334*** (1.125)	5.040*** (1.268)
Quant. financial loss aversion	5.632*** (1.096)	5.088*** (1.108)	7.905*** (1.102)	8.04*** (1.204)	4.317*** (1.140)	3.941*** (1.086)
Financial investing for thrill						
Professional experience in finance						
Consumption of financial news						
Financial knowledge						
Statistical knowledge						
Financial trading experience						
Trading frequency		3.539*** (1.064)				3.576** (1.174)
Risk awareness 1						
Risk awareness 2						
Risk awareness 3						
Risk awareness 4						
Age class		−2.754** (0.998)				
Female						
Number of children						
Education						
Professional status						
Monthly income		2.674** (1.009)				
Wealth						
Average past return						8.137*** (0.971)
Acquire information	3.956*** (1.011)	4.316*** (1.007)			4.637*** (1.051)	2.745** (1.042)
Adjusted R^2	0.2789	0.3491	0.2995	0.2978	0.2889	0.4363

The table reports the estimates of cross-validation analysis with the percentage of wealth invested in the risky asset (0–100) as a dependent variable in each regression. Standards errors are given in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Table 6 Predicting power of demographic and socioeconomic characteristics

	Decision 1	Decision 2	Decision 3	Decision 4	Decision 5	Decision 6
Age class		−3.416** (1.161)			−2.921* (1.162)	
Female	−3.044** (1.145)	−3.843** (1.160)	−3.772** (1.171)		−4.173*** (1.165)	−3.401** (1.078)
Number of children						
Education						
Professional status						
Monthly income						
Wealth	−2.703* (1.201)					
Average past return						10.463*** (1.078)
Acquire information		4.739*** (1.160)	4.995*** (1.171)	5.535*** (1.288)	4.861*** (1.170)	
Adjusted R^2	0.035	0.092	0.072	0.052		0.252

The table reports the estimates of cross-validation analysis with the percentage of wealth invested in the risky asset (0–100) as a dependent variable in each regression. Standards errors are given in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

5. Discussion and implications

We found strong evidence that individuals' risk tolerance is a more powerful predictor of risk taking than investors' self-assessed investment experience or risk awareness. More important, we found that the association between risk tolerance and risk-taking remains significant over different decision stages related to reduced ambiguity, extended experience and feedback on previous decisions.

With respect to the impact of these decision stages on risk taking, we find that reduced ambiguity influences risk taking, but it does not necessary increase it, as documented by Antoniou et al. (2015). However, we find that extending experience with the risky asset through simulations increases risk taking, which is in line with the results of Kaufmann et al. (2013) and Bradbury et al. (2014). Furthermore, we observe that the average return of previous decisions influences the subsequent risk taking, although the odds of the possible outcomes remain the same and returns cannot be accumulated. As suggested by Fischhoff (1975), this behavior can be explained with a stronger focus on the risks (returns) after negative (positive) returns. It is also possible that individuals use outcomes to judge the quality of their previous decisions, as suggested by Baron and Hershey (1988). In this case, positive (negative) outcomes would increase (decrease) the confidence in the decision quality and individuals would increase (decrease) subsequent risk taking, as we observe in our experiment.

Risk tolerance measures are usually multidimensional, and the components can be correlated (Guillemette et al., 2015). We analyzed the predicting power of the components and found that an individual's loss aversion is the most powerful predictor of risk taking in all decision modes. This supports previous findings that loss aversion measures are more powerful in explaining risk taking than the Arrow-Pratt measures (Guillemette et al., 2012). Moreover, we found that self-assessed risk tolerance has no predicting power. Among the questions assessing investment experience, we found that only the question related to the trading frequency can predict risk taking in some decision modes. Overall, we do not find a positive relationship between investment experience and risk taking, which is in contrast to the results of Corter and Chen (2006). This can be explained with differences in the measures. While Corter and Chen (2006) ask individuals to evaluate their investment experience relative to other individual investors, our measures are based on individual trading experience.

Several studies suggest that risky asset ownership can be explained by demographic and socioeconomic variables (see for example Grable and Lytton, 2003; Sundén and Surette, 1998; Xiao, 1996). We found that among the assessed demographic and socioeconomic characteristics, only gender can predict risk taking in most decision modes but only if the individual risk tolerance cannot be assessed. If the risk tolerance is assessed, gender loses its predicting power. This observation is in line with the results of Wärneryd (1996) and Grable and Lytton (2003).

Our results have important implications for the design of risk profilers. To predict risk taking, the latter should include questions assessing the individual risk tolerance, which should include a question on the investor's loss aversion. Gender is a useful predictor of risk taking only if the risk tolerance cannot be assessed. By contrast, self-assessed investment experience is not a reliable predictor of risk taking, but the stated trading frequency can be used as a proxy for investment experience when predicting risk taking.

Another important predictor of risk taking is the past investment return. The latter influences the desired risk taking beyond the level based on the assessed risk tolerance. Hence, in addition to assessing an individual's risk tolerance, a risk profiler should either consider an investor's misperception of risk, or the latter should be corrected through additional measures. Otherwise, investors will be willing to revise their risk taking for no good reason.

6. Conclusions

The optimal amount of risk an investor should take is one of the most important issues in wealth management. Since answering this question through real-life investment experience can be costly, several studies suggest risk profiling measures and prove their suitability by showing that they can explain risk taking.

This article studied whether and how the suitability of different risk profiling measures varies if individuals are involved in a process of discovering their willingness to take risks. This process included situations with reduced ambiguity, extended experience and feedback on the outcomes of previous decisions, which reflect the experience of private investors. The results show that private investors are often involved in the process of discovering their willingness to take risks. The average risk-taking behavior changes over the different stages of the learning process, but it is always associated with a composite measure of the individual's risk tolerance. Overall, we did not find any significant association between risk taking and investment experience outside of the study, although sometimes the self-reported trading frequency can predict risk taking. Letting investors experience the riskiness of different asset allocations through simulations reduces biases in the risk-reward perception of the investors, but the investors' risk tolerance and loss aversion in particular remains a significant predictor of the individual risk-taking behavior at all stages of the decision process. By contrast, self-assessed risk tolerance measures appear to not be suitable for predicting risk taking at any stage of the decision process.

These results suggest that risk profiling measures should be selected carefully. When investors are involved in a process of discovering their willingness to take risks, some measures are more stable predictors of risk taking than others and should not be missed by risk profilers. By contrast, other measures may predict risk taking in only some or none of the stages, which limits their suitability. Using measures that predict risk taking at all stages of the discovery process increases the probability that clients remain satisfied with the derived recommendations. At the same time, making recommendations based on questions that consistently predict risk taking at all stages of the discovery process should support the advisors' confidence that these recommendations match the clients' risk tolerance and do not create misperceptions that are corrected over time.

Notes

1 Online studies allow effective access to a sample of the general population. Moreover, they allow tracking of the time individuals spend on each question.

2 We excluded all individuals who needed less than one and a half minutes to read the instructions and less than 15 minutes to finish the survey.

3 For the quantitative financial loss aversion question, we presented eight answer options. The last two possibilities were merged because only three individuals used the seventh possibility in their choices. The results of a robustness test with the combined answer possibilities shows that the results remain stable.
4 According to the literature, Likert scales can be considered an interval-based measure, that is, parametric analysis is appropriate (Carifio and Perla, 2007; Norman, 2010; Pell, 2005).
5 The analysis uses recursive feature elimination that removes the least important predictors of a model step-by-step. First, a model with all predictors is trained on a training set. The model is then used to predict the test set. The least important predictor is then removed from the model, and the whole procedure is repeated for all the subsequent subsets of predictors. To avoid any selection bias (e.g., over-fitting predictors and samples), the train and test data sets are resampled with a 10-fold cross-validation. After the resampling iterations, the most appropriate number of predictors is determined based on the resampling output. The predictors with the best rankings across all the resampling iterations are then used to fit the final model.

Appendix

A Experience sampling

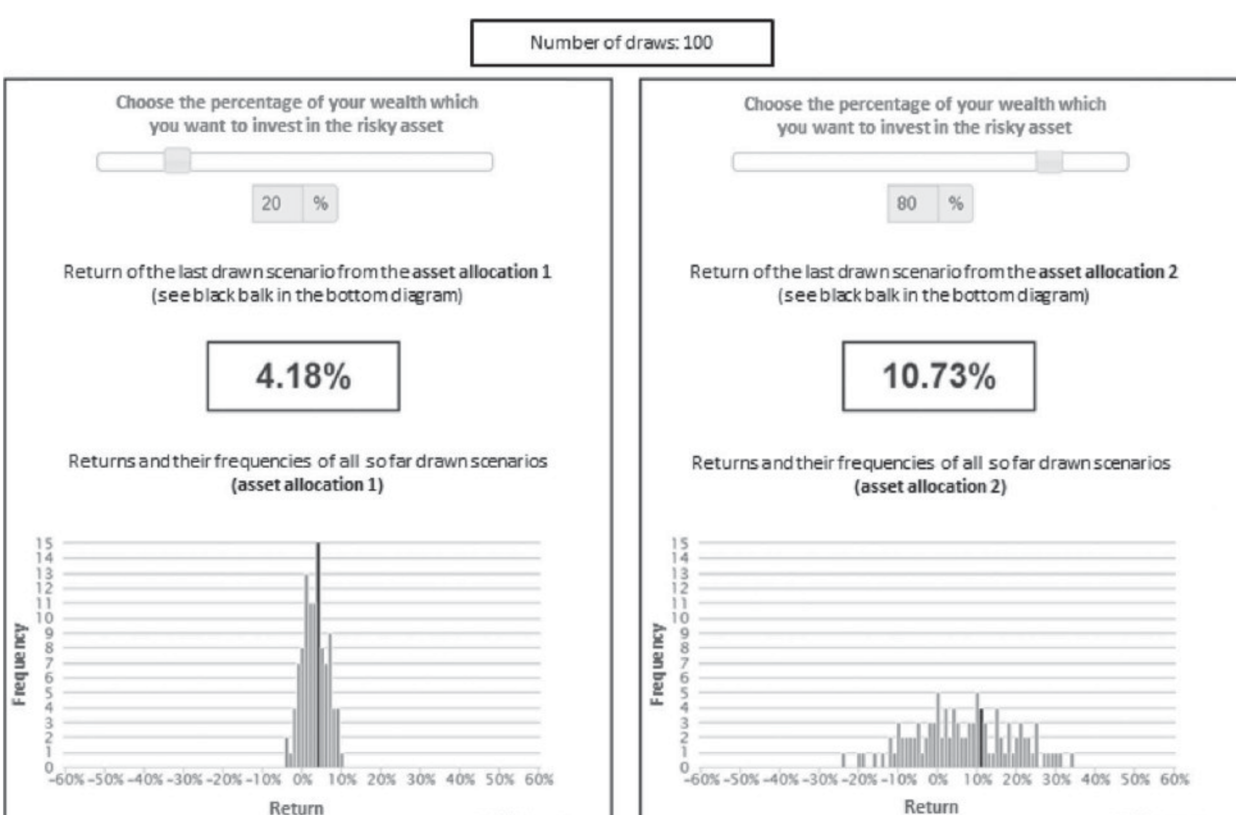

Fig. A-1: Illustration of the experience sampling.

B Socioeconomic and demographic characteristics

Table B-1: Sample description

	N	Percentage	Variable type
Age			Categorical variable
18–24	54	16.88%	0
25–34	44	13.75%	1
35–44	70	21.88%	2
45–54	82	25.63%	3
55–64	70	21.88%	4
Gender			Indicator variable
Male	147	45.94%	0
Female	173	54.06%	1
Number of children			Ordinal variable
0	201	62.81%	0
1	62	19.38%	1
2	43	13.44%	2
3	10	3.13%	3
4	4	1.25%	4
Education			Categorical variable
Primary school	10	3.13%	0
Secondary school	65	20.31%	1
High school	96	30.00%	2
Bachelor	39	12.19%	4
Master	45	14.06%	5
PhD	11	3.44%	6
Other education	53	16.56%	7
No education	1	0.31%	8
Professional status			Categorical variable
Self-employed/in family business	37	11.56%	0
Employee in top management	18	5.63%	1
Employee with leadership position	65	20.31%	2
Employee without leadership position	108	33.75%	3
Apprentice	47	14.69%	4
Unemployed	45	14.06%	5
Monthly income			Categorical variable
0–1,300 Euro	60	18.75%	0
1,300–2,600 Euro	94	29.38%	1
2,600–3,600 Euro	74	23.13%	2
3,600–5,000 Euro	54	16.88%	3
5,000–18,000 Euro	11	3.44%	4
> 18,000 Euro	1	0.31%	5
No answer	26	8.13%	
Wealth			Categorical variable
0–500 Euro	47	14.69%	0
500–2,500 Euro	44	13.75%	1
2,500–10,000 Euro	59	18.44%	2
10,000–30,000 Euro	46	14.38%	3
30,000–65,000 Euro	32	10.00%	4
65,000–175,000 Euro	30	9.38%	5
175,000 Euro	11	3.44%	6
No answer	51	15.94%	

C Factor analysis

Table C-1: Factor loadings with a varimax rotation

	Factors (before experience sampling)			Factors (after experience sampling)		
	Risk tolerance	Financial experience	Risk awareness	Risk tolerance	Financial experience	Risk awareness
General risk taking	**0.73**	0.18	−0.11	**0.73**	0.19	−0.11
General financial risk taking	**0.87**	0.29	−0.09	**0.87**	0.29	−0.04
Current financial risk taking	**0.65**	0.15	−0.01	**0.65**	0.15	−0.02
Past financial risk taking	**0.56**	0.34	−0.16	**0.56**	0.34	−0.17
General loss aversion	**0.4**	0.16	0.03	**0.4**	0.16	0.05
Verbal loss aversion	**0.74**	0.11	−0.16	**0.75**	0.11	−0.09
Quantitative loss aversion	**0.49**	0.11	0.13	**0.5**	0.11	0.17
Financial investing for thrill	**0.6**	0.49	−0.12	**0.61**	0.48	−0.08
Professional experience in finance	0.07	**0.59**	−0.14	0.08	**0.58**	−0.14
Consumption of financial news	0.3	**0.67**	−0.02	0.3	**0.66**	−0.01
Financial knowledge	0.33	**0.74**	0.01	0.32	**0.75**	−0.02
Statistical knowledge	0.16	**0.47**	0.27	0.15	**0.48**	0.18
Trading experience	0.15	**0.74**	0.14	0.14	**0.75**	0.13
Trading frequency	0.44	**0.63**	0.02	0.43	**0.64**	0.01
Risk awareness 1	0	0.07	**0.72**	0	0.09	**0.77**
Risk awareness 2	−0.16	0	**0.73**	−0.1	0.02	**0.68**
Risk awareness 3	−0.08	−0.03	**0.62**	−0.12	−0.08	**0.75**
Risk awareness 4	0.05	0.02	**0.89**	0.14	0.04	**0.88**
SS loadings	3.81	3.05	2.45	3.82	3.08	2.55
Proportion variance	0.21	0.17	0.14	0.21	0.17	0.14
Cumulative variance	0.21	0.38	0.52	0.21	0.38	0.53
Proportion explained	0.41	0.33	0.26	0.4	0.33	0.27
Cumulative proportion	0.41	0.74	1	0.4	0.73	1

D Questions

The following questions are assessed on a seven-point scale ranging from "not true at all" to "absolutely true."

General risk tolerance: In general, I am a risk loving person.

General financial risk tolerance: My risk tolerance when I am investing money is generally high.

Current financial risk tolerance: My current willingness to take risk in financial decisions is low.

Past financial risk tolerance: My risk tolerance in financial decisions was high in the past.

General financial loss aversion: When I am confronted with an important financial decision then I do concern more with the possible losses than with the possible gains.

Verbal financial loss aversion: For a 50-percent chance to earn a high amount of money with a financial investment I would be willing to risk an equal amount of money.

Financial investing for thrill: I already invested very often money because of the thrill if its value will go up or down.

Professional experience in finance: I collected the big part of my professional experience in the financial sector (investment advisory, insurance, asset management, trustee, tax counseling, auditing, and accounting).

Consumption of financial news: I am very interest in economic news.

Financial knowledge: I can explain to a friend very well at which things he or she has to look after in the case of risky financial assets.

Statistical knowledge: I can explain to a friend very well what a probability distribution is.

Quantitative financial loss aversion: You have the choice to invest 500 ECU in a risky or in a risk-free asset. The wealth will be invested for one year. With an equal probability (each with 50%) the risky asset will result in a positive return of 50% p.a. (i.e., 250 ECU) or in a negative return. The risk-free asset will result in a positive return of 2% p.a. (i.e., 10 ECU).

Risky asset		Decision		Risk-free asset
50% probability to get a return of	50% probability to get a return of	I prefer the risky asset	I prefer the risk-free asset	100% probability to get a return of
50% p.a. (250 ECU)	−8% p.a. (−40 ECU)			2% p.a. (10 ECU)
50% p.a. (250 ECU)	−15% p.a. (−75 ECU)			2% p.a. (10 ECU)
50% p.a. (250 ECU)	−22% p.a. (−110 ECU)			2% p.a. (10 ECU)
50% p.a. (250 ECU)	−29% p.a. (−145 ECU)			2% p.a. (10 ECU)
50% p.a. (250 ECU)	−36% p.a. (−180 ECU)			2% p.a. (10 ECU)
50% p.a. (250 ECU)	−43% p.a. (−215 ECU)			2% p.a. (10 ECU)
50% p.a. (250 ECU)	−50% p.a. (−250 ECU)			2% p.a. (10 ECU)

Are you sure? In comparison to the risk-free asset (2%) you prefer the risky asset (50% chance to get a return of 50% p.a. [i.e., 250 ECU]) if the possible negative return is not higher than −8%. p.a; beginning at a possible negative return of −15% p.a. you prefer the risk-free asset. Is this really your final decision?

Financial trading experience

Since how many years do you trade financial asset by yourself?

- I have never traded financial assets by myself.
- I buy and sell financial assets since about 1 to 3 years.
- I buy and sell financial assets since about 4 to 6 years.
- I buy and sell financial assets since about 7 to 9 years.

- I buy and sell financial assets since about 10 to 12 years.
- I buy and sell financial assets since about 13 to 15 years.
- I buy and sell financial assets since more than 15 years.

Trading frequency

How many times do you reallocate your financial assets, that is, how often do you buy and sell financial assets?

- Not at all
- About every second year
- About once a year
- About twice a year
- About four times a year
- About every month
- At least once a week

Risk awareness 1

The asset allocation with the highest probability for a strong negative and a strong positive return is:

- 10% risk-free asset/90% risky asset
- 40% risk-free asset/60% risky asset
- 80% risk-free asset/20% risky asset
- 35% risk-free asset/65% risky asset

How confident are you with your answer?: Not sure at all 1-2-3-4-5-6-7 Absolutely sure.

Risk awareness 2

Which asset allocation does not allow you to get a return higher than 2%?

- 5% risk-free asset/95% risky asset
- 0% risk-free asset/100% risky asset
- 100% risk-free asset/0% risky asset
- 75% risk-free asset/25% risky asset

How confident are you with your answer?: Not sure at all 1-2-3-4-5-6-7 Absolutely sure.

Risk awareness 3

The asset allocation with the greatest risk for negative return in the worst out of 100 cases is:

- 50% risk-free asset/50% risky asset
- 40% risk-free asset/60% risky asset
- 10% risk-free asset/90% risky asset
- 45% risk-free asset/55% risky asset

How confident are you with your answer?: Not sure at all 1-2-3-4-5-6-7 Absolutely sure.

Risk awareness 4

The asset allocation with the greatest potential for positive returns in the best out of 100 cases is:

- 60% risk-free asset/40% risky asset
- 20% risk-free asset/80% risky asset
- 5% risk-free asset/95% risky asset
- 15% risk-free asset/85% risky asset

How confident are you with your answer? Not sure at all 1-2-3-4-5-6-7 Absolutely sure.

Risk awareness 5

The asset allocation with the smallest variation of returns is:

- 20% risk-free asset/80% risky asset
- 45% risk-free asset/55% risky asset
- 80% risk-free asset/20% risky asset
- 30% risk-free asset/70% risky asset

How confident are you with your answer? Not sure at all 1-2-3-4-5-6-7 Absolutely sure.

Risk awareness 6

The asset allocation with the highest expected return is:

- 5% risk-free asset/95% risky asset
- 10% risk-free asset/90% risky asset
- 40% risk-free asset/60% risky asset
- 25% risk-free asset/75% risky asset

How confident are you with your answer? Not sure at all 1-2-3-4-5-6-7 Absolutely sure.

Descriptions on the risky asset

- Graphical description

In the following graphic, you see the realized returns and their frequencies of 280 randomly drawn scenarios for the risky asset. Higher bars mean higher frequencies.

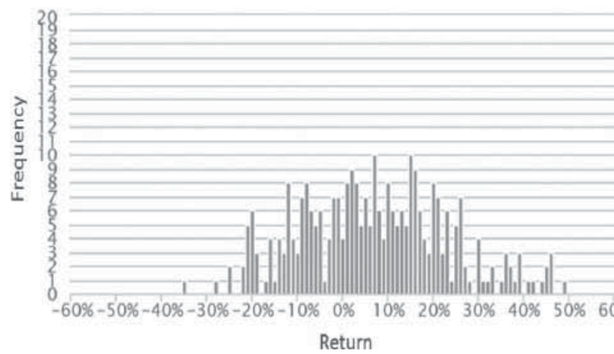

Fig. D-1: Example of a return distribution used in the graphical description of the risky asset.

- Verbal description

The average return for the risky asset over all possible scenarios is 7% per annum. In 70 out of 100 scenarios one can expect that the return falls between −10% and 24% per annum, and in 30 out of 100 scenarios the return is lower than −10% and higher than 24% per annum.

The positive or negative deviation from the average return is the same, and has the same probability. For example, a return of −3% has the same probability as a return of 17%.

- Statistical description

The returns are normally distributed with a mean of 7% and a SD of 16%. The normal distribution has the property that returns close to 7% are more probable than those further away, and that the probability of a return of −3% has the same probability as a return of 17%.

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Evaluating the relationship between IFA remuneration and advice quality: An empirical study

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Abstract

This article deals with the interaction between commission remuneration of independent financial advisers and selected sales factors, including the quality of advice. Utilizing data on investment transactions and a linear model with mixed effects, we have found that the link between commission and quality of the subsequent recommendation is not homogeneous, and advice-bias potential is present only in a limited range of organizational environments, connected mainly to the flat-structure business model. On the other hand, arbitrage between different product classes was found to create a biasing potential across almost all types of firms, creating potential for market systemic risk. Finally, the effect of information provided was proved to be significant only to a very limited extent.

JEL classification: G22; G23; G28; D14; D18

Keywords: Financial advice; Conflict of interests; Agent principal problem; Life insurance; Investments funds; Systemic distribution risk

1. Introduction

Commission based sales represent the principal distribution channel for financial products in many OECD countries. According to the Insurance Europe (2014) survey, financial agents (intermediaries, advisers etc.) accounted for nearly half (47.1%) of the new life insurance business in Germany, with other Central European countries showing a similar situation.[1]

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One of the most important areas in which advice is provided on a commission basis is pension planning, which in most cases leads to the purchase of a unit-linked life insurance, investment fund or personal pension product. As the OECD (2015) stated in its recent pension outlook, 24% of the member states' pension-linked assets are in those product classes, with a large portion of them being allocated on the basis of commission-remunerated advice.

While commission (third party inducement) remains the principal remuneration mechanism for agents, it is coming under increasing pressure chiefly on European soil. The main argument, as stated in the European Insurance and Occupational Pensions Authority (EIOPA, 2016, p. 41) advice on the Pan-European Pension Product (PEPP), is that "commissions which are often paid by product manufacturers potentially lead to a conflict of interest between the interest of the distributor to gain the commission and the interest of the customers to obtain nonbiased services from the distributor." Similar statements can be found in proposals linked to investment products (Markets in Financial Instruments Directive - MiFID II) and insurance distribution (Insurance Distribution Directive - IDD). Conflict of interest and its potentially detrimental effect on advice has even led to remuneration restrictions being applied, particularly in the area of unit-linked life insurance. From a theoretical perspective, potential bias created by commission based financial advice is grounded in the general agency theory, as the moral hazard and adverse selection problems (Ross, 1995). Both result in an inefficient contract for the primary principal (customer), whose bias is amplified by the introduction of a secondary principal (distribution firm). While there are abundant articles pointing to the biased service produced by agents operating on commission (e.g., Chalmers and Reuter, 2015; Gravelle, 1994; Inderst and Ottaviani, 2011; Palazzo and Rethel, 2008; Schwarz and Siegelman, 2015), many of them offer limited empirical background or are based on a less-conclusive (statistical) methodology. Some articles, on the other hand, did not find the commission-based remuneration to bear significantly negative consumer consequences (Gerhardt and Hackethal, 2009) or offered mixed results (Glazer, 2007; Tseng, 2011).

This article seeks to investigate the relationship between paid-out commission, complimentary sales factors and quality of advice provided by intermediaries (agents, financial advisors) in the area of investment products (investment funds, unit-linked insurance) in the Czech Republic, as the Central-Eastern Europe transit market. The article is divided into three parts: (1) an overview of current empirical findings is provided and research hypotheses constituted, (2) a statistical examination of the relationship of selected factors is carried out, and finally (3) resulting conclusions are summarized and discussed with reference to relevant literature.

2. Literature overview

As evinced by numerous studies (e.g., Lopez et al., 2006; Pullins, 2001), a reward scheme plays a crucial role in salesforce motivation. However, its interaction with the quality of advice provided to customers is the subject of scrutiny because of the central role such advice often plays in personal finance. In particular, the effect of a commission-based remuneration scheme is a well-covered theme of scientific literature. Table 1 summarizes the principal studies in this field.

From the factual perspective, the outcome of recent empirical studies underlines the schism outlined in the introduction. Although recent literature offers numerous articles on the topic, including an abundant group based on theoretical proofing (e.g., Gravelle, 1994; Inderst and Ottaviani, 2009), no unequivocally dominant pattern is evident. While many articles do point to a compromising effect of commission remuneration, there is a substantial body of research that fails to confirm this link, or even points to the opposite, in terms of customer benefit (a more detailed meta-analysis, with outcomes, can be found, e.g., in Burke et al., 2015). As a theoretical assumption for this article, taking a cautious approach, we shall presume that commission remuneration does have a negative effect on subsequent advice quality. Yet in reality, this is not a resolute hypothesis, but more of an open question.

Remuneration scheme, although deemed crucial, is not the only factor potentially influencing the quality of the advice and sales process. In this article, four additional variables were introduced to the model, with the following theoretical background.

2.1. Product type

Although to a large degree unit-linked insurance and investment funds share a common market and are often sold interchangeably, both product classes exhibit differences with regard to fee structure, product features as well as legal framework (for details see e.g., Ruprecht, 2007). These have been reported to affect advice quality in some markets, particularly in relation to the insurance business (Halan et al., 2014; Sane et al., 2013). Taking this experience into account, our expectation is that unit-linked life insurance will be more prone to poor advice.

2.2. Sales firm structure

Different internal structures of agent companies have been reported to provide different effects on quality of advice, especially in relation to multilevel marketing systems (Reifner et al., 2012). Looser structures with lower emphasis on group-incentivizing, on the other hand, have been found to be more supportive of advice quality (Danilov and Biermann, 2013). We expect to find a similar pattern, with structural networks generally more susceptible to biased advice than flatter "branch like" entities.

2.3. Sales firm size

There is a conflicting view of how the size of a distribution firm can potentially affect the quality of its service. While some studies suggest that increasing size leads to higher adviser misconduct (Egan et al., 2016), others have found quite the opposite, either praising advice provided by medium-large chains (Australian Securities and Investments

Table 1 Meta-analysis of recent empirical studies

Study	Method	Product/regional focus	Surveyed sample	Results
Anagol et al. (2012)	Mystery shopping (audits), univariate regression	Life insurance 2011 (India)	304 insurance sales-agents (557 audits)	Core findings of the quality of advice experiment: Between 60 and 80% of audits ended with a recommendation of less suitable insurance policy (whole insurance) with higher commission*** Even when auditors signaled that they are most interested in term insurance and need risk coverage, more than 60% of audits result in whole insurance (unit-link) being recommended*** Agents primarily cater to customers (either their beliefs or needs) by recommending that they purchase term insurance in addition to whole insurance, as opposed to recommending term insurance alone.
Popova (2010)	Behavioral experiment (sender-receiver game), Wald test, *F* test	Insurance dummy 2009–2010 (Germany)	314 undergraduate students	Major findings of the behavioral experiment: In all treatments but one, the frequency of truthful advice is higher with direct payment than with commission payment*** The obligatory direct payments by clients are not appropriate for reducing the conflict of interest of advisors*** The large voluntary direct payment by clients is the most successful mechanism for reducing the conflict of interest of advisors***
Chalmers and Reuter (2015)	Annual return, Annual volatility, OLS regression	Retirement portfolios (funds) 1999–2009 (USA)	5 807 participants of optional retirement plan (ORP)	Major differences of advised portfolios in comparison with target-date fund performance: Lower after-fee annual returns ($\Delta = -2.98\%$)*** Higher volatility of returns ($\Delta = 0.43\%$) Lower Sharpe ratio** Higher average fees ($\Delta = 0.90\%$)
Cupach and Carson (2002)	Questionnaire survey, *F* test, χ^2 test	Life insurance 2002 (USA)	336 insurance sales-agents	Results indicate that: Neither amount of coverage nor type of coverage recommended varied across the five alternative compensation conditions (no statistically significant link) Neither commission level nor fee for service level influenced the likelihood of product recommendation (no statistically significant link)

(continued on next page)

Table 1 (Continued)

Study	Method	Product/regional focus	Surveyed sample	Results
Gerhardt and Hackethal (2009)	Portfolio characteristics (equity share, Sharpe ratios, and so forth), *t*-test statistics	Investment funds 02/2006–07/2007 (Germany)	597 investors who switched from non-advised to advised during the sample period (subsample)	Major effects of investment advice in comparison with nonadvised investors: Higher trading activity*** Less risky and speculative trading Rising diversification**/*** No rising ratio of expensive products sold (kickback payments)
Li (2015)	Investment characteristics (excess returns, net flow, fees, front load), OLS regression	Investment funds 10/1999–6/2012 (USA)	424,115 total observations (actively managed equity funds)	Fund flows indicate that: Return chasing is stronger among funds sold with high (up-front) commissions*** Among multiple asset classes, return chasing increases with broker commissions*** Most of the impact is on the purchase of past winners***, with no detectable effect on the redemption of past losers Investors in institutional shares exhibit almost as much return chasing as retail investors***
Linainmaa et al. (2015)	Investment characteristics (net returns, excess returns, front-end loads, trailing commissions), *t*-test, *F* test	Investment funds 1/1999–6/2012 (Canada)	581,044 investors, 5,838 advisors	Major findings regarding advised portfolios: If the advisor benefits from the trade, the client also benefits from the trade 57% of the time (trades that are both costly to the client and without apparent benefits, but benefitting the adviser account for 5.4%) A disproportionate number of the trades identified as self-serving (costly, only advisor benefits) are concentrated among a small number of advisors (3.3%), net returns alphas decrease sharply in those clients' portfolios
Tseng (2011)	Questionnaire survey, χ^2 test	Life insurance 2010 (Taiwan)	361 full-time life insurance salespeople	Major outcomes in relation to the tested scenarios: 78.4% of the respondents would sell a policy with an interest rate beneficial to the customer instead of the one beneficial to their company*** 73.6% of the respondents would sell a policy in line with customer needs instead of the one beneficial to their company*** 68.8% of the respondents would sell a policy both to a healthy and unhealthy customer, notwithstanding the effect on his company

*p value < 0.1; **p value < 0.5; ***p value < 0.01.
OLS = Ordinary Least Squares regression.

Commission, 2003), or implying that smaller firms in fact offer limited services and restricted advice (Eckardt and Räthke-Döppner, 2010). Based on knowledge of the surveyed market, we presume that larger companies will incline to lower quality of advice, that is, increasing size of the company will have a negative effect on the excellence of its service.

2.4. Information available to the salesforce

There is little doubt that salesforce competence and professionalism represents a strong stimulus to customer satisfaction and trust (Ali et al., 2015; Johnson and Grayson, 2005; Tsoukatos and Mastrojianni, 2010). Furthermore, a direct link between specialized information provided to individual agents and the subsequent quality of their service has also been proven (Eckardt and Räthke-Döppner, 2010). Accordingly, a positive effect of information granted to the salesforce is also expected within our sample.

2.5. Research hypotheses

Based on the previous theoretical overview and prospected model composition, we set a total of five research hypotheses:

H_1: The amount of commission paid out for insurance products differs significantly from investment funds.

H_2: There is a significant correlation between the amount of commission paid out and the number of product trainings provided to the salesforce.

H_3: The there is a significant correlation between the amount of commission paid out and the advice quality.

H_4: There is a significant difference between the amount of commission paid out for insurance products among diverse sales firm structures.

H_5: There is a significant difference between the amount of commission paid out for insurance products among diverse sales firm sizes.

2.6. Data

The data for the empirical part of our survey was provided by eight independent advisory companies (no exclusive ties or direct ownership by financial institutions), who were asked to provide a full listing of the intermediated sales for a random month of the year.[2] Their overall sales performance is outlined in Table 2.

By combining the individual listings from the above participants, data on a total of 10,105 transactions performed in the years 2013–2015 on the basis of advice provided by financial agents was gathered. Only investment products (UCITS[3] vehicles) and investment-insurance products (unit-linked[4]) were concerned. Overall, the transactions recorded, encompass 55

Table 2 Overview of companies participating in the research

Company	Structure	No. of individual advisers (2015)	No. of new life insurance contracts[a] sold (2015)	Market share in life insurance[a]–IFA market (2015)	No. of new investment funds contracts sold (2015)	Market share in investment funds–IFA market (2015)
A	MLM	4 692	66 744	27.153%	37 808	19.105%
C	Pool	1 784	29 672	12.071%	17 780	8.984%
B	MLM	886	30 232	12.299%	20 472	10.345%
D	Flat	370	7 292	2.967%	14 844	7.501%
E	MLM	95	3 488	1.419%	916	0.463%
H	Flat	28	292	0.119%	324	0.164%
G	Flat	13	468	0.190%	160	0.081%
F	Flat	5	47	0.019%	21	0.011%
Total	—	7 873	138 235	56.237%	92 325	46.652%

IFA = Independent Financial Advisers.
[a]Regularly paid contracts.

unique insurance/investment products and were advised on by a total of 2,658 individual agents. Their basic overview is stated in Appendix 1, stipulating that the majority of the recommended investments were following dynamic strategy with a minimum of five years maturity, which is consistent with a longer-term horizon of most financial (pension) plans. Furthermore, the survey only incorporated regularly (monthly) paid instruments, which form the backbone of pension planning.[5]

Within the sample, each transaction was described by a set of variables linked to the factors described in the theory chapter. The linkage between general factors and research variables is outlined in Table 3.

From the structural perspective, the survey sample represents a very diverse portfolio. Summary statistics of all variables are outlined in Appendix 2.

2.7. *Quality assessment*

As mentioned in the theoretical part, the indicator of advice quality (QUAL) is one of the volatile parts of recent research. In this study, the indication of advice (recommendation) quality is based on the evaluation carried out by panel of independent experts.[6] The advantage of this approach is that it can capture additional information above the purely financial/quantitative metrices, as demonstrated by relationships indicated in Appendix 1. The panel rated every product that was recommended inside our sample in three basic dimensions: (1) Price – economical attributes of the product (fees, potential yield through the life-cycle of the product), (2) Quality – availability, accessibility of the product and related customer care, and (3) Sustainability – transparency and sustainability of the product (as it is being offered or promoted).

From a methodological perspective, all three dimensions of quality were defined in a way that is positively associated with customer utility (i.e., higher value always brings higher benefit) and not mutually contradictory (e.g., better Price rating not interfering with the Sustainability one), similarly to Tseng (2011) and Anagol et al. (2012) studies. Our aim was not to assess the individual suitability of given products, but rather to evaluate, whether advisers might be stipulated to offer lower quality products with a higher reward on a global scale.

Each of the experts had to provide his individual multicriterial assessment not only regarding the three quality dimensions, by ordinally sequencing products in given categories (IF, UIL), but also by setting weights for their relative importance to customer decision-making in a given year. Every product was then awarded a number of points based on individual weights assigned and their relative placing, normalized between 1 (best rating) and 5 (worst rating), with the points corrected for different numbers of products between categories.

The expert body itself was proportionally composed of 355 members: academicians, independent experts, senior bank specialists, and senior financial advisors; with every member being approved by the governing board composed of respected industry figures The internal validity of the framework was further tested on samples of five random products from each category through the governing board ex-post examination. By this procedure, two

Table 3 Independent model variables–explanation

Theoretical factor	Variable	Indicator	Type	Denomination
Commission remuneration	COMM	Amount of front commission paid to the final (individual) agent[a]	Continuous	Czech Crown (CZK)[b]
Product type	PROD	Product classification	Nominal	Investment fund, Unit-linked insurance
Sales firm structure	STRUC	Firm classification into three groups	Nominal	MLM, broker-pool, flat structure
Sales firm size	SIZE	Firm classification into three groups	Ordinal	Big (>500 IFAs), medium (50–500 IFAs), small (<50 IFAs)
Information available to the salesforce	INFO	Number of trainings provided in relation to given product during the last 12 months[c]	Ordinal	Much higher than average, higher than average, similar to average number (in relation to the product type), less than average, much less than average

IFA = Independent Financial Advisers.

[a]We take into account only the initial commission paid out for the sale (up-front), which is the vastly preferred method of remuneration in the target market. Trailer commissions are negligible.

[b]Advice companies in our sample utilize only variable remuneration with no fixed component (fixed-commission model is negligible on target market). Because of commission being derived from size of the transaction, all of the commission amounts were transformed to a common comparative basis, representing 1,000 CZK payment (the most common level of contribution on target market).

[c]Introductory trainings for newcomers were excluded, only product trainings were taken into account.

Table 4 MTHM matrix

	M1	M2
M1: Main measurement	0.83	0.76
M2: Control measurement	0.76	1.0

different measurements were obtained, gaining material for the construction of a Monotrait-heteromethod (MTHM) matrix (Campbell and Fiske, 1959; Crocker and Algina, 2008). After correlating the two data lines with Goodman and Kruskal's γ ($p = 0.000$), we achieved the following results (Table 4).

The level of correlation achieved shows strong correspondence with both methods of measurement (Crocker and Algina, 2008 recommend 0.50 to be the minimum), providing proof of the (convergent) construct validity of the panel evaluation carried out.

3. Method

As mentioned above, this article deals with the evaluation of the link between selected sales factors and the quality of financial advice, in terms of a client's subsequent purchase. From the given set of variables, our basic research model is constituted as follows:

$$\begin{aligned}\log(\text{COMM} + 1) &\sim (\text{SIZE} + \text{STRUC})\\ &\times (\text{PROD} + \text{INFO} + \text{QUAL})\\ &+ (1|\text{ID\_COMP/ID\_IFA}). \end{aligned} \tag{1}$$

For the data analysis, the linear mixed effects models were used. In a classical linear model, with only fixed effects considered, it is assumed that all observations are independent. Since this does not hold true for the analyzed data (transactions done by one sales person could not be independent since they depend on the sales person's knowledge, experience etc., and, moreover, also transactions done under a given company are not independent for similar reasons), the random effects were introduced. Two nested random effects appear in our model: an effect of the sales person nested in the random effect of the company. In the model equation is such a setup written as 1ID_comp/ID_IFA. The fixed effects appear in the model in interactions which is denoted in the model equation by an asterisk. The baseline model of the form (SIZE + STRUC) * (PROD + INFO + QUAL) in fact means that we assume that the commission depends on PROD, INFO and QUAL in a priori different ways in different kinds of companies (according to their size and structure). Such differences are further tested and interpreted. The purpose of breaking the whole sample to partial subsamples defined by SIZE and STRUC is to capture the effect of these factors described in background literature, such as Reifner's et al. (2012) comprehensive study.

A p-values less than 0.05 was considered statistically significant. Analysis was conducted using R statistical package, version 3.2.3 (R Core Team, 2015). Variance analysis outcomes for the model are summarized in Table 5.

Table 5 Variance analysis outcome

	Sum Sq	Mean Sq	NumDF	DenDF	*F* value	*p*-value
STRUC	6.9091	3.4546	2	3	11.3158	0.0348
SIZE	1.3570	1.3570	2	183	4.4450	0.0364
PROD	42.2420	42.2420	1	2527	138.3682	0.0000
INFO	0.5126	0.5126	1	8822	1.6792	0.1951
QUAL	0.0731	0.0731	1	7267	0.2395	0.6246
STRUC:PROD	7.9718	3.9859	2	8847	13.0563	0.0000
STRUC:INFO	31.0775	15.5388	2	8771	50.8989	0.0000
STRUC:QUAL	19.7648	9.8824	2	9320	32.3708	0.0000
SIZE:PROD	3.3587	1.6794	2	8267	5.5009	0.0041
SIZE:INFO	3.1736	1.5868	2	9375	5.1977	0.0055
SIZE:QUAL	2.6662	1.3331	2	9061	4.3668	0.0127

Going through the p-values of the model, we observe that while two of the sales factors (INFO, QUAL) do not have a significant effect on commission on average, all of the factors have a significant relationship with a dependent variable when grouping variables (STRUC, SIZE) are taken into account. In other words, all of the surveyed sales factors interacted with the amount of commission paid out in each of the company contexts (delimited by the size and sales structure) in a significantly different manner. Detailed results in this regard are presented next.

4. Results

Consequently, our results are divided into nine different combinations of company size and sales structure, summarized by Table 6. Let us use sales structure as our primary differentiator, summarizing MLM, Pool, and Flat companies of different sizes into three distinct chapters.

4.1. MLM companies

The model estimates indicate three principal findings. First, in all of the MLMs, irrespective of their size, the difference between the two surveyed product classes (IF, ULI) has a significant effect on commission paid out, with the unit-linked insurance always providing significantly higher commission. Secondly, the information provided to the IFA-force, in terms of training frequency, affects commission level significantly only in a single type of firm—small MLM (positively). In the medium and large sized networks, its effect was not found to be significant on the given p level. Finally, our last factor (quality of purchased product) provides a significant outcome only in one environment—large MLM firms. A positive value of the estimate indicates that increasing advice quality provides lower commissions and vice versa; thus, implying that the inducement paid out to the sales force can distort the quality of IFA service in terms of the recommended purchase. Intensity of the effect, however, seems rather negligible.

Table 6 Results overview

	Estimate	Standard error	z value	*p*-value	Hypotheses
MLM, large sized					
Prod. difference effect	−0.504	0.022	−22.666	0.000	H_1 accepted
INFO effect	−0.003	0.009	−0.341	0.992	H_2 not accepted
QUAL effect	0.086	0.034	2.539	0.040	H_3 accepted
MLM, medium sized					
Prod. difference effect	−0.793	0.141	−5.603	0.000	H_1 accepted
INFO effect	0.090	0.069	1.294	0.500	H_2 not accepted
QUAL effect	0.426	0.426	1.000	0.702	H_3 not accepted
MLM, small sized					
Prod. difference effect	−1.925	0.453	−4.253	0.000	H_1 accepted
INFO effect	0.669	0.209	3.201	0.005	H_2 accepted
QUAL effect	−1.742	0.872	−1.997	0.146	H_3 not accepted
Firm pool, large					
Prod. difference effect	−0.685	0.030	−23.172	0.000	H_1 accepted
INFO effect	−0.162	0.013	−12.301	0.000	H_2 accepted
QUAL effect	−0.447	0.062	−7.268	0.000	H_3 accepted
Firm pool, medium					
Prod. difference effect	−0.973	0.146	−6.656	0.000	H_1 accepted
INFO effect	−0.069	0.071	−0.973	0.740	H_2 not accepted
QUAL effect	−0.108	0.431	−0.249	0.997	H_3 not accepted
Firm pool, small					
Prod. difference effect	−2.106	0.454	−4.637	0.000	H_1 accepted
INFO effect	0.510	0.210	2.432	0.052	H_2 not accepted
QUAL effect	−2.275	0.875	−2.599	0.033	H_3 accepted
Firm flat, large					
Prod. difference effect	0.117	0.413	0.283	0.993	H_1 not accepted
INFO effect	−0.443	0.185	−2.396	0.055	H_2 not accepted
QUAL effect	2.141	0.769	2.782	0.019	H_3 accepted
Firm flat, medium					
Prod. difference effect	−0.172	0.387	−0.444	0.955	H_1 not accepted
INFO effect	−0.351	0.171	−2.046	0.119	H_2 not accepted
QUAL effect	2.480	0.640	3.874	0.000	H_3 accepted
Firm flat, small					
Prod. difference effect	−1.304	0.187	−6.969	0.000	H_1 accepted
INFO effect	0.228	0.097	2.347	0.057	H_2 not accepted
QUAL effect	0.313	0.412	0.759	0.820	H_3 not accepted

4.2. Pool companies

According to our results, IFAs gathered under pool structures also receive significantly different commissions for both product classes, in favor of the ULI. Contrary to MLMs, however, the information provided to the IFA-force does significantly affect the amount of commission in quite an opposite case: with the large companies and in a negative manner. In other words, the more training the salespeople go through, the lower commission they are achieving.[7] The most dramatic, however, is the relationship between the amount of commission and the quality of the client′s purchase. Found significant in two environments (large, small), this factor exhibited a consistently negative direction of effect. In other words, advisers operating under a pool umbrella gain significantly higher reward when recommending products with higher quality. In these settings, therefore, the amount of commission does not exhibit a negative potential in terms of advice distortion.

4.3. Flat companies

The model estimates and *p*-values indicate that the medium and large sized flat companies represent the most neutral advisory model in our sample. None of the two product classes and or their difference had a significant effect on final IFA remuneration, the same being true for the amount of information provided. The only significant factor was the quality of the recommended product, which interacted with commission in a positive manner. This implies that the rewarding scheme had distortive potential on the final recommendation. The situation with small organizations of flat structure is rather different and resembles previous types. Different product classes earn significantly different commissions (in favor of ULI). The number of trainings was found (just) to have no significant effect, and product quality is clearly insignificant. Such results draw a sharp distinction with medium and large sized flat organizations.

Reviewing the results through our five research hypotheses, we have obtained rather diverse outcomes. The first hypothesis, based on product class effect on commission, was found effective on a wide scale and was confirmed (H_1 accepted) in two-thirds of the organizational types. Regarding the hypothesized effect of information provided to the salesforce through product trainings, these significantly affected commission only in two cases (H_2 accepted) of diverse structure and size, with no apparent connecting pattern. Our third and crucial assumption, depicting a statistically significant link between commission and quality of advice, was found to hold in five out of nine surveyed organizational environments (H_3 accepted). Finally, the remaining hypotheses (H_4 and H_5) were both related to the grouping variables (sales firm structure and size) and as such were identified as accepted during the initial variance analysis. All in all, variables included in our model were found significant in most cases, retrospectively validating the model composition.

5. Discussion

Compared with the theoretical basis, our survey for the most part indicates more favorable results than expected by other articles. It was confirmed that in the majority of sales organizations there are significant incentive differences between investment fund and unit-linked life insurance, creating a potential for advice bias and client detriment as described by Sane et al. (2013) or Halan et al. (2014). Despite this outcome, there are organizations that hold limited market share, but prove resistant to commission divergences, operating with flat business structure. Regarding the effect of information provided to the sales force through product trainings, observations conducted by Eckardt and Räthke-Döppner (2010) were not confirmed. Significant effects produced by this factor were detected only in a very limited range, indicating that the popular thesis of more education leading to higher earnings is not valid in our IFA sample.

Sales firm structure and size were identified as crucial elements of the advice process, in accordance with indirect implications published by Reifner et al. (2012), Danilov and Biermann (2013), and Egan et al. (2016). Confirmation of those two factors shows that judging the whole IFA segment as an internally homogeneous sum of individuals, as exhibited in articles Cupach and Garson (2002), Anagol et al. (2012), and Popova (2010) is fundamentally inappropriate, as there are statistically significant functional differences between diverse organizational entities. A "one size fits all" approach, as embodied in many EU regulations (e.g., MiFID, IDD) and envisaged by part of the academia (Reifner et al., 2012), leads to redundant business costs and dubious consumer effect, given our empirical results.

Principal outcomes of the article are related to the remuneration–advice linkage. Theoretical expectations here were more in favor of a negative impact of commission remuneration on quality of subsequent advice. These expectations were largely disproved by our model. Only in three organizational environments did the data indicate a negative relationship between quality of a client's purchase and commission paid out to the IFA, creating a potential discord that could bias the advice. In only two environments of the same business structure (flat organizations) did the model estimate reach major value and these represent a minor part of the IFA market.[8] In other words, a remuneration scheme induced potential for recommending products with lower overall quality, as reported by Beyer et al. (2013) and Chalmers and Reuter (2015), or for mis-selling a totally inappropriate product as detected by Anagol et al. (2012) is not overly present in the target market. The results related to MLM systems mostly contrast with observations collected in other countries, notably by professor Reifner et al. (2012) and his team. Reifner's conclusion that "financial interest in the advice is much more biased" within the structured MLM networks (p. 78) cannot be considered confirmed.

6. Conclusions

The relationship between IFA remuneration and quality of subsequent advice is a frequent point of current research and policy making. Most of the previous studies found that a commission remuneration scheme has a biasing effect on IFA recommendations and subsequent client purchase. In this article, we found that the negative potential created by higher earnings for recommending less quality products is present only in a minority of the IFA organizations, particularly in the flat structures. Pool businesses, on the other hand, were diagnosed as more resistant in this regard, not exhibiting undesirable remuneration-based conflict of interest potential.

Our findings are bounded by three main limitations. We dealt just with the independent advisory part of the market, evading captive (dependent) bank and insurance company networks. Although similar results can be foreseen according to some articles

(Reifner et al., 2012), expanding the analysis on captive channels is vital as substantial sales production is realized through them on a (dependent) advice basis. The second limitation is related to the evaluation method utilized with regards to the quality indicator. Using a panel of experts' assessment brings an important new perspective on the topic, yet despite controlled validity, wider back testing of value-added by our alternative approach is vital. The final limitation is related to the macro level of the analysis. As such, it did not attempt to identify mis-selling in relation to individual transactions or clients, but aimed at uncovering main trends on the whole population, delimited by the survey sample. All these differences need to be taken into account, when interpreting study results and they also represent the main directions for following distribution research.

Notes

1 Slightly lower, yet proportionate numbers are true for investment funds (Kalus et al., 2015).
2 Excluding July, August, and December periods.
3 Collective investments as defined by the EU Undertakings for the collective investment in transferable securities (UCITS) directive.
4 Insurance-based investment products as defined by EU Directive on insurance distribution (IDD).
5 Third pillar pension savings product was omitted, because it already has a legal cap on commissions in force, preventing a meaningful analysis at this point. Second pillar and occupational pensions are not implemented in the target market.
6 For this purpose, we utilized the Financial Academy of the Golden Crown (Zlatá koruna, 2016) institute. Golden Crown provides an independent, arguably most renowned and prestigious high-level financial product rating in the Czech Republic. As of 2016, it evaluated a total of 191 products in 15 product categories.
7 In the case of small pools, the effect was nearly significant, in a positive direction.
8 According to analysis created by independent group (Experti na finance, 2016), out of the top 10 IFA companies in the Czech Republic, which account for about two-thirds of the independent advice market, MLM represent 78.64%, while pool structures remaining 21.36% (in terms of sales force size).

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Appendix 1 Products participating in the survey–an overview

Product	Product type	Profile	Recommended investment horizon (years)	Return - 1 year (%)[a]	Return - 3 years (cummulative, %)[a]	Costs (synthetic TER, %)[a]	Quality rating 2013	Quality rating 2014	Quality rating 2015
Product 1	IF	Life cycle program	25	10,2	15,92	2,3	2,480225	2,48536	
Product 10	IF	Life cycle program	15	1,37	3,43	2	2,273284	2,314452	2,138568
Product 11	IF	Conservative program	3	−0,49	1,38	1,73	2,497372		
Product 12	IF	Balanced program	5	4,31	6,28	2,32	2,743097		
Product 13	IF	Dynamic program	5	7,03	28,61	0,63		2,642656	
Product 14	ULI	Balanced program	5	7,31	15,9	4,62			2,885515
Product 15	ULI	Dynamic program	5	5,43	7,43	1,84			2,392672
Product 16	ULI	Dynamic program	5	14,12	17,99	2,8	2,20182	1,975459	2,180337
Product 17	ULI	Life cycle program	25	1,73	3,83	4,85	2,778998	2,607632	2,712775
Product 18	ULI	Dynamic program	5	−0,57	11,34	1,9	2,339839	2,361079	
Product 19	ULI	Dynamic program	5	8,18	5,27	3,86	2,627552	2,571915	2,864871
Product 2	IF	Dynamic program	5	6,76	18,43	2,3	2,493647	2,30985	2,339845
Product 20	ULI	Dynamic program	5	−0,04	3,98	2,5	2,671658		
Product 21	ULI	Dynamic program	5	5,72	12,92	2,22	2,889328		
Product 22	ULI	Dynamic program	5	11,41	16,96	3,06	1,971123	1,933884	2,024371
Product 23	ULI	Dynamic program	5	13,59	−1,1	1,98	2,772256	2,766622	2,723382
Product 24	ULI	Balanced program	5	0,55	9,23	2,29		2,217117	2,344764
Product 25	ULI	Balanced program	5	6,43	7,87	2,64		2,838216	
Product 26	ULI	Dynamic program	5	21,08	30,3	1,92	2,414762		2,560245
Product 27	ULI	Dynamic program	8	7,74	10,64	2,21	2,555123		2,684126
Product 28	ULI	Dynamic program	5	15,44	29,54	2,58	2,742654		
Product 29	ULI	Conservative program	6	1,08	6,91	2,3	2,856997	2,951176	
Product 3	IF	Dynamic program	5	23,28	24,27	2,4		2,461865	
Product 30	ULI	Dynamic program	5	9,02	14,68	3,54	2,868403	3,015177	3,007638
Product 31	ULI	Dynamic program	6	5,72	8,88	3,32	2,908875	2,863058	2,787148
Product 32	ULI	Dynamic program	5	7,8	15,73	3,85	2,991677		
Product 33	ULI	Dynamic program	8	8,46	12,77	2,29	3,019517		
Product 34	IF	Dynamic program	8	7,5	1,5	2,18	2,532791		
Product 35	IF	Dynamic program	7	20	33,7	1,78	2,573775		
Product 36	IF	Life cycle program	25	9,3	7,6	2,2	2,658701		
Product 37	IF	Dynamic program	5	20,9	21,1	2,16	2,744353		
Product 38	IF	Conservative program	3	2,7	5,2	1,37	2,758696		
Product 39	IF	Conservative program	3	−0,4	−0,7	0,75	2,767168		
Product 4	IF	Conservative program	3	4,88	1,79	2,05	2,27407		
Product 40	IF	Conservative program	3	−3,4	−1,3	1,39	2,786588	2,69611	
Product 41	IF	Dynamic program	5	1,9	19,2	0,81	2,812532		
Product 42	IF	Dynamic program	5	9,14	16,99	2,44	2,860614	2,652245	
Product 43	IF	Dynamic program	5	2,97	11,54	1,99	3,08283		3,009951
Product 44	ULI	Dynamic program	5	21,47	25,36	2,64		2,903099	
Product 45	ULI	Dynamic program	6	3,25	9,5	2,67		2,940381	2,849649
Product 46	IF	Dynamic program	5	4,56	6,78	1,3		2,427288	

(continued on next page)

Appendix 1 (Continued)

Product	Product type	Profile	Recommended investment horizon (years)	Return - 1 year (%)[a]	Return - 3 years (cummulative, %)[a]	Costs (synthetic TER, %)[a]	Quality rating 2013	Quality rating 2014	Quality rating 2015
Product 47	IF	Dynamic program	5	16,5	21,1	1,71		2,670891	2,538373
Product 48	IF	Balanced program	4	1,2	−3,1	1,54		2,85809	
Product 49	ULI	Dynamic program	5	−1,46	12,3	2,11			2,586947
Product 5	IF	Dynamic program	8	1,11	4,94	2,44			2,290644
Product 50	IF	Dynamic program	7	12,37	16	1,92			2,549412
Product 51	IF	Life cycle program	3	−0,05	2,68	2,51			2,665369
Product 52	IF	Balanced program	3	3,1	0,8	1,31			2,692909
Product 53	IF	Balanced program	4	4,7	11,3	2,27			2,728509
Product 54	IF	Conservative program	3	−0,6	1,3	0,6			2,766896
Product 55	IF	Conservative program	5	−0,4	1,4	1,14			2,89131
Product 6	IF	Life cycle program	20	9,91	8,11	2,38	2,376598		
Product 7	IF	Dynamic program	5	6,42	11,6	1,77		2,238884	2,229873
Product 8	IF	Dynamic program	5	15,4	21,91	2,6		2,198387	2,140763
Product 9	IF	Balanced program	3	2,75	3,7	1,22			2,624633

[a] As of 2016. TER = Total Expense Ratio.

Appendix 2 Independent model variables–overview

Year	2013 (n = 2585)			2014 (n = 3382)			2015 (n = 4361)		
	Lower quartile	Mean/ median	Upper quartile	Lower quartile	Mean/ median	Upper quartile	Lower quartile	Mean/ median	Upper quartile
COMM	3033.5	783.8	10139.6	3317.8	8733.2	11367.3	2913.8	9260.9	12644.9
		5892.4			6553.3			6550.2	
$COMM_{IF}$	1387.0	5300.6	6703.9	1320.0	5229.3	6839.8	1346.2	4691.6	5720.0
		3312.0			3178.0			2856.3	
$COMM_{ULI}$	3810.2	8666.1	11209.7	4320.0	9813.5	12720.1	4653.7	11320.5	14995.2
		6749.7			7568.8			8918.9	
PROD	IF = 24.6%; ULI = 75.4%			IF = 23.5%; ULI = 76.5%			IF = 31.1%; ULI = 68.9%		
STRUC	MLM = 65.1%; pool = 27.0%			MLM = 59.0%; pool = 33.3%			MLM = 54.5%; pool = 38.6%		
	Flat = 7.9%			Flat = 7.7%			Flat = 6.9%		
SIZE	Big = 92.1%; medium = 7.7%			Big = 92.4%; medium = 5.5%			Big = 93.1%; medium = 0.8%		
	Small = 0.2%			Small = 2.1%			Small = 6.1%		
INFO	Much less than average (−2) = 7.93%			Much less than average (−2) = 11.97%			Much less than average (−2) = 24.07%		
	Less than average (−1) = 14.78%			Less than average (−1) = 18.97%			Less than average (−1) = 2.20%		
	Similar to average number (0) = 12.07%			Similar to average number (0) = 20.27%			Similar to average number (0) = 25.85%		
	Higher than average (1) = 55.05%			Higher than average (1) = 48.55%			Higher than average (1) = 47.72%		
	Much higher than average (2) = 10.17%			Much higher than average (2) = 0.18%			Much higher than average (2) = 0.11%		
INDIV	1,014			1,300			1,399		

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Portfolio insurance using leveraged ETFs

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Abstract

This study examines the use of Leveraged Exchange Traded Funds (LETFs) within a constant proportional portfolio insurance (CPPI) strategy. The advantage of using LETFs in such a strategy is that it allows a greater percentage of the portfolio to be invested in the risk-free rate relative to a traditional CPPI. Where a standard CPPI strategy may require 50% of the portfolio to be invested in equities, using a 2x LETF only requires 25%, and a 3x LETF only requires 16.7% to attain the same effective exposure to equities. Results show when the risk-free asset is yielding at least 3% or the 1 year minus 90-day Treasury exceeds 1%, the use of LETFs within a CPPI framework results in annual returns approximately 1–2% higher with better Sharpe, Sortino, Omega, and Cumulative Prospect Values while reducing Value at Risk (VaR) and Excess Shortfall (ES) below VaR.

JEL classification: G11; G17

Keywords: Portfolio insurance; Leveraged Exchange Traded Funds

1. Introduction

With two major market crashes in the last 17 years, portfolio insurance, or the protection of downside risk, has become increasingly important as "once in a century" events are occurring multiple times instead. The two main types of portfolio insurance are option based (Leland and Rubinstein, 1976) and constant proportionate portfolio insurance (CPPI) strategies set forth by Black and Jones (1987). Most option based ideas are premised on purchasing or creating synthetic puts on an index, effectively a protective put. The cost of

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this protection is usually quite high and although it reduces downside exposure, gains tend to be moderated significantly. CPPI strategies are based on a portfolio floor value where a percentage of the portfolio is invested in the risky asset and the remainder in a risk-free asset. If the risky asset value declines, the percentage in the risky asset is reduced. This exposure can decrease to zero if a decline in the risky asset causes the portfolio value to reach the floor, where the floor is defined as the minimum value that the portfolio can fall to over an investment period.

Research on portfolio insurance strategies is extensive with most research coming down on the side of CPPI. Cesari and Cremonini (2003) test different dynamic strategies including CPPI and option based portfolio insurance among buy-and-hold and constant mix strategies. They find CPPI strategies are dominant in bear and no-trend markets and considered more beneficial overall. Zieling, Mahayni, and Balder (2014) review an extensive research list and show that using a time varying multiple to dictate the amount of market exposure improves CPPI results. Pezier and Scheller (2014) show CPPI strategies are superior to option based strategies when implemented in discrete time. Annaert, Osselaer, and Verstraete (2009) compare strategies under a stochastic dominance approach and generally find one strategy does not outperform another, including buy-and-hold when considering first, second, and third order stochastic dominance. However, Maalej and Prigent (2016) finds CPPI outperforms option based portfolio insurance based on third order stochastic dominance. Bertrand and Prigent (2011) analyze option based portfolio insurance and CPPI strategies using downside risk measures and performance measures that consider the nonnormality of returns, otherwise known as Kappa performance measures. They find the CPPI method outperforms option based portfolio insurance using the Omega measure.

Kahneman and Tversky's (1979) Prospect Theory, which assumes investors weigh losses more than gains, is particularly relevant in terms of portfolio insurance for mitigating downside risk. Tversky and Kahneman (1992) expand this idea with the introduction of cumulative prospect theory. Dichtl and Drobetz (2011) use this idea to show portfolio insurance strategies are superior to buy-and-hold based on higher cumulative prospect values (CPVs).

This study attempts to combine aspects of both CPPI and option based portfolio insurance. Specifically, by incorporating Leveraged Exchange Traded Funds (LETFs) within a CPPI strategy, this study shows CPPI results can be improved. In a typical CPPI strategy where 50% of the portfolio is invested in equities, the use of a 2x LETF only requires 25% to be invested in equities while attaining the same effective equity exposure. Thus, rather than having only 50% earning the risk-free rate, 75% of the portfolio is earning the risk-free rate. Using a 3x LETF only requires 16.67% in the risky asset to attain the same 50% exposure.

The drawbacks of using LETFs are their higher expense ratios, inherent financing costs through their use of derivatives, and return decay over time relative to what the daily leverage ratio might imply. For instance, a 2x LETF usually falls short of multiplying the index return by two over longer holding periods. However, with more of the portfolio earning the risk-free rate relative to a standard CPPI using the underlying index, the gains on average exceed the costs. This study finds that if the risk-free rate is at least 3% or the one year minus the 90-day Treasury exceeds 1%, the simple substitution of LETFs for the underlying index within a CPPI strategy results in higher returns with better Sharpe, Sortino, Omega, and CPV values while reducing Value at Risk (VaR) and Excess Shortfall (ES) below VaR. Treasury rates less than 3% or flat yield curves generally eliminate the value of using LETFs in a CPPI framework.

However, even under low interest rate conditions, using LETFs within a CPPI framework does not result in extreme underperformance (less than 0.4% annually) relative to a standard CPPI. The drawback is with low T-bill rates, the advantage of having a LETF effectively "borrow" short so the investor can earn a higher return with excess funds over the year is eliminated. This drawback can be overcome to the extent an investor is willing to take on more risk by investing excess funds in higher performing but riskier assets such as a diversified bond fund.

2. Review of LETFs

Although leveraged mutual funds have been around since at least 1993, they did not gain traction until ProShares introduced the first 2x LETF in 2006. Since that time, they have expanded dramatically and as of 2017, there are more than 170 LETFs with $40+ billion in assets on a variety of assets and indexes including, gold, oil, foreign currencies, Treasury-bond futures, and a myriad of equity indexes.

In general, most LETFs magnify the daily return of an underlying index up to ±3.0x, although there are few funds that magnify the monthly return. Recently, several funds have been proposed to deliver ±4.0x, (Hunnicutt and McCrank, 2017). Strictly speaking, the proposed 4x funds will magnify index futures, but the effect will generally be the same because the cost of carry is mitigated because of the underlying dividends paid.

LETFs attain their leverage by using derivative assets such as futures and swaps. It should be noted that although the swaps are based on the underlying daily index returns and Libor, there is counterparty risk. Thus, a large gain to the LETF could theoretically not be paid by the counterparty. Although an unlikely scenario, not an impossible one.

The primary drawback to LETFs is realized leverage over time is usually less than what the daily multiple might imply (Trainor and Baryla, 2008). Thus, while the realized return over time often falls short of the daily leverage ratio, the risk does not. To enumerate, assume an underlying index falls 5% on Day 1, and increases 10% on Day 2 for a 2-day return of 4.5%. A 3.0x LETF would lose 15%, then gain 30% for a 2-day return of 10.5% resulting in an effective leverage ratio of 2.3 (10.5%/4.5%) instead of 3.0. This is often referred to as leverage decay and is a function of time, leverage, return trend, and volatility, with volatility usually being the significant determinant.

Realized leverage can mathematically be expressed by Eq. (1):

$$\frac{LR_T}{XR_T} = \beta + \frac{T\frac{(\beta^2 - \beta)}{2} \times [\mu_r^2(T-1) - \sigma_r^2]}{XR_T} \tag{1}$$

where LR_T is the return to the leveraged fund, XR_T is the underlying index return, β is the daily leverage ratio, T is time in days, μ_r is the mean daily return, and σ_r^2 is the standard daily population variance (Avellaneda and Zhang, 2010; Cheng and Madhaven, 2009; Trainor and Caroll, 2013). When $[\mu_r^2(T-1)-\sigma_r^2]$ is negative, the realized leverage over time will be less than the daily leverage ratio β. This effect is greater with higher leverage since a daily leverage ratio of 2x multiplies this term by one, $[(2^2-2)/2]$, but a daily leverage ratio of 3x multiplies this term by three. Lu, Wang, and Zhang (2012) generalized this leverage decay and suggest over holding periods no greater than one month, an investor can assume that a 2x/-2x LETF will maintain its leverage ratio and provide the expected return applied to the underlying index.

Most research generally concludes LETFs should be used for short-term trading strategies only, and the providers market them as such. However, if the trend μ is high enough, Trainor (2011) shows an investor can end up with a great deal more than the daily leverage ratio might indicate. A perfect example of this is ProShare's 3.0x UltraPro (UPRO) fund that magnifies the daily return of the S&P 500. Since the fund was introduced in June of 2009, the S&P 500 increased 183% through December 2016, while the 3.0x fund increased 1,045% for an effective ratio of 5.7x. This occurred over a period with high return trend and lower than average volatility.

Within a portfolio setting, DiLellio, Hesse, and Stanley (2014) suggest there may be a place for long-term holdings of LETFs as their results show LETFs may reduce a portfolio's standard deviation. From an option based portfolio insurance strategy, Trainor and Gregory (2016) show the results of using covered calls and protective puts with LETFs. Both strategies reduce risk, but significant returns are often sacrificed. Scott and Watsun (2013) suggest a floor-leverage rule where an investor places 85% of wealth in a risk-free asset and 15% in a 3x LETF. With annual rebalancing, they find this strategy can be used to manage risk and appears to be optimal for sustainable investment in retirement.

This study considers the use of LETFs in a CPPI context. The logic for using LETFs within a CPPI setting is straight forward. In a standard CPPI portfolio, the investor may start out with 50% in the risk-free rate and 50% in the risky asset. With a 2x LETF, the investor only needs to invest 25% in the LETF leaving 75% to earn the risk-free rate. If a 4.0x LETF becomes available, only 12.5% is needed. If the benefits of the additional return from having a greater percentage of the portfolio in the risk-free asset exceeds LETF's decay and higher expenses, then a CPPI using LETFs will outperform a standard CPPI strategy using the underlying index. This study determines this is indeed the case when the risk-free asset yields at least 3% or the one year minus 90-day Treasury exceeds 1%.

3. Methodology

This study explores the benefits of LETFs within a CPPI format. The S&P 500 is used as the underlying index and the 1-year treasury is set as the risk-free asset. Four different CPPIs labeled CPPI S&P, CPPI 2x, CPPI 3x, and CPPI 4x are compared using a 90% floor. Although there currently are no 4x funds, both ForceShares and ProShares have proposed them. The 90% floor is used to account for a typical 50/50 stock/bond portfolio where an investor wants to limit a stock loss to approximately 20% over any given year. Assuming no change in the value of a bond fund, a 20% loss in equities would hit a 90% floor value.

Table 1 Initial positions for CPPI strategies

CPPI	Floor (F)	Cushion	Multiplier (m)	% in risky asset	% in risk-free
CPPI S&P	$90,000	$10,000	5	$50,000	$50,000
CPPI 2x	$90,000	$10,000	2.5	$25,000	$75,000
CPPI 3x	$90,000	$10,000	1.67	$16,667	$83,333
CPPI 4x	$90,000	$10,000	1.25	$12,500	$87,500

Constant proportional portfolio insurance (CPPI) positions are initially set based on a 90% floor and are rebalanced with every 2.5% move in the S&P 500. Floor values are reset each year based on the portfolio value at the end of the previous year.

The proportion in the risky asset for the CPPI S&P at time t is calculated as the $\max\{\min[(m(V_P - F),V_P],0\}/V_P$ where m is the multiplier, V_P is the value of the portfolio, and F is the floor. The index multiplier is set at 5 which implies an initial 50% investment in the risky asset. Following Cesari and Cremonini (2003), the portfolio is rebalanced only when the underlying risky-asset (the S&P 500 in this study) increases or decreases by 2.5% since the last rebalance. Rebalancing once a week or once a month is also tested. For the latter, even if the market sheds 20% over the month, the floor would not be breached. This seems reasonable even for very risk averse individuals since a 20% loss in a single month has only occurred once post-WWII in October 1987 (−21%). The drawback of monthly rebalancing for LETFs is the leverage decay that can be experienced over a month. With weekly or 2.5% price limits, this is less likely to be an issue.

The benefit of using LETFs is 50% exposure can be attained with a smaller equity position. In the case of a 2x, the multiplier only needs to be 2.5 to attain the same 50% exposure. For a 3x, the multiplier only needs to be 1.67, and for the 4x, 1.25. Because it is assumed the investment in the risky asset is capped at 100%, the LETFs maximum exposure must be additionally constrained. The proportion in the risky asset for CPPI 2x at time t is calculated as the $\min\{\max(\min[(m(V_P - F),V_P],0)/V_P,0.5\}$ while the proportion in the risky asset for CPPI 3x at time t is $\min\{\max(\min[(m(V_P - F),V_P],0)/V_P,0.33\}$. For a 4x, the maximum exposure is 25%. The four initial positions using a portfolio value (V_P) of $100,000 for exposition are shown in Table 1 below.

While Table 1 shows the initial positions, Table 2 demonstrates how the CPPIs are adjusted after each rebalance using the S&P 500 SPY ETF and Proshare's 3x S&P 500

Table 2 Percentage changes in the CPPI strategies

2016	SPY Ret	% in S&P	CPPI S&P V_P	3x UPRO Ret	% in 3x	CPPI 3x V_P
1/4-1/7	−4.82%	50.00%	$0.98	−14.12%	16.67%	$0.98
1/7-1/13	−2.69%	39.00%	$0.97	−8.16%	13.12%	$0.97
1/13-1/29	2.59%	34.26%	$0.98	7.29%	11.52%	$0.98
1/29-2/5	−2.98%	38.75%	$0.96	−9.15%	12.99%	$0.96
2/5-2/11	−2.71%	33.91%	$0.96	−7.71%	11.16%	$0.96

Results show the returns of the underlying risky asset designated as the SPY ETF, the allocation to the risky asset (% in S&P, % in 3x), and the portfolio value with a start value of $1 for two of the constant proportional portfolio insurance CPPI strategies (CPPI S&P Vp, CPPI 3x Vp) from 1/4/16 to 2/11/16. UPRO is Proshare's 3x S&P LETF.

(Ticker UPRO) as an example. With each 2.5% change in the underlying index, the exposure is adjusted. The floor is rebalanced annually to 90% of the value of the portfolio at the end of the year. This implies an investor could be 100% in equities if the returns are positive enough. Because the floor is only reset annually, more than a 10% loss could occur within the year, but not for the entire year assuming there are no historic losses in any given day. The floor could be breached if equities declined by at least 20% in any given day before the portfolio could be rebalanced. Even this loss is likely not enough to breach the floor as the value of the bond portion of the portfolio would increase dramatically in such a scenario. In addition, even if a 100% equity position was held because of the increase in the portfolio value over the year, a 20% daily decline in equities would still be required to breach the 90% floor.

As an example of how the rebalancing is implemented, Table 2 shows the SPY falls −4.8% in the first 3 days of 2016. This breaches the 2.5% limit and the portfolios are rebalanced. This results in a reduction in the risky asset from 50% of the portfolio to 39% for the CPPI S&P. A similar type of reduction is made in the CPPI 3x portfolio as UPRO's 3x return is −14.12%. Alternatively, from 1/13/16 to 1/29/16, the market increases 2.6% leading to a percentage increase in the risky asset. Rebalancing occurs every time the index changes by 2.5% or more since the previous rebalancing. On average, 23 trades a year are required using a 2.5% barrier.

In January of the following year, the percentages are reset to their original values with a 90% floor based on the value of the portfolio at the end of December. It should be noted the results in this study do not explicitly account for brokerage costs or for bid-ask spreads, although the latter are usually a few cents a share at most. Because all the CPPI strategies require equal number of transactions, the relative results between the CPPI strategies are not biased, but depending on the size of the portfolio, may overstate results relative to buy-and-hold. For a $100,000 portfolio, brokerage costs would be approximately 0.2% annually.

Because the two major LETFs on the S&P 500 were not introduced until 2006 and 2009, respectively, theoretical LETF returns are calculated to attain a clearer picture of the risk/return characteristics from the CPPI strategies. The Center for Research in Security Price's (CRSP) S&P 500 value weighted portfolio is used as the risky asset and 2x, 3x, and 4x returns are calculated assuming a 1.2% annual expense ratio which is approximately 0.2 percentage points higher than the expense ratio for S&P 500 LETFs. The reason for the higher expense ratio is explained below.

Following Scott and Watsun (2013), the daily returns for the 2x, 3x, and 4x LETFs are calculated as:

$$R_L = L \times R_{S\&P} - R_{exp} - (L\text{-}1) \times R_f \tag{2}$$

where R_L is the daily return to the LETF with a daily leverage ratio of L, $R_{S\&P}$ is the daily return of the S&P, R_{exp} is the daily expense ratio, and R_f is the borrowing rate using the 90-day T-bill rate as a proxy. Strictly speaking, the one-week/month Libor rate should be used, but Libor data begins in 1986 and to remain consistent with sampled returns before this date, the 90-day T-bill rate is used. The 90-day T-bill has a 98% correlation with Libor and averages 0.2% less than Libor.

The logic behind Eq. (2) is a 2x has increased exposure by borrowing \$1 for every \$1 invested. A 3x borrows \$2 for every \$1 invested. Since LETFs primarily attain their exposure using swaps, there are imbedded financing costs increasing with leverage (Charupat and Miu, 2014). In addition, there are additional transactions costs not reflected in LETFs expense ratio that are generally higher for these funds because of the use of derivative contracts.

To test this pricing equation, theoretical daily, monthly, and annual returns for a 2x and 3x are compared with the actual daily, monthly, and annual returns of ProShare's 2x SSO and 3x UPRO on the S&P 500, and their 2x SQD and 3x TQQQ on the Nasdaq 100. To create near equivalence for daily, monthly, and annual returns between the LETFs and the simulated returns, the annual expense ratio is increased from 1.0 to 1.2% which coincides with the exact amount of the average difference between the 90-day T-bill and Libor. This results in average daily and monthly differences at or close to zero and average annual differences less than 0.1%. As an example of the differences, for 2016, the 2x SSO return is 21.5% while the theoretical return was 21.6%. For the Nasdaq 2x, both the 2x SQD and simulated 2x had returns of exactly 10.2%.

Based on the reliability of the results above, LETF returns are calculated from Jan. 1947 to Dec. 2016 using daily data based on Eq. (2). In addition to these results, empirical data using ProShare's 2x SSO is presented for 2007–2016. Finally, to determine the robustness of the results, block bootstrapping is used to resample 252 daily return windows to create 10,000 unique annual returns. The 252-day blocks are used to keep the continuity of the interest rate environments associated with the stock returns during that 252-day period, although 5, 22, and 63-day blocks are also examined with no substantial change in the average results. Because the floor is reset each year, this covers thousands of historically relevant 252-day periods. The drawback of using shorter blocks is that the interest rates experienced both in terms of financing and the risk-free asset used for investing excess funds tends to average out, and does not show what may occur in sustained extreme interest rate environments. Thus, sampling shorter blocks would bias the results.

Results are analyzed using a variety of measures. These include the average return, minimum return, maximum return, standard deviation, Sharpe ratio, Sortino ratio, VaR, ES, Omega ratio, and cumulative prospect values. The risk metrics are explained in Appendix 1.

4. Results

4.1. Historical results

Table 3 shows the annual performance and risk measures from 1947 to 2016 for the CPPI S&P, CPPI 2x, CPPI 3x and CPPI 4x. The multipliers of 5, 2.5, 1.67, and 1.25, respectively, determine the exposure to the risky asset that is rebalanced with a 2.5% or greater move in the S&P 500 relative to the last rebalance. The remaining allocation is invested in one-year T-bills. The floor is set to 90% of the portfolio value and is reset annually. Return data are provided for the respective risky assets with a 1.2% annual expense ratio and daily financing costs assumed for the LETFs based on Eq. (2).

Table 3 Annual returns from 1947 to 2016 for the underlying indexes and CPPI portfolios

	S&P	S&P 2x	S&P 3x	S&P 4x	CPPI S&P	CPPI 2x	CPPI 3x	CPPI 4x
Average	12.53%	21.91%	33.97%[b]	47.55%[b]	10.13%	10.60%	11.15%	11.48%
Standard deviation	17.02%	36.11%	58.89%	87.00%	11.79%	12.23%	12.58%	12.78%
Median	13.81%	24.51%	33.07%	42.43%	8.18%	8.38%	8.87%	9.24%
Minimum	−36.65%	−66.82%	−85.24%	−94.55%	−8.65%	−8.64%	−8.63%	−8.64%
Maximum	52.85%	127.45%	239.66%	402.99%	46.32%	46.65%	47.54%	48.15%
Sharpe Ratio	0.49	0.49	0.51	0.50	0.51	0.53	0.56	0.57
Sortino	0.80	0.78	0.87	1.02	2.21	2.39	2.62	2.78
VAR 5%	−15.47%	−34.35%	−49.77%	−62.56%	−6.58%[b]	−6.64%[b]	−6.34%[b]	−6.31%[b]
ES	−5.62%	−12.87%	−19.01%	−24.55%	−0.23%[b]	−0.40%[b]	0.33%[b]	0.38%[b]
Omega	5.96	4.67	4.66	4.79	13.52	14.56	16.06	17.11
CPV	7.47	5.76	5.34	5.33	14.20	14.56	15.01	15.24

Results show average annual returns from January 1947 to December 2016 for the S&P 500 along with three Leveraged Exchange Traded Funds (LETFs) and four constant proportional portfolio insurance (CPPI) strategies. 2x, 3x, and 4x CPPI strategies replace the standard S&P 500 with 2x, 3x, and 4x LETFs.

[a]Significantly better than the CPPI S&P at the 5% level.

[b]Significantly better than the S&P 500.

The first item to note is that all the LETFs suffer decay and their returns are positively skewed. For example, the S&P 3x average annual return of 33.97% is only 2.71 times the average annual return of the S&P. The riskiness of the LETFs is also apparent with extreme minimums, VaRs, and ES values. Based on Sharpe ratios, there is not a huge difference between them although LETF's minimums are daunting ranging from −67% to −95%.

However, there does appear to be benefits for LETFs within a CPPI strategy as all the LETF CPPIs display better average annual returns over the standard S&P CPPI ranging from 0.47% for the CPPI 2x to 1.35% for the CPPI 4x. There is some increase in the standard deviation for these higher returns, but the minimums, VARs, and ES are lower as reflected in their higher Sortino, Omega, and CPV values.

From a risk-return perspective, all four CPPI strategies dominate the S&P 500 based on risk metrics, but they do give up 2.46% to 1.37% annually moving from the CPPI S&P to the CPPI 4x. Because the LETFs are rebalanced after every 2.5% move, the −95% possibility of buying and holding a 4x is eliminated along with the fact the 4x can only be a maximum of 25% in the portfolio. Downside protection for the leveraged CPPIs is confirmed as the 90% floor is never breached for any of the CPPI strategies. For prospect theory type investors, the CPVs of the CPPIs do exceed the S&P 500 with increasing levels of CPV from CPPI S&P to the CPPI 4x.

Graphically, Fig. 1 demonstrates the value of CPPI strategies relative to a 100% investment in the S&P, and the value of using LETFs in a CPPI strategy as opposed to a standard CPPI portfolio. All of the CPPI strategies avoided the major drawdowns of wealth in the early 1970s, as well as in 2001 and 2008. There is a cost for CPPI strategies as their cumulative values all fall short of the S&P 500. It is also the case all the LETF CPPIs outperform the standard S&P CPPI.

Results thus far suggest LETF CPPI strategies appear to outperform a standard S&P CPPI strategy. However, part of the outperformance of LETF CPPI strategies has been the greater percentage of wealth that earns the risk-free rate. In effect, the LETFs are borrowing to attain

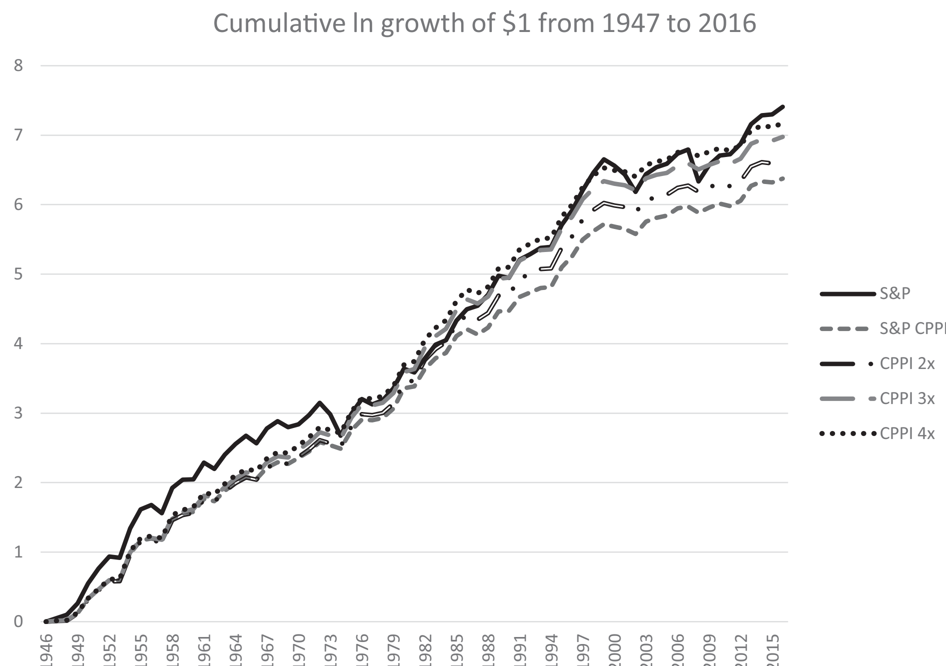

Fig. 1. Cumulative ln growth of $1 for the four CPPI strategies and the S&P 500 from 1947 to 2016.

increased exposure to the index. An investor using a LETF CPPI strategy needs to attain additional return with the excess funds to overcome the financing costs from the leverage and the associated higher expense ratio. To ascertain how well this works in different interest rate environments, Table 4 shows historical subperiods from 1947 to 1959, 1960–1978, 1979–1991, 1992–2008, and 2009–2016. These periods correspond to average rates of 2.0%, 5.59%, 10.87%, 4.71%, and 0.39% respectively.

As might be expected, when rates are low with a relatively flat yield curve as seen in 1947–1959 and especially during 2009–2016, there is little advantage to using a LETF CPPI with average returns less or not much greater than a traditional CPPI. During more "normal" interest rate periods such as 1960–1978 and 1992–2008, LETF CPPIs outperform a traditional CPPI by 0.3% to as much as 1.5%. An interesting find was that the CPPI portfolios have higher average returns than the S&P 500 during the 1960–1978 period as they avoided

Table 4 Average annual returns for different interest rate environments during 1947–2016

Time period	1-year T-bill	S&P	CPPI S&P	CPPI 2x	CPPI 3x	CPPI 4x
1947–2016	5.10%	12.53%	10.13%	10.60%	11.15%	11.48%
1947–1959	2.00%	18.30%	13.57%	13.38%	13.78%	14.06%
1960–1978	5.59%	7.51%	7.94%	8.50%	9.11%	9.51%
1979–1991	10.87%	17.56%	14.96%	16.72%	17.80%	18.40%
1992–2008	4.71%	8.81%	7.93%	8.20%	8.60%	8.82%
2009–2016	0.39%	14.81%	6.59%	6.20%	6.36%	6.41%

Results show average annual returns from January 1947 to December 2016 for the S&P 500 along with four constant proportional portfolio insurance (CPPI) strategies for various sub-periods corresponding to changing interest rate environments.

Table 5 CPPI annual returns based on SPY and ProShares 2x SSO LETF from 2007–2016

Year	1-year T-bill	SPY	SSO 2x	CPPI S&P	CPPI 2x	CPPI S&P w/AGG	CPPI 2x w/AGG
2007	5.94%	5.14%	1.04%	2.45%	2.26%	2.92%	3.23%
2008	4.60%	−36.81%	−67.94%	−8.62%	−8.60%	−2.94%	−2.51%
2009	0.56%	26.37%	47.26%	8.25%	8.13%	9.70%	10.58%
2010	0.55%	15.06%	26.84%	5.81%	5.66%	11.37%	13.70%
2011	0.37%	1.89%	−2.92%	−3.40%	−3.58%	−1.06%	0.40%
2012	0.16%	15.99%	31.04%	8.04%	7.64%	9.33%	10.68%
2013	0.34%	32.31%	70.47%	23.66%	22.92%	23.10%	20.34%
2014	0.24%	13.46%	25.53%	6.25%	5.81%	9.77%	12.08%
2015	0.16%	1.25%	−1.19%	−1.49%	−1.79%	−1.16%	−1.36%
2016	0.76%	12.00%	21.55%	6.22%	6.03%	9.41%	9.89%
Geo. Ann. Ret.	1.35%	6.87%	7.06%	4.40%	4.15%	6.79%	7.47%

Results show annual returns from 2007 to 2016 for the S&P 500 SPY, the S&P 500 2x (SSO), along with constant proportional portfolio insurance (CPPI) strategies using the S&P and S&P 2x. The last two columns replace the one-year T-bill with IShares AGG aggregate bond portfolio within the CPPI portfolios.

large losses and gave up little relative performance by investing in one-year T-bills. LETF CPPI's performed best during the 1979–91 period when the one-year T-bill return averaged 10.87%. Although this was much less than the S&P's 17.56% average, the 3x and 4x CPPI still outperformed the S&P itself. Relative to the standard S&P CPPI, all the LETF CPPIs outperformed by 1.76% to 3.44%.

Thus, during low interest rate or flat yield curve environments, there appears to be little advantage of creating LETF CPPI portfolios. In average or high interest rate environments, they outperform a standard CPPI. With LETF ETFs not being introduced until mid-2006, the results using actual LETFs are unlikely to be favorable relative to a traditional CPPI since the Federal Reserve has followed a near zero interest rate policy since the 2008 financial crisis. However, it is informative to examine how a LETF CPPI performs in practice.

Table 5 shows the returns from 2007 through 2016 using the SPY for the S&P 500 and ProShares 2x SSO. Although not shown, ProShares 3x UPRO has similar results. Both CPPI strategies perform as advertised as downside risk is mitigated and the −10% floor is not breached even in 2008 when the S&P fell 37%. Both CPPI strategies track each other, but the S&P CPPI strategy outperforms the CPPI 2x every year with the exception of near equal results in 2008. These results are mainly because of the fact the 2x still must deal with decay along with higher expenses and cannot make up the difference with additional earnings on the risk-free rate. These results reinforce the conclusions from Table 4 when rates are low.

In addition, when the risk-free rate was still relatively high in 2007 and 2008, the SSO 2x still underperforms because of the high volatility during that period causing serious return decay. In fact, for 2007, the 2x SSO only returns 1.04% compared with SPY's 5.14%, although half of the 4% underperformance is because of the large tracking error this fund had when first introduced. This tracking error has not been observed since. Furthermore, 2008 had the next largest tracking error when SSO returned −67.94% relative to the predicted −67.06% from Eq. (2). This tracking error has continually fallen since then and over the last 3 years has been less than 0.1% on an annual basis.

Table 6 Bootstrapped annual returns for the underlying indexes and CPPI portfolios

	S&P	S&P 2x	S&P 3x	S&P 4x	CPPI S&P	CPPI 2x	CPPI 3x	CPPI 4x
Average	12.31%	21.60%[b]	33.30%[b]	46.41%[b]	10.07%	10.59%	11.09%[a]	11.39%[a]
Standard deviation	16.72%	35.68%	57.99%	84.45%	11.88%	12.40%	12.74%	12.93%
Median	12.97%	21.22%	29.35%	35.74%	8.11%	8.36%	8.81%	9.06%
Minimum	−46.99%	−77.09%	−91.77%	−97.60%	−9.79%	−9.79%	−9.79%	−9.79%
Maximum	71.24%	175.88%	327.36%	530.57%	60.62%	66.33%	68.88%	70.19%
Sharpe Ratio	0.49	0.49	0.50	0.50	0.50	0.52[ab]	0.54[ab]	0.56[ab]
Sortino	0.95	1.08	1.29	1.50	1.37	1.51	1.66	1.75
VAR 5%	−15.63%	−34.94%	−53.34%	−70.40%	−5.51%[b]	−5.38%[b]	−5.26%[ab]	−5.17%[ab]
ES	−25.53%	−50.09%	−68.56%	−82.70%	−7.40%[b]	−7.32%[b]	−7.25%[b]	−7.20%[b]
Omega	6.18	4.75	4.73	4.86	14.10	15.18	16.40	17.17
CPV	8.70	9.43	8.71	7.17	14.83	15.48	15.98	16.28

Results show annual statistics based on 10,000 bootstrapped simulations for the S&P 500 along with three Leveraged Exchange Traded Funds (LETFs) and four constant proportional portfolio insurance (CPPI) strategies.

[a]Significantly better than the CPPI S&P at the 5% level.

[b]Significantly better than the S&P 500.

It is also interesting to note that both CPPI strategies lost money in 2011 and 2015 even though the SPY was slightly positive, 1.89% and 1.15%, respectively. This occurs because CPPI strategies are reactionary. When the market falls, the percentage of the portfolio in equities is reduced. When it bounces back, there is less wealth in the portfolio to regain the losses. Similarly, if the market increases (more is allocated to equities) then decreases. Thus, CPPI strategies tend to do poorly in volatile flat markets. The same holds true for LETFs because of their daily rebalancing. In fact, the SSO 2x lost money both in 2011 and 2015 despite the market increasing. This is a perfect demonstration of LETF's return decay.

For the less risk averse, Table 5 shows one alternative to overcoming extremely low interest rates. The last two columns show CPPI returns by combining a composite bond ETF within a CPPI strategy. Instead of using the one-year treasury from 2007 to 2016, IShares AGG bond ETF is used as a proxy for a relatively safe asset with higher expected returns. Both CPPI strategies show improvement and the LETF CPPI outperforms the standard CPPI except for 2013 and is only slightly worse in 2015. In 2013, both CPPI strategies using the IShares bond ETF underperform CPPI strategies using the one-year treasury. This is because of the −1.98% return the IShares bond ETF experienced that year. It was the only negative year for the aggregate bond fund, but highlights the fact that increasing expected return, even with a relatively safe bond fund, does have risks.

4.2. Bootstrapped results

To check on the robustness of the data, the historical data are blocked bootstrapped by sampling 252-day trading periods to create 10,000 annual returns to remove any bias from the January to January annual returns that may have favored one method or another. In addition, this will hopefully encompass most future possibilities while maintaining the relationship between interest rates and returns along with systemic low or high interest rate environments that may be experienced. Table 6 shows the results.

The returns and risk statistics confirm the earlier results with the LETF CPPI portfolios showing better returns and risk metrics relative to the standard CPPI based on Sortino, Value at Risk (VaR), Expected Shortfall (ES), Omega, and CPV. Although there are no statistical tests for significance for the Sortino and Omega values, the differences are monotonically increasing. The Sortino measure also suggests the 4x by itself has better return relative to downside risk even over the CPPI S&P, but this is mainly because of the very positively skewed returns for this asset resulting in a high average return. The median return shows the more likely result and is significantly less than the average for the 4x fund. Reconfirming the historical results, all four CPPI portfolios have better CPV values relative to the S&P 500, with the LETF CPVs greater than the CPPI S&P as well.

Both the CPPI 3x and CPPI 4x have significantly greater returns than the CPPI S&P. The CPPI 4x gives the best results despite using the riskiest asset. The caveat to the CPPI 4x results is there are no 4x LETFs currently in existence, and when and if they do make it to market, the expense ratio and cost of running these funds may be more expensive than what is assumed in this study. With no way to test the pricing model on an actual 4x fund, the 4x results should be interpreted with caution.

From an absolute return standpoint, CPPI portfolios have annual average returns 1% to 2% less and median returns 4% to 5% less than the S&P 500. Thus, CPPI portfolios do not provide "free" downside protection. However, the amount of average return sacrificed to avoid large losses would seemingly be appealing to risk-averse investors. The reduction in the minimums, VaR, and ES values bear this out along with much higher CPV values that measure the value to prospect theory type investors. For the risk-speculators, the average returns to the LETFs by themselves are enticing, up to an average 46% return with the 4x. However, these returns are coupled with up to −98% losses in any given year.

The question going forward is which CPPI strategy is likely to do best? Noting what has happened since 2007 when the T-bill rate is close to zero, a LETF CPPI loses its advantage if the additional funds are simply invested in the risk-free rate if rates are very low. To ascertain what risk-free rate of return one would need to overcome decay and the higher expenses from using a LETF, 40,000 bootstrapped annual returns are sorted based on the average T-bill return attained each year. The average T-bill return was 5.13% with a standard deviation of 3.84%. The top section of Table 7 shows the return data for when the T-bill rate is below 1% to greater than 7%.

Two conclusions are apparent from examining the top section of Table 7. For a LETF CPPI to outperform, a rate of 2.5% or more is required to make up for the additional costs from using LETFs. Two, when the rate is less than 2%, for those constructing a CPPI, a standard CPPI will be slightly better. Alternatively, an investor could redefine the "risk-free" asset to accommodate a relatively "risk-free" bond fund providing higher yield. Interest rates above 6% are very favorable to LETF CPPIs with returns up to 3% greater over the standard CPPI. In addition, rates over 7% seem to favor any CPPI, even over the S&P itself. They are particularly favorable to LETF CPPIs with average returns 1.5% to 3% greater than both the S&P and the CPPI S&P.

By using LETFs in a CPPI, the investor is in effect borrowing short via the LETF and investing in one-year Treasuries. Thus, the slope of the yield curve is a critical issue. Generally, lower rates are associated with a flatter yield curve and vice versa. Thus, returns

Table 7 Bootstrapped annual returns sorted by 1-year T-bill return and slope of the yield curve

	S&P	S&P 2x	S&P 3x	S&P 4x	CPPI S&P	CPPI 2x	CPPI 3x	CPPI 4x
T-bill return								
0–1%	17.41%	34.46%[b]	53.96%[b]	74.70%[b]	10.21%	9.81%	9.99%	10.09%
1–2%	17.92%	35.14%[b]	55.24%[b]	77.22%[b]	11.31%	11.05%	11.27%	11.39%
2–3%	6.62%	11.54%[b]	19.84%[b]	31.19%[b]	6.06%	6.03%	6.28%	6.44%[a]
3–4%	6.87%	11.64%[b]	19.02%[b]	28.32%[b]	6.36%	6.60%	6.97%[a]	7.22%[a]
4–5%	8.39%	13.59%[b]	20.55%[b]	28.08%[b]	7.05%	7.38%	7.80%[a]	8.06%[a]
5–6%	8.62%	12.45%[b]	16.97%[b]	20.99%[b]	6.92%	7.37%	7.84%[a]	8.15%[a]
6–7%	13.49%	23.08%[b]	34.69%[b]	47.07%[b]	10.90%	11.65%	12.26%[a]	12.62%[a]
>7%	13.44%	21.32%[b]	31.42%[b]	42.69%[b]	13.79%	15.43%[ab]	16.35%[ab]	16.87%[ab]
1 year to 90-day								
<0%	23.47%	47.97%[b]	79.43%[b]	117.76%[b]	17.03%	16.32%	16.51%	16.65%
0–1%	12.55%	23.08%[b]	35.23%[b]	47.77%[b]	7.61%	7.42%	7.64%	7.76%
1–2%	10.39%	17.51%[b]	26.64%[b]	36.83%[b]	8.18%	8.43%	8.83%[a]	9.08%[a]
2–3%	10.48%	17.26%[b]	26.23%[b]	36.41%[b]	9.41%	10.01%	10.54%[a]	10.86%[a]
>3%	12.02%	19.40%[b]	29.07%[b]	40.00%[b]	12.51%	14.12%[ab]	15.02%[ab]	15.54%[ab]

Results show average annual returns based on 40,000 bootstrapped simulations sorted by 1-year T-bill returns and the slope of the yield curve measured by the 1-year minus 90-day T-bill return.

[a]Significantly different from constant proportional portfolio insurance CPPI S&P at the 5% level.

[b]Significantly better than the S&P 500.

are also sorted by the yield curve slope as measured by the one year minus 90-day Treasury. The bottom of Table 7 shows the results. When the 90-day Treasury exceeds the return from the one-year Treasury, the standard CPPI outperforms a CPPI 2x by 0.7% to 0.4% moving from a CPPI 2x to a CPPI 4x. As soon as the slope exceeds 1%, all the LETF CPPIs outperform a tradition CPPI and this outperformance increases the greater the difference in treasury rates. These results reaffirm what may be obvious; the advantage of using a LETF CPPI strategy is what return an investor can attain with the excess funds relative to the intrinsic financing costs of the LETFs leverage.

4.3. Rebalancing rules

There is nothing magic about using a 2.5% market move to rebalance. In fact, using a 2% or 3% market move gives virtually the same results. Taken to the extreme, daily rebalancing could be implemented, but trading costs would increase. Although this study did not account for brokerage costs explicitly in the return calculations, with two trades a day at $5 a trade, even a $1,000,000 account faces an additional 0.25% in trading cost if using daily rebalancing. Table 8 shows the average returns from 10,000 bootstrapped simulations for the CPPI strategies based on the 2%, 2.5%, and 3.0% rule along with daily, weekly, and monthly rebalancing.

Weekly rebalancing is not significantly different from the 2.5% rule, nor is monthly worse suggesting the decay drag, even over a month, is not significant confirming Lu, Wang, and Zhang (2012) findings that investors can generally expect to earn the leverage ratio for up to a month. Daily rebalancing does improve results, but not by enough to overcome transaction costs. With the exception of daily rebalancing, the average returns for the CPPI S&P varied from 10.01% to 10.05%. The same type of range held for the LETF CPPIs.

Table 8 Average annual returns for different rebalancing rules

Rebalance	Avg. no. of trades	S&P	CPPI S&P	CPPI 2x	CPPI 3x	CPPI 4x
2% rule	31	12.33%	10.04%	10.53%	11.01%[a]	11.28%[a]
2.5% rule	23	12.31%	10.01%	10.53%	11.03%[a]	11.32%[a]
3.0% rule	17	12.35%	10.05%	10.52%	10.98%[a]	11.24%[a]
Daily	252	12.30%	10.27%	10.74%	11.17%[a]	11.39%[a]
Weekly	50	12.28%	10.03%	10.53%	11.00%[a]	11.28%[a]
Monthly	12	12.34%	10.01%	10.50%	10.95%[a]	11.22%[a]

Results show average annual returns based on 10,000 bootstrapped simulations for the S&P 500 along with four constant proportional portfolio insurance (CPPI) strategies based on various rebalancing rules. Percentage rules based on absolute return of the S&P 500 relative to previous rebalance.

[a]Significantly better than the CPPI S&P at the 5% level.

In summary, the additional return from using a LETF CPPI strategy relative to just using the index appears robust to the rebalancing method chosen with a CPPI 2x, CPPI 3x, and a CPPI 4x earning approximately 0.5%, 1.0% and 1.3% more, respectively.

5. Conclusion

LETFs are proclaimed to be risky-short term trading vehicles with plenty of warnings, (Carver, 2009; Justice, 2009; Zweig, 2009, 2017). As an individual asset, there is no denying the extremes that can be experienced by buy-and-hold investors. However, more active traders can moderate this risk by periodic rebalancing which fits in perfectly with a CPPI strategy. By managing the exposure as LETFs change in value, downside losses can be mitigated.

One of the disadvantages of a CPPI is the need for constant rebalancing. However, with only periodic rebalancing based on market movements, this study shows using LETFs instead of the underlying risky asset in a CPPI portfolio leads to greater returns with less risk. This outcome is possible because the same amount of exposure to the risky asset can be attained with a smaller percentage of the portfolio, leaving a larger amount available to earn the risk-free rate. If the return from the additional amount in the risk-free asset exceeds the LETF decay and higher expenses, the LETF CPPI will outperform. Results suggest risk-free yields of 3% or if the one-year exceeds the 90-day Treasury by more than 1% appear to be sufficient for LETF CPPIs to outperform a standard CPPI using the index itself.

Both simulated results from 1947 to 2016 and bootstrapped data show CPPI strategies created with LETFs outperform a CPPI strategy using the underlying index. Average annual returns over all interest rate environments are 0.5% to 1.3% higher with better minimums, Sharpe ratios, Sortino ratios, Omegas, VARs, ES, and CPVs. Using LETFs in a CPPI strategy will underperform slightly when the risk-free rate is extremely low as it has been for the last seven years with the yield below 1%. There is simply no additional return from having a greater percentage of wealth in the risk-free rate to compensate for LETFs higher expenses and leverage decay.

For the less risk averse, more aggressive CPPI portfolios could be created by using a smaller multiplier, lower floors, letting the amount in the 2x, 3x, or 4x LETFs exceed 50%, 33%, or 25%, respectively, and/or using a more risky "risk-free" asset such as longer-term treasuries or some type of composite bond ETF as demonstrated in the last two columns of Table 5 where a bond ETF was substituted for the one-year Treasury. The latter adjustment is likely the safest when yields are extremely low, while allowing the amount in the LETF to increase up to 100% is certainly the riskiest. Two days like October 16 and October 19, 1987 when the market fell 5.1% then 19.5% would see a CPPI 4x lose 84% of its value if exposure to a 4x LETF is allowed to increase to 100%. This would seem to defeat the purpose of a CPPI strategy in the first place.

LETFs are relatively new instruments. The reception from investors has been mostly positive despite their risk as seen by the phenomenal growth both in number and in asset growth. Like options and futures, LETFs can be used for highly speculative gambles, hedging, or risk management. This study demonstrates that LETFs, even a 4x LETF if it becomes available, can be used to enhance return, and reduce risk within the right context.

Appendix 1

The risk metrics used to evaluate the results are described below:

1. The Sharpe ratio is the excess return divided by the standard deviation and is reported for completeness, even though it is not the best measure for assessing the downside risk portfolio insurance portfolios are attempting to mitigate, (Sharpe, 1964). Opdyke's (2007) testing procedure is used to determine whether the LETFs CPPI Sharpe ratios are better than the S&P 500 and the CPPI S&P.
2. The Sortino ratio is a modification of the Sharpe ratio and only considers the downside deviation removing the aspect of "good volatility" (Sortino and Price, 1994). It is more appropriate for analyzing portfolio insurance strategies that are designed to mitigate large losses and whose returns may not be normally distributed. The Sortino ratio is written as:

$$\mathrm{S} = \frac{R - T}{\mathrm{TDD}} \text{ where TDD} = \sqrt{\frac{1}{\mathrm{N}}\sum\nolimits_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{Min}(0,\mathrm{X_i} - \mathrm{T}))^2} \tag{3}$$

where R is the return, T is the target return, N is the total number of returns and X_i is the ith return. The higher the ratio, the greater the return per unit of downside risk. T is set at the one-year treasury return for this study.

3. The Omega ratio, reported by Keating and Shadwick (2002) also measures downside risk. Omega is the sum of the returns above a certain threshold divided by the sum of the returns below that threshold, which is also set at zero in this study. The Omega ratio is written as,

$$\Omega_X[\Gamma] = \frac{\int_{\Gamma}^{\infty}(1 - F_x(x)dx}{\int_{-\infty}^{\Gamma}F_x(x)dx} \tag{4}$$

where F is the cumulative distribution function and Γ is the threshold return. In this study, it is simply the sum of the returns above zero divided by the absolute value of the sum of the returns below zero.

4. Value at Risk measures the expected maximum loss with a given confidence level over a specific time; 5% of the observations are less than the VaR. To test for differences in VaR, an unconditional coverage test is applied as put forth in Annert, Osselaer, and Verstraete (2009) and is written as:

$$\frac{\left(\frac{1}{N}\sum_{n=1}^{N}Hit_n - \alpha\right)}{\sqrt{\frac{\alpha(1-\alpha)}{N}}} \tag{5}$$

where Hit_n equals one if the LETF CPPI return is lower than the S&P CPPI VaR, zero otherwise, N is the number of returns, and α is the 5% VaR. All statistical tests for significant differences are set at the 95% confidence level.

5. As pointed out in Acerbi, Nordio, and Sirtori (2001), Excess Shortfall (ES) shows the average loss beyond the VaR threshold and represents the severity of a dramatic loss. It addresses the “what if” factor and makes up for the discrepancies with the VaR calculation. Acerbi and Tasche (2002) confirm the appropriateness of this definition compared with other shortfall calculations. Annaert et al. (2009) is followed to test for differences in ES values.
6. Because there is an expectation portfolio insurance appeals more to prospect theory investors, cumulative prospect values (CPV) are calculated using the function and parameters set forth in Tversky and Kahnemen (1992). The probability weighting parameter for gains is 0.61 and 0.69 for losses. Dichtl and Drobetz (2011b) use a similar methodology in comparing dollar cost averaging to lump sum investing.

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FINANCIAL
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Who seeks financial advice?

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Abstract

The determinants of seeking five types of financial advice are examined and are found to be consistent across the different types of advice. In addition, no significant differences are found among subsamples defined by gender, age, and financial literacy. Income and risk tolerance are related positively to the demand for financial advice and more greatly affect the probability of seeking advice than do other variables. A low perception of financial knowledge, which can be a proxy for self-confidence, and financial fragility decrease the probability of seeking financial advice. © 2017 Academy of Financial Services. All rights reserved.

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Keywords: Financial advice; Risk tolerance; Financial knowledge; Financial literacy; Financial fragility

1. Introduction

The demand for professional financial advice by the U.S. population is estimated to be within the range of 25–33% (Collins, 2012) despite the fact that many American households are experiencing financial difficulty (Brooks, Wiedrich, Sims, and Rice, 2015). According to a liquid asset poverty measure by Assets and Opportunities Scorecard,[1] for example, 44% of U.S. households have less than three months of savings. Moreover, 55% of consumers have credit scores that make reasonably priced loans unattainable (Brooks et al., 2015), and only 22% of workers are very confident about having enough money to live comfortably during retirement (VanDerhei and Copeland, 2015). Understanding the correlates of financial-

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advice-seeking behavior helps to explain the coexistence of reported low financial satisfaction and measured low demand for financial advice among American households.

Investors who rely on their own understanding often make poor financial decisions because of a lack of knowledge, information costs, and behavioral biases (Fischer and Gerhardt, 2007). These challenges warrant the use of professional advisers, who serve different purposes, deal with various products, and can help their clients navigate the high degree of financial uncertainty.

Using the 2012 National Financial Capability Study (NFCS), a cross-sectional study that was funded by the Financial Industry Regulatory Authority's (FINRA) Investor Education Foundation, this article investigates the characteristics of financial-advice-seeking behavior for five types of financial advice: debt counseling, savings/investment, mortgages/loans, insurance, and tax planning. A probit regression model is estimated to examine the associations between income, risk tolerance, financial knowledge, financial literacy, financial fragility, and a set of demographic variables and the probability of seeking financial advice. Additionally, this article examines the determinants of financial-advice-seeking behavior for subsamples defined by gender, age, and financial literacy.

2. Literature review

The existing literature on the characteristics of financial-advice-seeking behavior examines this conduct generally and for specific types of advice such as debt counseling, retirement planning, and investment management (Collins, 2012; Finke, Huston, and Winchester, 2011; Grable and Joo, 1999; Hackethal, Haliassos, and Jappelli, 2012; Heo, Grable, and Chatterjee, 2013; Inderst and Ottaviani, 2012; Kramer, 2012; Robb, Babiarz, and Woodyard, 2012; Heo, Grable, & Chatterjee, 2013; Salter, Harness, and Chatterjee, 2010; Scott and Finke, 2013; Seay, Kim, and Heckman, 2016; Simms, 2014). These studies identify age, gender, wealth, income, home ownership, education, financial knowledge, confidence, risk tolerance, and negative life events as factors that influence the demand for financial advice.

Age is a significant determinant of seeking advice in all areas of personal finance, has been found to be related positively to debt counseling for those aged 25–54, and is related negatively to debt counseling for respondents who are aged 65 or older (Robb et al., 2012). Grable and Joo (1999) find that younger households and those who do not own homes are more likely to seek financial help compared with homeowners and older individuals who may experience self-concealment[2] to protect their perceived life achievement. In addition, individuals who demonstrate bad financial behaviors (e.g., overspending, overusing credit, and not saving for retirement) and who experience financial stressors (e.g., death of a family member, divorce, and loss of a job) are more likely to seek financial help. However, Hackethal et al. (2012) find that older clients (over 50) are more likely to use a financial adviser compared with younger clients aged 18–30.

Gender influences the decision to seek financial advice. Because of their overconfidence in managing finances, males resist financial counseling and are less likely to seek financial advice compared to females (Finke et al., 2011; Hackethal et al., 2012; Robb et al., 2012).

In contrast, Tang and Lachance (2012) find that gender and home ownership do not affect the demand for financial advice.

Income has been found to be related positively to the demand for financial advice (Robb et al., 2012). However, other studies indicate that wealth has more of an impact on the decision to seek financial advice compared to income (Finke et al., 2011; Hackethal et al., 2012; Hanna, 2011). Advisers are inclined to provide their services to clients who are self-employed, female, have high wealth, and have more work experience (Hackethal et al., 2012). On the other hand, Calcagno and Monticone (2014) do not find support for the predicted associations between high wealth or high income and the probability of seeking financial advice.

Although education increases the likelihood of seeking financial advice (Finke et al., 2011; Hanna, 2011; Inderst and Ottaviani, 2012), perceived knowledge about managing finances reduces the likelihood of asking for help (Finke et al., 2011). However, other studies find that knowledge and confidence are correlated positively with the use of financial advice (Calcagno and Monticone, 2014; Collins, 2012; Inderst and Ottaviani, 2012; Robb et al., 2012).

The literature also investigates the determinants of advice-seeking behavior from other angles. Studies about the sources of advice examine an individual's tendency to seek financial advice from nonprofessional versus professional sources (Grable and Joo, 2001), bank-affiliated versus independent advisers (Hackethal et al., 2012), social networks versus paid advisers (Chang, 2005; Loibla and Hira, 2006), and the use of financial planners (Hanna, 2011; Letkiewicz, Robinson, and Domian, 2016). Studies that examine advice seeking by certain groups focus on less-sophisticated or low-income clients (Kramer, 2012; Tang and Lachance, 2012), older adults (Cummings and James, 2014), affluent retirees (Salter et al., 2010), and the middle class (Winchester and Huston, 2015). They also examine the effects of financial literacy on the use of financial advice (Calcagno and Monticone, 2014; Collins, 2012; Robb et al., 2012; Seay et al., 2016) and the determinants of seeking comprehensive versus partial financial advice (Elmerick, Montalto, and Fox, 2002; Finke et al., 2011; Tang and Lachance, 2012).

Financial risk tolerance and financial satisfaction have been found to play a role in determining whether people seek financial help from professionals or nonprofessionals such as family members, friends, or work colleagues (Grable and Joo, 2001; Lin and Lee, 2004). Chang (2005) finds that low socioeconomic status affects people's decisions to seek information about investment and savings from their social network rather than from paid financial advisers.

Elmerick et al. (2002) find that the determinants of seeking comprehensive financial advice and seeking advice regarding savings and investment are different from the determinants of seeking advice regarding debt and borrowing. Education, income, net worth, and financial assets are related positively to the probability of seeking comprehensive financial advice, while age is related negatively to the use of comprehensive financial planners. Hanna (2011) studies the demand for personal financial planners and finds that age increases the likelihood of using a planner until the age of 42 then decreases it. The determinants that increase the likelihood of using a financial planner include education, risk tolerance, being a single-female-headed household, and being black (Hanna, 2011).

Cummings and James (2014) examine the factors that influence the decision to begin or discontinue the use of financial advisers among older adults and find that becoming widowed, receiving family help, and experiencing an increase in income or net worth are significant factors in influencing the demand for financial advisers. Studying the sentiment of financial-advice-seeking behavior among the middle class, Winchester and Huston (2015) find that the expected benefit relative to income is a more significant determinant of seeking financial advice than individuals' attitudes regarding cost.

Financial literacy increases the probability of seeking financial advice (Calcagno and Monticone, 2014), and such advice is a complement to rather than a substitute for financial capability (Collins, 2012). As income, education, and financial knowledge increase, the likelihood of seeking financial advice increases; however, self-assessment of financial literacy is related negatively to seeking financial advice, while measured financial literacy has no effect on the demand for such advice (Kramer, 2016).

This article contributes to the literature that examines the determinants of seeking professional financial guidance by focusing on five specific types of financial advice and investigating three subsamples that are defined by gender, age, and financial literacy. Because each type of financial advice has a specific purpose, studying the determinants of seeking advice about debt, savings/investment, mortgages/loans, insurance, and tax planning provides valuable insights into advice-seeking behavior. In addition to financial knowledge and risk attitudes that Robb et al. (2012) examine in their study, this article constructs two variables, financial fragility and financial literacy, to comprehend the effect of financial difficulty and the grasp of basic financial concepts on seeking financial advice.

The focus on females, the young, and the financially illiterate is related to specific characteristics, examined in the empirical literature, that distinguish and influence the financial behavior of these subsamples. Females and young respondents are most likely to experience financial stress and difficulties (ORC, 2015; Simms, 2014), and the financially illiterate are susceptible to suboptimal financial decisions (Lusardi, 2008; Lusardi and Mitchell, 2009; Lusardi and Tufano, 2009; van Rooij, Lusardi, and Alessie, 2011).

The empirical literature about gender differences in financial knowledge finds that females score lower than males in financial literacy tests, are more likely to be dissatisfied with their personal financial situation, and are less confident in their financial skills and their ability to manage financial emergencies (Goldsmith and Goldsmith, 2006; Hira and Mugenda, 2000; Hung, Yoong, and Brown, 2012). Gender differences in investment knowledge, financial skills, and risk tolerance between females and males might explain and exacerbate the economic status disadvantage of females that manifests in lower lifetime earnings, lower wealth, and lower retirement-plan participation (Bajtelsmit and Bernasek, 1996; Hung et al., 2012). While females are more patient than males in the measurement of rate of time preference, they exhibit more risk aversion and less interest in financial subjects (Donkers and van Soest, 1999). The gender role differences and division of labor within households provide another explanation for the disparity in the consumption of financial services (Burton, 1995; Morris and Meyer, 1993).

The literature on financial competency among young adults shows weak financial literacy and a lack of understanding of basic financial knowledge, which affect the quality of their financial decisions and lead them to commit costly financial mistakes (Lusardi, 2008; Lusardi and Mitchell, 2014; Lusardi, Mitchell, and Curto, 2010). A high level of debt at an early age, for example, impedes the accumulation of wealth and forestalls their contributions to employer-provided retirement plans (Lusardi et al., 2010). Additionally, weak financial numeracy has negative impacts on critical decisions related to financing an education and making major purchases such as buying a car (Lusardi, 2012). Laibson, Gabaix, Driscoll, and Agarwal (2007) find that financial sophistication has a hump-shaped pattern, which could explain the high borrowing costs in terms of interest rates and fees by younger and older adults.

Research indicates that financial literacy influences financial-decision making and that the understanding of basic financial concepts is associated with retirement planning, stock market participation, and individuals' borrowing behavior (Hastings and Mitchell, 2011; Lusardi, 2008; Lusardi and Mitchell, 2009; van Rooij et al., 2011). Individuals who are not financially sophisticated are less likely to own stocks because they do not comprehend the working of financial markets and asset pricing and are more likely to seek financial advice from friends and family members than from financial professionals (van Rooij et al., 2011).

3. Data

The dependent variables in the analysis in this article are indicators for whether or not five different types of financial advice were sought, debt counseling, savings/investment, taking out a mortgage/loan, insurance of any type, and tax planning. Each variable takes a value of 1 if the specific type of advice was sought from a financial professional and 0 if it was not.

The independent variables are gender, age, race, education, marital status, number of children, income, risk tolerance, perceived financial knowledge, financial literacy, and financial fragility. Because the three subsamples are defined by age, gender, and financial literacy, those variables are excluded from their regressions.

Female is a dichotomous variable that takes a value of 1 if the respondent is female and 0 if the respondent is male. Age is categorized into six ranges: 18–24, 25–34, 35–44, 45–54, 55–64, and 65 or more. A categorized dichotomous variable for each age range is defined (the omitted category is 65+). Race is a dichotomous variable that takes a value of 1 if the respondent is white and 0 if the respondent is nonwhite.[3] Education is categorized into three levels: high school or less, some college, and college or more (the omitted category is college or more). Marital status is categorized as married, living with a partner, and single (the omitted category is married).

The number of financially dependent children is categorized into five choices: not having any children, having one child, having two children, having three children, and having four children or more. The omitted category is not having any children. Income is categorized into eight ranges, and for each range a dichotomous variable is defined. The comparison group is less than $15,000. The risk tolerance variable is a subjective answer by respondents to the following question: "When thinking of your financial investment, how willing are you to take risk?" The answers fall on a 10-point scale that ranges from 1 (not at all willing) to 10 (very willing). In this analysis, they are aggregated into three risk tolerance levels[4] and the omitted category is low risk tolerance. The financial knowledge variable is a subjective assessment by respondents to the following question: "How would you assess your overall financial knowledge?" The answers fall on a seven-point scale that ranges from 1 (very low) to 7 (very high). In this analysis, they are aggregated into three perceived financial knowledge levels[5] and the omitted category is high financial knowledge.

Financial fragility is constructed from seven questions that examine respondents' tendency to experience overspending, difficulty in covering expenses, the lack of an emergency fund, inability to come up with \$2000 in the next month, the absence of a retirement plan, and incurring too much debt. This variable is a sum of these signs of financial fragility. Overspending is a dichotomous variable that takes a value of 1 if the respondent's spending is more than income and 0 otherwise. The difficulty of covering expenses and paying all bills is a dichotomous variable that takes a value of 1 if the respondent indicated it was very difficult or somewhat difficult to cover expenses and 0 otherwise. Having no emergency fund that would cover three months of expenses is a dichotomous variable that takes a value of 1 if the respondent answered "no" and 0 otherwise. The confidence to come-up with \$2000 is a dichotomous variable that takes a value of 1 if the respondent could probably not or is certain she/he could not come-up with that amount and 0 otherwise. Having no retirement plan is a dichotomous variable that takes a value of 1 if the respondent has neither a private plan nor a plan through a current or a previous employer and 0 otherwise. Having too much debt is a dichotomous variable that has a value of 1 if the respondent agrees or strongly agrees with that statement and 0 otherwise.

Financial literacy consists of five questions that measure respondents' understanding of compound interest, inflation, bond prices, mortgage interest, and risk. This variable is a sum of the correct answers to these questions and has a range of 0–5. Table 1 provides the distribution of correct financial literacy answers and shows that respondents who answered 4–5 questions correctly are between 16 and 26%. Fig. 1 shows that respondents have difficulty understanding the effect of interest rates on bond prices and the risk-return trade-off in buying a single company's stock versus purchasing a share of a mutual fund.

4. Model

The model estimated in this article is a probit model:

$$Y_{ij}^{*} = B_0 + X_i^{'}B + \mu_{ij} \tag{1}$$

$$Y_{ij} = \begin{cases} 1 \; if \; Y_{ij}^{*} > 0 \\ 0 \; if \; Y_{ij}^{*} \leq 0 \end{cases}$$

where Y_{ij}^{*} is a latent variable representing the net benefit an individual i perceives he or she will receive from seeking financial advice related to task j where j is one of the following: debt counseling, savings/investment, a mortgage/a loan, insurance, and tax planning,[6] Y_{ij} is equal to 1 if the respondent reported seeking that type of financial advice and 0 otherwise; X_i is a matrix of explanatory variables representing income,[7] risk tolerance, perceived financial knowledge, financial literacy, financial fragility, female, white, age, education, marital status, and number of children; and u_{ij} is an error term that follows the standard normal distribution.

Table 1 Summary statistics

	Mean	Standard error
Dependent variables		
Debt counseling	0.0906	0.0022
Savings or investment advice	0.2871	0.0033
Mortgage or loan advice	0.2020	0.0030
Insurance advice	0.3028	0.0034
Tax planning	0.1812	0.0029
Independent variables		
Gender		
Male	0.4858	0.0037
Female	0.5142	0.0037
Age (years)		
18–24	0.1231	0.0027
25–34	0.1830	0.0030
35–44	0.1635	0.0027
45–54	0.1962	0.0029
55–64	0.1791	0.0028
65+	0.1551	0.0026
Race		
White	0.6647	0.0037
Non-White	0.3353	0.0037
Education level		
High school or less	0.3812	0.0037
Some college	0.3591	0.0036
College or more	0.2597	0.0030
Marital status		
Married	0.5403	0.0037
Living with a partner	0.0816	0.0021
Single	0.3782	0.0037
Number of children		
No children	0.3181	0.0035
One child	0.1699	0.0028
Two children	0.1312	0.0025
Three children	0.0567	0.0018
Four children or more	0.0337	0.0014
No financial dependent children	0.2905	0.0033
Annual income		
Less than $15,000	0.1426	0.0027
$15,000 to less than $25,000	0.1225	0.0025
$25,000 to less than $35,000	0.1155	0.0024
$35,000 to less than $50,000	0.1470	0.0026
$50,000 to less than $75,000	0.1882	0.0029
$75,000 to less than $100,000	0.1153	0.0023
$100,000 to less than $150,000	0.1076	0.0023
$150,000 or more	0.0613	0.0017
Risk-tolerance level		
Low	0.3517	0.0035
Medium	0.4388	0.0037
High	0.1746	0.0029

(continued on next page)

Table 1 (Continued)

	Mean	Standard error
Perceived financial knowledge		
Low	0.0915	0.0022
Medium	0.1487	0.0027
High	0.7288	0.0034
Financial literacy	2.8781	0.0110
Financial fragility	2.3821	0.0133
Number of observations	25,509	

5. Hypotheses

H1: Income is expected to be related positively to seeking financial advice about savings/investment, mortgages/loans, insurance, and tax planning, and to relate negatively with debt counseling for the entire sample and subsamples. Previous literature finds a positive relation between income and the demand for financial advice.

H2: Risk tolerance is expected to be related positively to seeking financial advice for the entire sample and subsamples. Research indicates that this factor has been found to increase the likelihood to seek financial help from professionals.

H3: Perceived financial knowledge is expected to be related negatively to seeking financial advice for the entire sample and subsamples. Although some studies find that perceived knowledge reduces the likelihood of asking for advice, others report a positive relation between knowledge and the use of financial advice.

H4: Financial literacy is expected to be related positively to seeking all types of financial advice except debt counseling for the entire sample and subsamples. The literature finds that financial literacy increases the probability of seeking advice. However, some studies differentiate between the effect of subjective and objective assessment of financial literacy on the demand for financial advice.

H5: Financial fragility is expected to be related positively to seeking financial advice for the entire sample and subsamples. Although respondents who experience financial stressors are more likely to seek advice, those who are financially fragile might not afford the purchase of financial advice.

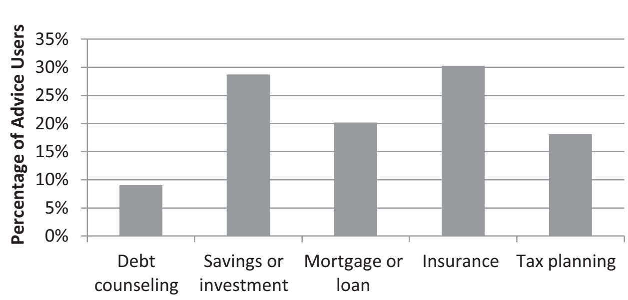

Fig. 1. Demand for financial advice. *Source:* Author's tabulation of data from the 2012 FINRA National Financial Capability Study.

Table 2 Distribution of financial fragility measure

Fragility degree level	Percentage of respondents
0	23.56%
1	15.88%
2	14.59%
3	14.98%
4	16.63%
5	11.14%
6	3.21%

The financial fragility measure consists of seven questions in the 2012 NFCS, which examine a respondent's tendency to experience overspending, difficulty in covering expenses, lack of an emergency fund, inability to raise $2,000 in the next month, lack of any retirement plan, and having a high level of debt. The Table shows the percentage of respondents who experience different degrees of financial fragility.

6. Descriptive statistics

The summary statistics of the dependent and independent variables are provided in Table 1. The first important observation to be made is the low demand for financial advice, which is utilized by 9–30% of the population, depending on the type of advice. Sixty-six percent of respondents are White and 34% are non-White respondents. Seventy-four percent of respondents have some college education or less. Married individuals are the majority at 54%, followed by singles at 38%, and individuals who are living with partners at 8%. Thirty-two percent of respondents have no children and 29% have children who are financially independent.

Proportions are distributed evenly among the income categories, except for the $50,000 to $75,000, which represents 19% of the population, and those making $150,000 or more, which represents 6% of the population. Only 17% of respondents have a high-risk-tolerance level, while the majority of respondents (44%) have a medium-risk-tolerance level.[8]

Each type of financial advice serves a specific purpose, which explains the advice use distribution in Fig. 1 and shows that the two most sought after types of financial advice are insurance and savings/investment. Even though 86% of respondents to a CFP stress awareness survey point to debt and daily expenses as the two primary sources of stress (ORC, 2015), debt counseling is the least demanded type of advice at 9%.

Although 73% of respondents rated themselves high when asked to give a subjective assessment of their overall financial knowledge,[9] average financial literacy on a scale of 0–5 is only 2.9. Financial fragility is measured on a scale of 0–6, and each number represents the cumulative signs of financial difficulty across the seven financial fragility questions. Table 2 reveals that only a quarter of respondents do not experience any of the six signs of financial fragility. Fig. 2 shows that 56% of respondents report difficulty in covering expenses and paying bills and that 55% have no emergency fund that could cover expenses for 3 months.

The comparison between females and males is provided in Table 3. The *t* test results indicate that the significant difference between females and males is related to seeking financial advice about savings/investment, mortgages/loans, and tax planning. As for debt counseling, and insurance, there is no evidence of a statistically significant difference.

The comparison between the young (18–44) and the old (45+) is provided in Table 4. The *t* test results indicate that the significant difference between the young (18–44) and the old

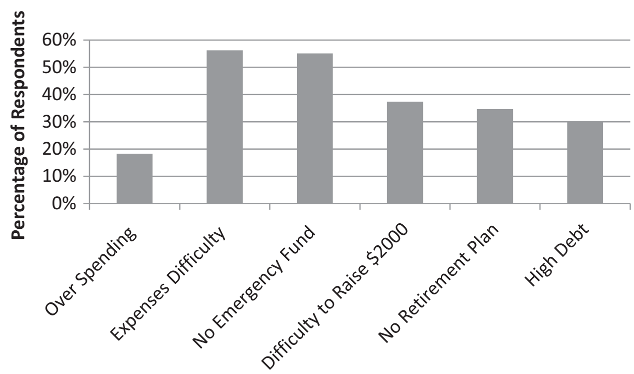

Fig. 2. Distribution of financial fragility issues. *Source:* Author's tabulation of data from the 2012 FINRA National Financial Capability Study.

(45+) is related to seeking financial advice about debt counseling, savings/investment, and mortgages/loans. As for insurance and tax planning, there is no evidence of a statistically significant difference.

The comparison between the financially illiterate and financially literate respondents is provided in Table 5. Financial illiteracy is defined as answering two questions or less

Table 3 Summary statistics (females vs. males)

	Female		Male		
	Mean	Standard error	Mean	Standard error	
Dependent variables					
Debt counseling	0.0878	0.0028	0.0935	0.0034	
Savings or investment advice	0.2718	0.0043	0.3033	0.0051	***
Mortgage or loan advice	0.1872	0.0037	0.2177	0.0046	***
Insurance advice	0.3019	0.0045	0.3037	0.0051	
Tax planning	0.1660	0.0036	0.1973	0.0045	***
Independent variables					
Annual income					
Less than $15,000	0.1517	0.0036	0.1329	0.0040	***
$15,000 to less than $25,000	0.1385	0.0035	0.1055	0.0035	***
$25,000 to less than $35,000	0.1267	0.0033	0.1037	0.0035	***
$35,000 to less than $50,000	0.1490	0.0036	0.1449	0.0039	
$50,000 to less than $75,000	0.1774	0.0037	0.1997	0.0045	***
$75,000 to less than $100,000	0.1031	0.0029	0.1281	0.0037	***
$100,000 to less than $150,000	0.0950	0.0029	0.1209	0.0035	***
$150,000 or more	0.0586	0.0023	0.0642	0.0026	
Risk-tolerance level					
Low	0.4286	0.0049	0.2703	0.0049	***
Medium	0.4169	0.0049	0.4620	0.0056	***
High	0.1130	0.0032	0.2397	0.0049	***
Perceived financial knowledge					
Low	0.1055	0.0031	0.0768	0.0031	***
Medium	0.1647	0.0037	0.1317	0.0039	***
High	0.6930	0.0046	0.7668	0.0049	***
Financial literacy	2.6110	0.0141	3.1609	0.0166	***
Financial fragility	2.5171	0.0180	2.2391	0.0195	***

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

Table 4 Summary statistics (young vs. old)

	Young (18–44)		Old (45+)		
	Mean	Standard error	Mean	Standard error	
Dependent variables					
Debt counseling	0.1160	0.0037	0.0681	0.0025	***
Savings or investment advice	0.2610	0.0050	0.3103	0.0045	***
Mortgage or loan advice	0.2272	0.0047	0.1796	0.0037	***
Insurance advice	0.3060	0.0052	0.2999	0.0044	
Tax planning	0.1790	0.0044	0.1831	0.0037	
Independent variables					
Annual income					
Less than $15,000	0.1876	0.0045	0.1027	0.0031	***
$15,000 to less than $25,000	0.1302	0.0039	0.1157	0.0032	***
$25,000 to less than $35,000	0.1201	0.0037	0.1115	0.0031	*
$35,000 to less than $50,000	0.1444	0.0040	0.1493	0.0035	
$50,000 to less than $75,000	0.1812	0.0044	0.1944	0.0039	**
$75,000 to less than $100,000	0.1100	0.0035	0.1199	0.0031	**
$100,000 to less than $150,000	0.0820	0.0031	0.1303	0.0033	***
$150,000 or more	0.0444	0.0023	0.0763	0.0025	***
Risk-tolerance level					
Low	0.2784	0.0050	0.4166	0.0049	***
Medium	0.4508	0.0057	0.4283	0.0048	***
High	0.2288	0.0049	0.1266	0.0033	***
Perceived financial knowledge					
Low	0.1091	0.0036	0.0760	0.0027	***
Medium	0.1727	0.0043	0.1274	0.0033	***
High	0.6832	0.0053	0.7693	0.0042	***
Financial literacy	2.5062	0.0164	3.2074	0.0140	***
Financial fragility	2.7394	0.0190	2.0657	0.0180	***

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

correctly out of the five financial literacy questions in the survey. The *t* test results indicate that the significant difference between the two groups is related to seeking all types of financial advice.

7. Results

Table 6 reports the estimation results for five probit regression models on the entire sample. The dependent variables are indicators for whether or not five different types of financial advice were sought, debt counseling, savings/investment, taking out a mortgage/loan, insurance of any type, and tax planning. To examine how advice seeking varies by gender, age, and financial illiteracy, three dummy variables representing those subsamples are included in the model.

The results of the probit regression models on the entire sample show consistently that income and risk tolerance are related positively to seeking all types of financial advice. These results confirm that the existing findings in the literature extend to these specific applications. The two constructed variables, financial literacy and financial fragility, have an opposite

Table 5 Summary statistics (financially illiterate vs. financially literate)

	Financially illiterate		Financially literate		
	Mean	Standard error	Mean	Standard error	
Dependent variables					
Debt counseling	0.1078	0.0041	0.0799	0.0026	***
Savings or investment advice	0.2036	0.0051	0.3387	0.0043	***
Mortgage or loan advice	0.1523	0.0046	0.2327	0.0039	***
Insurance advice	0.2459	0.0054	0.3379	0.0043	***
Tax planning	0.1351	0.0044	0.2097	0.0037	***
Independent variables					
Annual income					
Less than $15,000	0.2300	0.0052	0.0886	0.0027	***
$15,000 to less than $25,000	0.1748	0.0048	0.0901	0.0027	***
$25,000 to less than $35,000	0.1436	0.0044	0.0982	0.0028	***
$35,000 to less than $50,000	0.1450	0.0044	0.1482	0.0033	
$50,000 to less than $75,000	0.1500	0.0045	0.2118	0.0038	***
$75,000 to less than $100,000	0.0723	0.0032	0.1418	0.0032	***
$100,000 to less than $150,000	0.0545	0.0029	0.1405	0.0032	***
$150,000 or more	0.0298	0.0022	0.0808	0.0024	***
Risk-tolerance level					
Low	0.3931	0.0061	0.3261	0.0043	***
Medium	0.3700	0.0060	0.4814	0.0046	***
High	0.1741	0.0049	0.1749	0.0036	
Perceived financial knowledge					
Low	0.1419	0.0044	0.0604	0.0023	***
Medium	0.1827	0.0048	0.1276	0.0031	***
High	0.6118	0.0061	0.8012	0.0037	***
Financial fragility	2.8809	0.0209	2.0738	0.0166	***

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

effect on seeking financial advice. While financial literacy is related positively to the demand for all types of financial advice, except for debt counseling, financial fragility decreases the demand for advice about savings/investment, insurance, and tax planning, but increases the demand for debt counseling. Financial literacy alerts people to the value of financial advice in improving their well-being because they realize the complexity of financial topics and issues. However, financial literacy might be endogenous to the demand for advice. To test this potential endogeneity and revers causality, the article instruments for financial literacy using scores for the quality of public schools for 50 states and the District of Columbia in 2012. The results of a Wald test of exogeneity indicate endogeneity of financial literacy. Therefore, it cannot be concluded that changes in financial literacy influence the demand for financial advice. On the other hand, financial difficulties such as overspending, lack of an emergency fund, and having a high level of debt discourage people from purchasing financial advice. In addition, a low perception of financial knowledge, which could proxy self-confidence, has been found to decrease the probability of seeking financial advice. The correlation between a high perception of financial knowledge and financial literacy is found to be 0.26, which reflects a weak positive linear relation between these key variables. This finding reveals a lack of consistency between objective and subjective assessment of financial knowledge.

Table 6 Financial advice probit

	Debt counseling			Savings/investment			Mortgage/loan			Insurance			Tax planning		
	Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)	
Independent variables															
Gender (male)															
Female	−0.0034	0.0044		0.0302	0.0063	***	0.0040	0.0059		0.0365	0.0069	***	0.0060	0.0057	
Race (non-White)															
White	−0.0205	0.0048	***	−0.0017	0.0073		0.0204	0.0067	***	−0.0100	0.0078		−0.0088	0.0064	
Age (65+)															
18–24	0.0240	0.0104	**	0.0155	0.0140		0.1343	0.0141	***	0.0476	0.0158	***	0.0395	0.0128	***
25–34	0.0398	0.0094	***	−0.0410	0.0122	***	0.1500	0.0117	***	0.0398	0.0136	***	0.0111	0.0109	
35–44	0.0118	0.0088		−0.1115	0.0119	***	0.0792	0.0115	***	0.0086	0.0134		−0.0476	0.0106	***
45–54	0.0085	0.0083		−0.0997	0.0105	***	0.0394	0.0104	**	0.0064	0.0120		−0.0469	0.0095	***
55–64	0.0180	0.0078	**	−0.0391	0.0097	***	0.0306	0.0098	***	0.0144	0.0112		−0.0202	0.0086	**
Education level (college or more)															
High school or less	−0.0328	0.0059	***	−0.0935	0.0084	***	−0.0622	0.0079	***	−0.0705	0.0091	***	−0.0605	0.0076	***
Some college	−0.0158	0.0052	***	−0.0429	0.0075	***	−0.0133	0.0069	*	−0.0146	0.0082	*	−0.0322	0.0065	***
Marital status (married)															
Living with a partner	−0.0043	0.0084		0.0086	0.0124		−0.0101	0.0110		−0.0110	0.0130		−0.0196	0.0111	*
Single	0.0024	0.0055		0.0090	0.0079		−0.0410	0.0075	***	−0.0160	0.0085	*	−0.0151	0.0070	**
Number of children (no children)															
One child	0.0387	0.0067	***	0.0359	0.0099	***	0.0491	0.0090	***	0.0662	0.0105	***	0.0450	0.0087	***
Two children	0.0457	0.0073	***	0.0354	0.0110	***	0.0542	0.0098	***	0.0797	0.0117	***	0.0433	0.0096	***
Three children	0.0403	0.0094	***	0.0157	0.0151		0.0585	0.0132	***	0.0447	0.0155	***	0.0234	0.0134	*
Four children or more	0.0546	0.0113	***	0.0656	0.0190	***	0.0697	0.0164	***	0.0880	0.0196	***	0.0451	0.0164	***
No financially dependent children	0.0053	0.0071		0.0173	0.0091	*	0.0209	0.0089	**	0.0309	0.0101	***	0.0139	0.0085	
Annual income (less than $15,000)															
$15,000 to less than $25,000	0.0454	0.0089	***	0.0608	0.0142	***	0.0566	0.0141	***	0.1021	0.0144	***	0.0516	0.0137	***
$25,000 to less than $35,000	0.0504	0.0090	***	0.0745	0.0142	***	0.0825	0.0135	***	0.1031	0.0146	***	0.0685	0.0135	***
$35,000 to less than $50,000	0.0581	0.0086	***	0.0863	0.0135	***	0.0850	0.0130	***	0.1158	0.0140	***	0.0836	0.0127	***
$50,000 to less than $75,000	0.0616	0.0089	***	0.1163	0.0134	***	0.1151	0.0128	***	0.1311	0.0139	***	0.1068	0.0125	***
$75,000 to less than $100,000	0.0696	0.0100	***	0.1320	0.0147	***	0.1300	0.0139	***	0.1167	0.0155	***	0.1253	0.0136	***
$100,000 to less than $150,000	0.0629	0.0112	***	0.1516	0.0152	***	0.1433	0.0146	***	0.1391	0.0163	***	0.1402	0.0140	***
$150,000 or more	0.0519	0.0127	***	0.1751	0.0173	***	0.1682	0.0161	***	0.1575	0.0185	***	0.1866	0.0153	***

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Table 6 (Continued)

	Debt counseling			Savings/investment			Mortgage/loan			Insurance			Tax planning		
	Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)	
Risk-tolerance level (low)															
Medium	0.0092	0.0050	*	0.1111	0.0070	***	0.0395	0.0066	***	0.0738	0.0076	***	0.0555	0.0064	***
High	0.0499	0.0062	***	0.1685	0.0093	***	0.0655	0.0087	***	0.1187	0.0102	***	0.1046	0.0082	***
Perceived financial knowledge (high)															
Low	−0.0089	0.0073		−0.0342	0.0133	***	−0.0516	0.0118	***	−0.0515	0.0131	***	−0.0367	0.0122	***
Medium	−0.0160	0.0062	***	−0.0190	0.0095	**	−0.0139	0.0086		−0.0336	0.0099	***	−0.0163	0.0085	*
Financial literacy	−0.0034	0.0016	**	0.0223	0.0024	***	0.0168	0.0022	***	0.0212	0.0026	***	0.0117	0.0021	***
Financial fragility	0.0209	0.0016	***	−0.0386	0.0023	***	0.0079	0.0019	***	−0.0066	0.0025	***	−0.0146	0.0021	***
Bankruptcy	0.1803	0.0080	***												
Homeownership							0.1234	0.0072	***						
The financially illiterate	0.0207	0.0083	**	0.0328	0.0123	***	0.0237	0.0115	**	0.0132	0.0133		0.0228	0.0110	**
The young	0.0157	0.0049	***	0.0099	0.0073		0.0665	0.0068	***	0.0211	0.0079	***	0.0255	0.0065	***
Interaction variables															
Female*Income															
$15,000 to less than $25,000	0.0856	0.1200		−0.2089	0.1018	**	0.0392	0.1118		−0.1647	0.0907	*	−0.0762	0.1179	
$25,000 to less than $35,000	0.0624	0.1228		−0.0753	0.1015		0.1787	0.1085	*	−0.0929	0.0916		0.1511	0.1161	
$35,000 to less than $50,000	0.0531	0.1134		−0.0568	0.0948		0.1994	0.1009	**	−0.1277	0.0856		0.1403	0.1060	
$50,000 to less than $75,000	−0.0272	0.1135		−0.0143	0.0908		0.0880	0.0965		−0.0134	0.0823		0.1391	0.1007	
$75,000 to less than $100,000	−0.1301	0.1265		−0.1914	0.0978	**	0.1862	0.1035	*	−0.1085	0.0901		0.1367	0.1076	
$100,000 to less than $150,000	−0.1195	0.1396		−0.1125	0.1001		0.1606	0.1068		−0.1705	0.0933	*	0.2560	0.1095	**
$150,000 or more	−0.0174	0.1644		−0.0167	0.1127		0.2336	0.1180	**	−0.0585	0.1051		0.2787	0.1196	**
Female*Risk-Tolerance															
Medium	−0.0226	0.0698		−0.0208	0.0512		0.0697	0.0531		−0.0172	0.0481		0.0399	0.0567	
High	0.0595	0.0858		−0.1009	0.0654		−0.0747	0.0680		−0.0559	0.0623		−0.0539	0.0704	
Female*Perceived financial knowledge															
Low	−0.2068	0.1063	*	−0.0929	0.0959		0.0471	0.0943		−0.0788	0.0843		−0.0900	0.1071	
Medium	−0.1314	0.0843		−0.0176	0.0681		−0.0171	0.0701		−0.0499	0.0628		0.0742	0.0761	
Female*Financial fragility level															
1	0.1167	0.1203		0.0963	0.0643		0.0553	0.0700		0.0760	0.0646		0.0893	0.0687	
2	0.1146	0.1207		−0.0278	0.0678		0.0864	0.0732		0.0143	0.0673		0.0299	0.0735	
3	0.2559	0.1175	**	−0.0828	0.0730		0.1349	0.0775	*	−0.0102	0.0703		0.0111	0.0793	
4	0.3861	0.1197	***	−0.0458	0.0786		0.1959	0.0817	**	0.0722	0.0734		0.1632	0.0881	*

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Table 6 (Continued)

	Debt counseling			Savings/investment			Mortgage/loan			Insurance			Tax planning		
	Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)	
5	0.3706	0.1273	***	−0.0275	0.0959		0.1864	0.0952	**	0.1104	0.0848		0.1254	0.1021	
6	0.1015	0.1943		0.0644	0.1853		0.4324	0.1622	***	−0.1030	0.1399		0.1310	0.1815	
Young*Income															
$15,000 to less than $25,000	−0.1842	0.1169		−0.2533	0.1002	**	0.0615	0.1086		0.1770	0.0875	**	0.1444	0.1186	
$25,000 to less than $35,000	−0.2326	0.1165	**	−0.3187	0.1007	***	−0.0319	0.1060		0.1115	0.0884		−0.0712	0.1168	
$35,000 to less than $50,000	−0.1088	0.1104		−0.3020	0.0948	***	−0.1547	0.0995		0.1233	0.0832		−0.0858	0.1084	
$50,000 to less than $75,000	−0.0026	0.1123		−0.3025	0.0914	***	−0.0834	0.0966		0.1768	0.0808	**	−0.2167	0.1045	**
$75,000 to less than $100,000	−0.0936	0.1257		−0.4964	0.0983	***	−0.1058	0.1040		0.0476	0.0891		−0.2727	0.1111	**
$100,000 to less than $150,000	−0.1354	0.1376		−0.4752	0.1025	***	−0.1058	0.1083		0.0660	0.0937		−0.3164	0.1154	***
$150,000 or more	−0.3143	0.1605	**	−0.6188	0.1186	***	−0.2346	0.1226	*	−0.0258	0.1091		−0.4551	0.1277	***
Young*Risk-Tolerance															
Medium	0.1443	0.0678	**	−0.0123	0.0518		0.0471	0.0527		0.0356	0.0479		0.0876	0.0567	
High	0.1475	0.0860	*	0.1807	0.0664	***	0.0966	0.0692		0.1416	0.0630	**	0.2627	0.0710	***
Young*Perceived financial knowledge															
Low	−0.1370	0.1008		−0.0882	0.0905		−0.0597	0.0899		−0.1849	0.0787	**	−0.0182	0.1002	
Medium	−0.0831	0.0818		−0.1566	0.0663	**	−0.1036	0.0682		−0.1496	0.0611	**	−0.0394	0.0739	
Young*Financial fragility level															
1	−0.0671	0.1173		0.1653	0.0691	**	−0.0793	0.0735		0.1116	0.0691		0.1541	0.0739	**
2	−0.2043	0.1162	*	0.3197	0.0721	***	−0.2743	0.0760	***	0.0465	0.0714		0.2109	0.0785	***
3	−0.3815	0.1152	***	0.3656	0.0764	***	−0.2288	0.0804	***	0.0368	0.0736		0.1820	0.0834	**
4	−0.4057	0.1174	***	0.4513	0.0825	***	−0.3256	0.0828	***	−0.0793	0.0756		0.2811	0.0895	***
5	−0.5529	0.1250	***	0.3721	0.0964	***	−0.3378	0.0952	***	−0.0511	0.0852		0.2028	0.1029	**
6	−0.4597	0.1721	***	0.3657	0.1649	**	−0.2403	0.1488		−0.0666	0.1322		0.0882	0.1775	
Illiterate*Income															
$15,000 to less than $25,000	0.2735	0.1190	**	0.0951	0.1011		−0.0490	0.1102		0.1576	0.0893	*	−0.0473	0.1193	
$25,000 to less than $35,000	0.1527	0.1203		0.0018	0.1021		−0.1351	0.1077		0.0414	0.0907		−0.0324	0.1184	
$35,000 to less than $50,000	0.0681	0.1138		−0.0267	0.0975		−0.1542	0.1030		0.1303	0.0869		−0.0576	0.1101	
$50,000 to less than $75,000	0.1131	0.1161		0.0086	0.0945		−0.1386	0.1005		0.1008	0.0852		0.0059	0.1065	
$75,000 to less than $100,000	0.1277	0.1320		0.1247	0.1071		−0.2774	0.1123	**	0.0630	0.0983		−0.0541	0.1185	
$100,000 to less than $150,000	0.3937	0.1459	***	0.0697	0.1136		−0.2538	0.1225	**	0.0847	0.1081		−0.2023	0.1267	
$150,000 or more	0.4575	0.1681	***	0.2866	0.1372	**	−0.2536	0.1399	*	0.2996	0.1261	**	−0.1163	0.1422	

(continued on next page)

Table 6 (Continued)

	Debt counseling			Savings/investment			Mortgage/loan			Insurance			Tax planning		
	Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)	
Illiterate*Risk-tolerance															
Medium	−0.0201	0.0698		0.0878	0.0549		0.0457	0.0571		0.0113	0.0503		0.0502	0.0613	
High	0.2239	0.0838	***	0.2348	0.0686	***	0.3093	0.0722	***	0.1900	0.0654	***	0.2523	0.0735	***
Illiterate*Perceived financial knowledge															
Low	−0.0187	0.1037		0.0857	0.0940		0.1639	0.0912	*	0.1499	0.0813	*	0.0097	0.1044	
Medium	−0.0828	0.0856		0.1943	0.0708	***	0.0304	0.0729		0.0404	0.0645		0.0370	0.0798	
Illiterate*Financial fragility level															
1	−0.1071	0.1274		−0.0588	0.0789		−0.0575	0.0896		−0.0238	0.0798		0.0254	0.0860	
2	−0.1230	0.1229		0.0292	0.0790		0.0166	0.0877		0.0528	0.0786		0.1316	0.0875	
3	−0.3804	0.1230	***	−0.0044	0.0835		−0.1814	0.0917	**	0.0649	0.0806		−0.0412	0.0920	
4	−0.4484	0.1244	***	−0.0820	0.0886		−0.1169	0.0940		0.0361	0.0821		−0.0639	0.0993	
5	−0.3945	0.1312	***	0.0222	0.1019		−0.1758	0.1042	*	0.0109	0.0907		−0.1711	0.1109	
6	−0.0788	0.1815		0.0266	0.1764		−0.0926	0.1570		−0.1504	0.1380		−0.0380	0.1811	
Number of observations	25,509			25,509			25,509			25,509			25,509		

The young variable is included in a separate regression without the age ranges to avoid collinearity.
*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

Table 7 *T*-test of means for financial advice (liquidity constraint)

Type of advice	Have difficulty		No difficulty		
	Mean	Standard error	Mean	Standard error	
Debt counseling	0.1186	0.0033	0.0523	0.0027	***
Savings/investment	0.2201	0.0041	0.3785	0.0054	***
Mortgages/loans	0.1934	0.0039	0.2137	0.0046	***
Tax planning	0.1512	0.0036	0.2220	0.0046	***

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

To examine additional reasons that can explain the demand for different types of advice, the article uses as a proxy for liquidity constraints the difficulty to cover expenses and pay one's bills. The *t* test results in Table 7 indicate that respondents who do not experience liquidity constraints show a higher demand for advice about saving/investment, mortgages/loans, and insurance compared with those with a liquidity problem. Furthermore, homeownership has been used as a proxy for socioeconomic status and financial stability. The *t* test results in Table 8 show significant differences between homeowners and non-homeowners. The percentage of homeowners who seek financial advice is higher than that for non-homeowners across all types of advice except debt counseling. In addition, Table 9 shows that seeking debt counseling by respondents who declared bankruptcy is significantly different from those who did not experience bankruptcy.

To test the presence of significant differences in financial advice seeking behavior by females, the young, and the financially illiterate, the regression model in Table 6 uses interaction terms between those groups and the factors of interest over the whole sample. The results for females indicate that financial fragility only is related positively to seeking debt counseling and advice about mortgages/loans for respondents who experience at least three signs of financial difficulty. For the young group, the results show a negative relation between income and seeking advice about savings/investment, and tax planning. High risk tolerance is related positively to seeking advice about savings/investment, insurance, and tax planning. However, financial fragility is related negatively to debt counseling and advice about mortgages, and positively to advice about savings/investment, and tax planning. For the financially illiterate group, high risk tolerance is related positively to seeking all types of financial advice, while financial fragility has a negative association to seeking debt counseling.

Table 8 *T*-test of means for financial advice (home ownership)

Type of advice	Yes		No		
	Mean	Standard error	Mean	Standard error	
Savings/investment	0.3668	0.0046	0.1782	0.0046	***
Mortgages/loans	0.2671	0.0042	0.1130	0.0037	***
Insurance	0.3533	0.0045	0.2338	0.0050	***
Tax planning	0.2386	0.0041	0.1028	0.0036	***

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

Table 9 *T*-test of means for financial advice (bankruptcy)

Type of advice	Bankrupt		No bankruptcy		
	Mean	Standard error	Mean	Standard error	
Debt counseling	0.4873	0.0208	0.0760	0.0021	***

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

7.1. Subsample results: Females versus males

The female variable is found to be significant for seeking financial advice about savings/investment, and insurance only. The probit regression results for the female subsample are provided in Table 10. Income and risk tolerance are related positively, while a low perception of financial knowledge and financial fragility are related negatively to seeking both types of financial advice. These findings for the female subsample are identical to the findings for the male subsample in Table 11, except for the effect of financial knowledge. A low perception of financial knowledge has a greater effect on the demand for financial advice for females compared with males. Therefore, the characteristics that influence the demand for financial advice for females and males appear to be similar and gender differences do not distinguish the consumption of financial advice between these two groups.

7.2. Subsample results: Young versus old

The young (aged 18–44)[10] variable is found to be significant for seeking all types of financial advice, except savings/investment. Table 12 reports the estimates of four probit regression models for the young subsample. Income and risk tolerance are related positively to seeking all types of financial advice. A low perception of financial knowledge decreases the probability of seeking financial advice about mortgages/loans, insurance, and tax planning, while financial fragility is related positively to seeking debt counseling and negatively to seeking advice about insurance and tax planning. These findings are similar to those for the old group in Table 13, except for the low perception of financial knowledge, which does not appear as significant for the old compared with the young subsample. Age classification does not explain the consumption of financial advice.

7.3. Subsample results: Financially illiterate versus financially literate

The financially illiterate variable is found to be significant for seeking all types of financial advice except insurance. Table 14 provides the estimates of four probit regression models for the financially illiterate subsample. Income and risk tolerance are related positively to seeking the four types of financial advice. A low perception of financial knowledge is related negatively to seeking advice about mortgages/loans and tax planning and appears to have no significance on seeking advice about debt and savings/investment. While financial fragility increases the probability of seeking debt counseling, it decreases the probability of seeking advice about savings/investment and tax

Table 10 Financial advice probit (female)

Independent variables	Savings/investment			Insurance		
	Marg. effects	(SE)		Marg. effects	(SE)	
Race (non-White)						
White	−0.0024	0.0096		−0.0101	0.0103	
Age (65+)						
18–24	−0.0375	0.0184	**	0.0049	0.0210	
25–34	−0.1167	0.0170	***	−0.0246	0.0191	
35–44	−0.1710	0.0167	***	−0.0269	0.0186	
45–54	−0.1207	0.0145	***	−0.0160	0.0166	
55–64	−0.0570	0.0134	***	0.0052	0.0156	
Education level (college or more)						
High school or less	−0.1095	0.0113	***	−0.0786	0.0125	***
Some college	−0.0429	0.0105	***	−0.0023	0.0116	
Marital status (married)						
Living with a partner	0.0224	0.0164		−0.0122	0.0171	
Single	0.0218	0.0106	**	−0.0002	0.0114	
Number of children (no children)						
One child	0.0175	0.0133		0.0570	0.0141	***
Two children	0.0232	0.0151		0.0674	0.0157	***
Three children	−0.0093	0.0204		0.0493	0.0206	**
Four children or more	0.0711	0.0240	***	0.0804	0.0248	***
No financially dependent children	−0.0035	0.0126		0.0176	0.0141	
Annual income (less than $15,000)						
$15,000 to less than $25,000	0.0302	0.0181	*	0.0819	0.0183	***
$25,000 to less than $35,000	0.0610	0.0186	***	0.0909	0.0187	***
$35,000 to less than $50,000	0.0758	0.0177	***	0.0996	0.0185	***
$50,000 to less than $75,000	0.1137	0.0175	***	0.1318	0.0184	***
$75,000 to less than $100,000	0.1058	0.0196	***	0.1035	0.0209	***
$100,000 to less than $150,000	0.1300	0.0205	***	0.1087	0.0223	***
$150,000 or more	0.1728	0.0233	***	0.1509	0.0251	***
Risk-tolerance level (low)						
Medium	0.1154	0.0092	***	0.0774	0.0099	***
High	0.1762	0.0138	***	0.1341	0.0151	***
Perceived financial knowledge (high)						
Low	−0.0418	0.0168	***	−0.0563	0.0167	***
Medium	−0.0188	0.0124		−0.0403	0.0128	***
Financial literacy	0.0311	0.0033	***	0.0312	0.0035	***
Financial fragility	−0.0407	0.0031	***	−0.0060	0.0034	*
Number of observations	14,127			14,127		

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

planning. These findings are similar to the results for the financially literate subsample in Table 15. Therefore, the factors affecting the demand for financial advice show no significant differences based on the financial literacy level only.

8. Conclusion

This article uses the 2012 NFCS to investigate the correlates of seeking five types of financial advice: debt counseling, savings/investment, mortgages/loans, insurance, and tax

Table 11 Financial advice probit (male)

Independent variables	Savings/investment			Insurance		
	Marg. effects	(SE)		Marg. effects	(SE)	
Race (non-White)						
White	−0.0004	0.0108		−0.0073	0.0117	
Age (65+)						
18–24	0.0756	0.0212	***	0.1025	0.0238	***
25–34	0.0312	0.0175	*	0.1054	0.0196	***
35–44	−0.0501	0.0172	***	0.0502	0.0193	***
45–54	−0.0691	0.0153	***	0.0392	0.0173	**
55–64	−0.0174	0.0141		0.0281	0.0160	*
Education level (college or more)						
High school or less	−0.0808	0.0124	***	−0.0615	0.0134	***
Some college	−0.0439	0.0106	***	−0.0251	0.0116	**
Marital status (married)						
Living with a partner	−0.0021	0.0184		−0.0074	0.0198	
Single	−0.0159	0.0120		−0.0452	0.0130	***
Number of children (no children)						
One child	0.0519	0.0147	***	0.0703	0.0159	***
Two children	0.0476	0.0160	***	0.0900	0.0174	***
Three children	0.0429	0.0221	*	0.0365	0.0236	
Four children or more	0.0671	0.0311	**	0.1042	0.0320	***
No financially dependent children	0.0350	0.0133	***	0.0401	0.0147	***
Annual income (less than $15,000)						
$15,000 to less than $25,000	0.0920	0.0222	***	0.1259	0.0228	***
$25,000 to less than $35,000	0.0832	0.0220	***	0.1146	0.0231	***
$35,000 to less than $50,000	0.0916	0.0207	***	0.1327	0.0215	***
$50,000 to less than $75,000	0.1096	0.0204	***	0.1275	0.0213	***
$75,000 to less than $100,000	0.1446	0.0218	***	0.1260	0.0233	***
$100,000 to less than $150,000	0.1582	0.0227	***	0.1582	0.0241	***
$150,000 or more	0.1624	0.0257	***	0.1565	0.0272	***
Risk-tolerance level (low)						
Medium	0.1066	0.0109	***	0.0697	0.0119	***
High	0.1590	0.0128	***	0.1046	0.0142	***
Perceived financial knowledge (high)						
Low	−0.0234	0.0214		−0.0453	0.0214	**
Medium	−0.0192	0.0148		−0.0240	0.0157	
Financial literacy	0.0151	0.0036	***	0.0124	0.0039	***
Financial fragility	−0.0373	0.0035	***	−0.0080	0.0037	**
Number of observations	11,382			11,382		

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

planning. Although only 24% of respondents are satisfied with their personal financial condition, the use of financial advice is within the range of 9–30% of the U.S. population, depending on the type of advice. While 73% of respondents assessed themselves as financially knowledgeable, only 16% were able to answer five basic financial literacy questions correctly. This discrepancy raises the complex question of why individuals are reluctant to seek professional financial advice.

The analysis of the multivariate results reveals a consistent effect of key factors on the demand for the five types of financial advice and no significant differences have been found among the subsamples, which are defined by gender, age, and financial literacy. Income and

Table 12 Financial advice probit (the young 18–44)

Independent variables	Debt counseling			Mortgage/loan			Insurance			Tax planning		
	Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)	
Gender (male)												
Female	−0.0157	0.0069	**	−0.0148	0.0098		0.0020	0.0107		−0.0281	0.0088	***
Race (non-White)												
White	−0.0149	0.0068	**	0.0098	0.0100		−0.0220	0.0107	**	−0.0332	0.0089	***
Education level (college or more)												
High school or less	−0.0376	0.0091	***	−0.0787	0.0129	***	−0.0646	0.0139	***	−0.0459	0.0117	***
Some college	−0.0180	0.0080	**	−0.0278	0.0115	**	−0.0268	0.0127	**	−0.0314	0.0104	***
Marital status (married)												
Living with a partner	−0.0075	0.0113		−0.0246	0.0154		−0.0124	0.0168		−0.0136	0.0141	
Single	−0.0003	0.0090		−0.0874	0.0126	***	−0.0362	0.0137	***	−0.0301	0.0112	***
Number of children (no children)												
One child	0.0544	0.0096	***	0.0326	0.0133	**	0.0714	0.0146	***	0.0418	0.0120	***
Two children	0.0610	0.0102	***	0.0364	0.0139	***	0.0819	0.0154	***	0.0328	0.0126	***
Three children	0.0474	0.0124	***	0.0353	0.0180	**	0.0393	0.0195	**	0.0238	0.0166	
Four children or more	0.0608	0.0148	***	0.0452	0.0216	**	0.0647	0.0237	***	0.0261	0.0195	
No financially dependent children	0.0093	0.0162		−0.0040	0.0236		0.0104	0.0238		0.0027	0.0215	
Annual income (less than $15,000)												
$15,000 to less than $25,000	0.0430	0.0130	***	0.0701	0.0203	***	0.1207	0.0199	***	0.0619	0.0179	***
$25,000 to less than $35,000	0.0454	0.0133	***	0.0920	0.0197	***	0.1074	0.0202	***	0.0551	0.0178	***
$35,000 to less than $50,000	0.0628	0.0126	***	0.0806	0.0188	***	0.1258	0.0195	***	0.0728	0.0169	***
$50,000 to less than $75,000	0.0720	0.0127	***	0.1305	0.0185	***	0.1451	0.0192	***	0.0769	0.0167	***
$75,000 to less than $100,000	0.0722	0.0142	***	0.1429	0.0207	***	0.1031	0.0217	***	0.0872	0.0186	***
$100,000 to less than $150,000	0.0623	0.0167	***	0.1588	0.0226	***	0.1299	0.0241	***	0.0900	0.0203	***
$150,000 or more	0.0521	0.0187	***	0.1689	0.0258	***	0.1403	0.0282	***	0.1175	0.0227	***
Risk-tolerance level (low)												
Medium	0.0223	0.0079	***	0.0543	0.0112	***	0.0796	0.0120	***	0.0645	0.0106	***
High	0.0579	0.0089	***	0.0950	0.0135	***	0.1333	0.0146	***	0.1292	0.0120	***
Perceived financial knowledge (high)												
Low	−0.0166	0.0116		−0.0661	0.0179	***	−0.0686	0.0187	***	−0.0379	0.0168	**
Medium	−0.0198	0.0092	**	−0.0312	0.0132	**	−0.0502	0.0142	***	−0.0184	0.0121	
Financial literacy	−0.0073	0.0024	***	0.0163	0.0035	***	0.0187	0.0038	***	0.0023	0.0031	
Financial fragility	0.0163	0.0024	***	−0.0055	0.0035		−0.0081	0.0037	**	−0.0125	0.0032	***
Number of observations	11,135			11,135			11,135			11,135		

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

Table 13 Financial advice probit (the old 45+)

Independent variables	Debt counseling			Mortgage/loan			Insurance			Tax planning		
	Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marge	(SE)	
Gender (male)												
Female	0.0039	0.0059		0.0161	0.0071	**	0.0667	0.0089	***	0.0330	0.0066	***
Race (non-White)												
White	−0.0299	0.0069	***	0.0302	0.0090	***	0.0024	0.0112		0.0209	0.0085	**
Education level (college or more)												
High school or less	−0.0236	0.0075	***	−0.0464	0.0095	***	−0.0700	0.0119	***	−0.0667	0.0089	***
Some college	−0.0106	0.0070		−0.0018	0.0082		0.0001	0.0105		−0.0261	0.0075	***
Marital status (married)												
Living with a partner	0.0105	0.0129		0.0101	0.0162		−0.0062	0.0207		−0.0276	0.0165	*
Single	0.0037	0.0070		−0.0031	0.0089		0.0014	0.0109		0.0086	0.0082	
Number of children (no children)												
One child	0.0133	0.0095		0.0539	0.0119	***	0.0471	0.0149	***	0.0203	0.0113	*
Two children	0.0158	0.0109		0.0540	0.0139	***	0.0542	0.0177	***	0.0138	0.0133	
Three children	0.0352	0.0152	**	0.0690	0.0205	***	0.0307	0.0260		−0.0440	0.0200	**
Four children or more	0.0538	0.0191	***	0.0828	0.0264	***	0.1225	0.0358	***	0.0153	0.0281	
No financially dependent children	−0.0056	0.0076		0.0243	0.0095	**	0.0236	0.0116	**	0.0060	0.0089	
Annual income (less than $15,000)												
$15,000 to less than $25,000	0.0592	0.0122	***	0.0561	0.0191	***	0.0616	0.0205	***	0.0326	0.0195	*
$25,000 to less than $35,000	0.0744	0.0122	***	0.1067	0.0187	***	0.0777	0.0209	***	0.0764	0.0190	***
$35,000 to less than $50,000	0.0770	0.0119	***	0.1320	0.0180	***	0.0874	0.0201	***	0.0931	0.0179	***
$50,000 to less than $75,000	0.0714	0.0126	***	0.1638	0.0179	***	0.0974	0.0202	***	0.1278	0.0176	***
$75,000 to less than $100,000	0.0841	0.0143	***	0.1909	0.0191	***	0.1050	0.0223	***	0.1495	0.0188	***
$100,000 to less than $150,000	0.0809	0.0151	***	0.2079	0.0195	***	0.1243	0.0227	***	0.1661	0.0190	***
$150,000 or more	0.0865	0.0173	***	0.2501	0.0211	***	0.1506	0.0253	***	0.2159	0.0203	***
Risk-tolerance level (low)												
Medium	0.0020	0.0066		0.0319	0.0078	***	0.0735	0.0097	***	0.0391	0.0074	***
High	0.0353	0.0094	***	0.0497	0.0114	***	0.0924	0.0143	***	0.0650	0.0104	***
Perceived financial knowledge (high)												
Low	−0.0051	0.0104		−0.0516	0.0149	***	−0.0211	0.0182		−0.0271	0.0152	*
Medium	−0.0098	0.0082		−0.0081	0.0111		−0.0111	0.0137		−0.0106	0.0110	
Financial literacy	−0.0025	0.0023		0.0188	0.0029	***	0.0252	0.0035	***	0.0192	0.0027	***
Financial fragility	0.0246	0.0021	***	0.0092	0.0026	***	−0.0064	0.0033	*	−0.0149	0.0026	***
Number of observations	14,356			14,356			14,356			14,356		

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

Table 14 Financial advice probit (the financially illiterate)

Independent variables	Debt counseling			Savings/investment			Mortgage/loan			Tax planning		
	Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)	
Gender (male)												
Female	−0.0186	0.0085	**	−0.0148	0.0114		−0.0194	0.0104	*	−0.0227	0.0099	**
Race (non-White)												
White	−0.0301	0.0086	***	−0.0184	0.0115		0.0049	0.0106		−0.0210	0.0100	**
Age (65+)												
18–24	0.0138	0.0194		0.0317	0.0226		0.1017	0.0234	***	0.0691	0.0214	***
25–34	0.0237	0.0184		−0.0091	0.0222		0.1095	0.0220	***	0.0454	0.0206	**
35–44	−0.0084	0.0192		−0.0944	0.0229	***	0.0453	0.0229	**	−0.0149	0.0212	
45–54	0.0012	0.0183		−0.0755	0.0211	***	0.0290	0.0218		−0.0211	0.0200	
55–64	0.0023	0.0183		−0.0153	0.0211		0.0298	0.0221		−0.0124	0.0202	
Education level (college or more)												
High school or less	−0.0563	0.0107	***	−0.1103	0.0145	***	−0.0804	0.0135	***	−0.0709	0.0130	***
Some college	−0.0453	0.0106	***	−0.0489	0.0145	***	−0.0336	0.0131	**	−0.0467	0.0126	***
Marital status (married)												
Living with a partner	−0.0115	0.0141		0.0309	0.0189		−0.0148	0.0166		0.0013	0.0161	
Single	−0.0072	0.0103		0.0151	0.0137		−0.0322	0.0122	***	−0.0216	0.0117	*
Number of children (no children)												
One child	0.0462	0.0119	***	0.0531	0.0161	***	0.0506	0.0141	***	0.0468	0.0138	***
Two children	0.0413	0.0136	***	0.0427	0.0185	**	0.0631	0.0159	***	0.0319	0.0158	**
Three children	0.0527	0.0167	***	−0.0213	0.0249		0.0464	0.0205	**	0.0323	0.0203	
Four children or more	0.0423	0.0203	**	0.0331	0.0284		0.0494	0.0241	**	0.0306	0.0241	
No financially dependent children	0.0039	0.0139		0.0192	0.0171		0.0268	0.0168		0.0159	0.0169	
Annual income (less than $15,000)												
$15,000 to less than $25,000	0.0775	0.0140	***	0.0660	0.0189	***	0.0622	0.0182	***	0.0461	0.0178	***
$25,000 to less than $35,000	0.0726	0.0145	***	0.0671	0.0202	***	0.0842	0.0180	***	0.0627	0.0183	***
$35,000 to less than $50,000	0.0765	0.0145	***	0.0728	0.0198	***	0.0847	0.0181	***	0.0732	0.0174	***
$50,000 to less than $75,000	0.0784	0.0153	***	0.1116	0.0199	***	0.1243	0.0182	***	0.0992	0.0174	***
$75,000 to less than $100,000	0.0912	0.0183	***	0.1362	0.0237	***	0.1268	0.0215	***	0.1050	0.0207	***
$100,000 to less than $150,000	0.1080	0.0210	***	0.1554	0.0256	***	0.1431	0.0246	***	0.0979	0.0232	***
$150,000 or more	0.1109	0.0230	***	0.2152	0.0314	***	0.1636	0.0278	***	0.1439	0.0260	***
Risk-tolerance level (low)												
Medium	0.0135	0.0095		0.1092	0.0122	***	0.0438	0.0113	***	0.0517	0.0113	***
High	0.0704	0.0114	***	0.1807	0.0153	***	0.1000	0.0142	***	0.1124	0.0134	***
Perceived financial knowledge (high)												
Low	−0.0157	0.0127		−0.0292	0.0186		−0.0385	0.0158	**	−0.0338	0.0170	**
Medium	−0.0274	0.0113	**	0.0013	0.0150		−0.0171	0.0136		−0.0100	0.0136	
Financial fragility	0.0176	0.0030	***	−0.0396	0.0039	***	−0.0034	0.0036		−0.0181	0.0035	***
Number of observations	8,921			8,921			8,921			8,921		

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

Table 15 Financial advice probit (the financially literate)

Independent variables	Debt counseling			Savings/investment			Mortgage/loan			Tax planning		
	Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)		Marg. effects	(SE)	
Gender (male)												
Female	0.0001	0.0053		0.0473	0.0076	***	0.0131	0.0070	*	0.0183	0.0066	***
Race (non-White)												
White	−0.0140	0.0061	**	0.0120	0.0095		0.0348	0.0085	***	0.0022	0.0082	
Age (65+)												
18–24	0.0328	0.0149	**	−0.0154	0.0199		0.0555	0.0197	***	0.0053	0.0184	
25–34	0.0392	0.0113	***	−0.0706	0.0153	***	0.1111	0.0143	***	−0.0119	0.0133	
35–44	0.0216	0.0107	**	−0.1234	0.0145	***	0.0567	0.0136	***	−0.0593	0.0127	***
45–54	0.0088	0.0102		−0.1099	0.0126	***	0.0189	0.0122		−0.0551	0.0111	***
55–64	0.0295	0.0093	***	−0.0467	0.0113	***	0.0212	0.0111	*	−0.0219	0.0098	**
Education level (college or more)												
High school or less	−0.0235	0.0072	***	−0.0976	0.0103	***	−0.0632	0.0096	***	−0.0616	0.0092	***
Some college	−0.0046	0.0062		−0.0504	0.0089	***	−0.0108	0.0082		−0.0300	0.0077	***
Marital status (married)												
Living with a partner	0.0059	0.0110		−0.0026	0.0163		−0.0009	0.0146		−0.0333	0.0149	**
Single	0.0080	0.0067		0.0045	0.0099		−0.0447	0.0094	***	−0.0092	0.0087	
Number of children (no children)												
One child	0.0349	0.0085	***	0.0221	0.0125	*	0.0439	0.0115	***	0.0406	0.0111	***
Two children	0.0506	0.0089	***	0.0296	0.0138	**	0.0455	0.0123	***	0.0458	0.0121	***
Three children	0.0323	0.0116	***	0.0378	0.0196	*	0.0609	0.0172	***	0.0066	0.0170	
Four children or more	0.0687	0.0143	***	0.0896	0.0264	***	0.0843	0.0225	***	0.0499	0.0222	**
No financially dependent children	0.0075	0.0084		0.0135	0.0112		0.0172	0.0107		0.0113	0.0099	
Annual income (less than $15,000)												
$15,000 to less than $25,000	0.0253	0.0124	**	0.0543	0.0208	***	0.0677	0.0205	***	0.0529	0.0205	***
$25,000 to less than $35,000	0.0440	0.0124	***	0.0809	0.0205	***	0.1126	0.0197	***	0.0701	0.0197	***
$35,000 to less than $50,000	0.0574	0.0116	***	0.0976	0.0191	***	0.1279	0.0186	***	0.0916	0.0187	***
$50,000 to less than $75,000	0.0596	0.0118	***	0.1236	0.0189	***	0.1690	0.0182	***	0.1153	0.0183	***
$75,000 to less than $100,000	0.0661	0.0128	***	0.1375	0.0199	***	0.2005	0.0193	***	0.1414	0.0192	***
$100,000 to less than $150,000	0.0496	0.0140	***	0.1592	0.0206	***	0.2176	0.0198	***	0.1640	0.0196	***
$150,000 or more	0.0451	0.0162	***	0.1744	0.0226	***	0.2532	0.0214	***	0.2124	0.0209	***
Risk-tolerance level (low)												
Medium	0.0087	0.0061		0.1162	0.0087	***	0.0389	0.0081	***	0.0567	0.0078	***
High	0.0356	0.0078	***	0.1661	0.0119	***	0.0573	0.0110	***	0.0969	0.0104	***
Perceived financial knowledge (high)												
Low	−0.0067	0.0104		−0.0447	0.0189	**	−0.0890	0.0165	***	−0.0362	0.0165	**
Medium	−0.0091	0.0075		−0.0392	0.0122	***	−0.0244	0.0111	**	−0.0219	0.0108	**
Financial fragility	0.0222	0.0019	***	−0.0407	0.0030	***	0.0030	0.0028		−0.0140	0.0026	***
Number of observations	16,588			16,588			16,588			16,588		

*Significance at 10% level; **significance at 5% level; ***significance at 1% level.

risk tolerance are related positively to the demand for all types of financial advice and more greatly affect the probability of seeking advice than do other variables. The finding for income is consistent with the article's expectation that those with relatively high incomes might have a sufficient level of financial sophistication to seek financial advice in the areas of savings/investment, mortgages/loans, insurance, and tax planning. The positive relation between income and debt counseling was not expected, however. This relation could be interpreted as the result of a tendency of those who see increases in income to accumulate debt to fund a lifestyle that exceeds their income level.

Risk tolerance plays a significant role and demonstrates a strong positive effect on the demand for all types of financial advice. However, the subjective assessment of risk tolerance in the survey raises a question about the accuracy and reliability of this measure in reflecting respondents' actual risk tolerance and their understanding of its significance for their financial investments.

A low perception of financial knowledge decreases the demand for all types of financial advice except debt counseling. This finding does not support the expected negative relation between perceived financial knowledge and the demand for financial advice and contradicts some findings in prior research. This subjective assessment of financial knowledge might become a psychological barrier that decreases the demand for financial advice because respondents are not confident in their ability to assess financial products and monitor agency relationships.

On the other hand, financial fragility, has been found to be related negatively to seeking financial advice about savings/investment, insurance, and tax planning, and related positively to seeking debt counseling. People who struggle with their expenses and are not able to save for retirement might not have the luxury to think about investment or tax planning. Financial stress would draw their attention away from long-term plans toward immediate short-term concerns.

The survey question about seeking the five types of financial advice refers to this behavior in the past five years and does not necessarily indicate that respondents never seek professional financial advice or use alternative sources such as their social network. Furthermore, because the survey focuses on individual responses, the household's behavior may not be observed accurately. If the spouse, for example, seeks financial advice, then the other spouse may not indicate seeking such advice.

Understanding the demand for professional financial advice requires an examination of the effect that salient and hidden fees have on people's decisions to contract financial advisers. In addition, future research has to examine the determinants of trust because respondents lack the ability to assess service quality and evaluate outcomes. Financial advice is a mosaic of services, and several factors influence the demand for different types of advice. The similarity of payment-reward trade-off (i.e., fee payment for investment return) makes financial advice a unique service arrangement because individuals' mode of payment is that exact commodity that they aim to preserve and grow to smooth their consumption power over their life cycle.

Notes

1 The Assets & Opportunities Scorecard is a comprehensive look at Americans' financial security based on 130 outcome and policy measures. The Scorecard enables states

to benchmark their outcomes and policies against other states in five areas: Financial Assets & Income, Businesses & Jobs, Housing & Homeownership, Health Care, and Education. http://assetsandopportunity.org/scorecard

2 Self-concealment refers to the psychological tendency to keep perceived negative or intimate personal information secret. Older homeowners might conceal their financial difficulty to protect their social status and perceived financial competency.

3 The survey's questionnaire asks for detailed race and ethnicity information but the dataset provides information regarding White and non-White only.

4 The subjective risk tolerance levels as per the 10-point scale are as follows:
- 1–3: low risk tolerance
- 4–7: medium risk tolerance
- 8–10: high risk tolerance

5 The financial knowledge levels as per the seven-point scale are as follows:
- 1–3: low financial knowledge
- 4: medium financial knowledge
- 5–7: high financial knowledge

6 The survey question for the dependent variables is: In the last five years, have you asked for any advice from a financial professional about any of the following? Debt counseling—savings or investment—taking out a mortgage or a loan—insurance of any type—tax planning.

7 Wealth is a preferable factor in the decision to purchase financial advice, but is not included in the 2012 NFCS. Therefore, income has been used to proxy wealth in the model as the level of earning power might indicate a level of financial sophistication and capability to seek professional financial advice.

8 Risk tolerance has been aggregated into three levels because the survey question measures it on a scale from 1-very low to 10-very high and the responses are almost evenly distributed across the scale.

9 Subjective assessment of financial knowledge has been aggregated into three levels because the survey question measures it on a scale from 1 to 7.

10 The classification of younger respondents as those aged 18–44 follows the methodology in CFP 2015 Stress Awareness Month Survey Report.

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1. In "Does Financial Risk Tolerance Change Over Time? A Test of the Role Macroeconomic, Biopsychosocial and Environmental, and Social Support Factors Play in Shaping Changes in Risk Attitudes" by Kuzniak and Grable, a client's risk tolerance is most closely related to:
   a. the client's perception of an investment's risk.
   b. the client's willingness to take risk.
   c. the client's preference for one investment over another.
   d. the client's capacity to take risk.

2. In Kuzniak and Grable, some financial planners use client demographic characteristics to gauge a client's risk tolerance. Which of the following characteristics is generally positively associated with the willingness to take financial risk?
   a. Being female.
   b. Being older.
   c. Having more than poverty level income but less than $599,999 in household income.
   d. Holding a college degree or higher level of education.

3. In Kuzniak and Grable, which of the following statements is true regarding similarities and differences among the United Kingdom, United States, and Australia?
   a. Social support is highest in the United Kingdom.
   b. Australian GDP tends to move in the opposite direction from the United States.
   c. The securities markets in these three countries are not highly correlated, making investments across the three countries a valuable diversification tool.
   d. United Kingdom (UK) and United States (US) GDP is positively correlated with UK and US unemployment.

4. In Kuzniak and Grable, Jamal recently met with two prospective clients. The first client was 68 years of age. The second client was 42 years of age. Which client is most likely to exhibit a decrease in their risk tolerance over time?
   a. The younger client.
   b. The younger client only if their initial risk-tolerance test score starts off low.
   c. The older client.
   d. The older client only if their initial risk-tolerance test score starts off low.

5. In Kuzniak and Grable, across a sample of financial planning clients, approximately what percent are likely to exhibit consistent financial-risk tolerance test scores across time?
   a. 25%.
   b. 55%.
   c. 75%.
   d. 85%.

6. In "Which Measures Predict Risk Taking in a Multi-stage Controlled Investment Decision Process?" by Bachmann, Hens, and Stössel, which measure best explains the investment risk taking behavior of individuals?
   a. The individual ability to take risk
   b. The individual loss aversion
   c. The individual ability to assess the riskiness of investments
   d. The individual investment experience

7. In Bachmann, Hens, and Stössel, how does simulated investment experience affect risk taking?
   a. Risk taking decreases but not significantly
   b. Risk taking decreases significantly
   c. Risk taking increases but not significantly
   d. Risk taking increases significantly

8. In Bachmann, Hens, and Stössel, does simulated investment experience improve the ability to assess the risk-reward trade-offs of investments?
   a. Yes
   b. No
   c. Yes, but only if individuals have a strong financial literacy
   d. Yes, but only if individuals do not overestimate their investment skills

9. In Bachmann, Hens, and Stössel, which questions assessing the individual risk preferences consistently predict individual risk taking?
   a. Questions on loss aversion
   b. Questions on risk aversion
   c. Questions on investment experience
   d. Questions on general risk taking

10. In Bachmann, Hens, and Stössel, if risk preferences cannot be assessed, which of the following measures can be considered as a consistent predictor of individual risk taking?
    a. Age
    b. Gender
    c. Education level
    d. Profession

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