

Common:**1. Introduction**

The recent household finance literature shows large and persistent heterogeneity in people's portfolio composition and returns (e.g., Fagereng et al., 2020). While investment differences have been related to individual characteristics such as age, wealth, intelligence and financial literacy, these individual characteristics do not fully account for the observed heterogeneity (e.g., Gomes et al., 2021). A similar challenge arises when using demographic variables to explain investor beliefs—a key ingredient of portfolio decisions. For example, Giglio et al. (2021) show that there is persistent heterogeneity in investor expectations and an exhaustive list of demographic variables can only explain a small fraction of this variation. Overall, the empirical evidence suggests a need to expand the set of characteristics to explain the process through which people make investment decisions.

In this paper, we bring in a new set of individual attributes to shed light on the process of financial decision-making. Our overarching hypothesis is that persistent differences in personality traits are related to persistent differences in both beliefs and investment decisions. This, we argue, is plausible ex-ante for two reasons. First, extensive research has shown that personality traits matter for a variety of life outcomes, including health and aging, marital and career success, and economic decisions such as spending behaviors (Becker et al., 2012). As investment decisions just represent another form of life decisions, it is reasonable to expect personality traits to also play a role. Second, many concepts coined by personality psychologists, such as Neuroticism and Conscientiousness, are related and potentially complementary to concepts developed by economists, such as risk aversion and time preference. These psychology-based concepts can potentially provide new ways to measure and demonstrate the forces behind investment decisions above and beyond the traditional measures in economics.

To organize our empirical analysis, we first present a stylized portfolio-choice model to illustrate the potential connections between personality traits and portfolio decisions. In this model, an investor weighs between optimizing a standard mean-variance utility and maintaining a “target portfolio.” The former captures the pecuniary effects of standard mean-variance preferences while the latter, in a reduced form, reflects non-pecuniary effects. For example, some individuals may enjoy investing in the stock market as a social activity and therefore derive utility from a source independent of investment returns. Such a tendency, in our model, would be reflected by a target portfolio with a high equity share. Hence, portfolio choice is determined through two channels: the standard mean-variance optimization and the target portfolio.

We hypothesize that personality traits are related to portfolios through both channels. Motivated by the growing literature that uses surveys to study people's investment decision process (Choi and Robertson, 2020; Giglio et al., 2021; Chinco et al., 2022; Liu et al., 2022), we design and administer a nationwide survey to collect information on personality traits and investment decisions. This approach is particularly well-suited for the study of personality traits, because psychologists have spent decades refining the measurement of personality traits and have come up with well-established questionnaires ready for use. Our survey uses a 20-item questionnaire to elicit each respondent's personality traits in the Big Five dimensions, including Extraversion, Agreeableness, Openness, Conscientiousness, and Neuroticism (Condon and

Revelle, 2015). In addition to having a module on personality traits, the survey also asks about expectations of key economic indicators, risk preferences, social interaction tendencies, and asset allocation decisions. The American Association of Individual Investors (AAII) distributes our survey to its members. The survey yields 3,325 completed voluntary responses, with median reported wealth of 3.5 million U.S. dollars.

We document four main findings about the relationship between personality traits and investment decisions. First, the Big Five personality traits have significant power for explaining belief heterogeneity. Neuroticism stands out: investors high in Neuroticism are more pessimistic about average future stock returns and assign a greater probability to a crash. They are also more pessimistic about future economic growth and expect higher inflation. When explaining expectations about stock market returns, the explanatory power of the five personality traits, measured by the adjusted R-squared, is comparable to that of all demographic variables combined.

Second, personality traits are also related to risk preferences. In particular, investors high in Openness are more willing to take risks. Moreover, an investor's elicited expected stock return and risk aversion are uncorrelated, suggesting that these two measures reflect different aspects of individual characteristics.

Third, we connect personality traits to portfolio holdings and examine the underlying mechanisms. Investors who score high on Neuroticism or low on Openness tend to invest less in equities. However, these two traits appear to affect investment decision-making through different channels: high Neuroticism is associated with pessimistic beliefs about future stock returns and tail risks, whereas low Openness is associated with high risk aversion. Moreover, the two traits remain significant in explaining asset allocations even after controlling for risk aversion and return expectations. This suggests that personality traits carry additional explanatory power for investment decisions beyond the traditional measures of beliefs and preferences.

Fourth, we find that personality traits also affect other aspects of belief formation and portfolio decisions. For example, investors react differently to the behavior of the people in their social circles: those who score high on Neuroticism and Extraversion are more likely to adopt a certain investment when it becomes popular among people around them. We also find that personality traits are correlated with how people form conditional expectations on stock returns. Once again, Neuroticism and Openness stand out: higher Neuroticism is associated with stronger beliefs in mean-reversion, while higher Openness is associated with more extrapolative beliefs. The above results are based on correlations between personality traits and asset allocations. A natural concern is omitted variables, the variation of which affects both personalities and investment decisions. We address this concern in two ways. First, in investor-level regressions, we include a large set of demographic variables, such as income and wealth, as well as preference and belief characteristics as controls. The explanatory power of personality traits is robust to the inclusion of these controls. Second, we note that personality traits display remarkable stability within individuals over time (Cobb-Clark and Schurer, 2012; Flinn et al., 2018; Parise and Peijnenburg, 2019).¹ The high persistence in personality traits mitigates the concern that the documented correlation between personality traits and equity allocations is due to concurrent omitted variables, since personality traits have been mostly determined before the

realizations of concurrent variables. Instead, personality traits capture persistent differences across individuals that also manifest themselves in financial decisions.

We also note that, interestingly, personality traits important for financial decisions are different from those that covary with other economic outcomes. For example, the labor economics literature finds Agreeableness to be a key personality trait that drives economic outcomes in the labor market.² However, we find no evidence that Agreeableness plays a direct role in financial decisions.³ Therefore, the importance of each personality trait may vary from one economic domain to another, and our exercise shows that Neuroticism and Openness are the most relevant traits in the domain of financial decisions. Moreover, this domain specificity imposes additional limitations on the scope of alternative explanations. If, for example, the explanatory power of personality traits is driven by some fixed unobserved characteristics, these characteristics need to be more relevant in this financial setting but not so much other economic settings that have been examined.

Our analysis has important implications for how economists could bring personality traits into a financial-decision framework. First, personality traits are not equally important, and their relative importance may be domain-specific. Second, personality traits may operate through different channels. Therefore, even though multiple traits may affect asset allocation simultaneously, the underlying mechanisms could be completely different, as in the case of Neuroticism and Openness in our analysis. Third, to fully connect personality traits to investment decisions, we may need to go beyond the traditional framework by considering the social aspect of investment decision-making, a topic that has recently received growing attention (Han et al., 2022; Hirshleifer, 2020). Finally, the measurement system of personality traits and that of preferences (e.g., risk, time, and social) complement each other in explaining individuals' economic behavior (Becker et al., 2012). In light of this complementarity, personality traits can provide a useful set of noncognitive attributes. Indeed, many household panels begin to include a module of personality traits, and it would be useful for researchers to begin including these additional variables either as explanatory variables or as controls in household-level analysis.⁴

To examine the robustness of our results, we conduct similar analysis using two additional datasets: the "Household, Income and Labour Dynamics in Australia" (HILDA) Survey and the "German Socio-Economic Panel (GSOEP)" Survey. The two datasets cover representative panels of the Australian and German population, respectively. Again, traits Neuroticism and Openness stand out and their associations with investors' equity shares are qualitatively the same as those in our U.S. survey. These results not only offer an important out-of-sample test, but also demonstrate the robustness of our findings in different populations across business cycles.

A vast literature documents persistent heterogeneity in investment decision-making and outcomes across households (Benhabib and Bisin, 2018; Bach et al., 2020; Campbell et al., 2019; An et al., 2022; Fagereng et al., 2020). The heterogeneity in portfolio decisions can be attributed to demographic variables, such as age, gender, wealth, IQ, and geographic location (Barber and Odean, 2001; D'Acunto et al., 2019a, D'Acunto et al., 2019b), and to other characteristics, such as own or friends' past experience and political orientation (Malmendier and Nagel, 2011, Malmendier and Nagel, 2016; Bailey et al., 2018; Meeuwis et al., 2018; Nagel and Xu, 2022). Giglio et al. (2021) recently show that beliefs are mostly characterized by large and persistent individual differences unexplained by demographic variables. Our paper

contributes to this literature by showing that personality traits are related to the cross-sectional difference in beliefs after controlling for demographic variables. This result puts forward personality traits as promising variables for understanding why some people are persistently optimistic while others are persistently pessimistic. In a similar spirit, we also show that personality traits are correlated with cross-sectional differences in risk aversion and social interaction. The latter result adds to the recent literature on the social aspects of investment decisions (Hirshleifer, 2020).

Our paper is also related to the growing literature on the implications of personality for economic outcomes, including income, wealth, educational attainment and achievement (Almlund et al., 2011). In the domain of financial decisions, Grinblatt and Keloharju (2009) studies how sensation seeking—one particular personality trait—affects excessive trading, Conlin et al. (2015) examine the correlation between an alternative set of personality traits and stock market participation, and Parise and Peijnenburg (2019) show that low noncognitive abilities contribute to a greater probability of financial distress. Bucciol and Zarri (2017) examine the relationship between personality traits and investment decisions, although the effects of personality traits are likely absorbed by variables such as anxiety. Compared to these earlier works, our paper is distinct in two dimensions. First, our survey covers the respondents' personality traits and financial investments, as well as beliefs, risk preferences, and social interaction. In doing so, we are able to examine the underlying mechanisms through which personality traits affect investment decisions. Second, by surveying thousands of Americans who have invested substantial amounts in financial markets, we focus on a more sophisticated spectrum of market participants and show personality traits matter among these people.

Our paper complements the literature that attempts to link financial decision-making to genetics. For example, Kuhnen et al. (2013) study how a particular genetic variation explains financial decisions through its effects on Neuroticism. There is further evidence that both financial decisions and personality traits are persistent and appear correlated with genetics.⁵ In a recent study, Sias et al. (2020) study how genetic traits predict an individual's Neuroticism and therefore equity market participation. It has been shown that personality traits are shaped by both genetics and environment (Bouchard et al., 1994). Hence, genetics provide an a priori source of variation with clean measurement. In comparison, while survey-based measurements of personality traits may be more noisy, they summarize information from both genes and experiences.

Finally, our paper contributes to a growing literature that uses a survey-based approach to study how people make financial decisions. Previous literature has shown how survey expectations explain equity holdings (Giglio et al., 2021), how surveys can differentiate various finance theories (Choi and Robertson, 2020; Liu et al., 2022), and how surveys can shed light on the subjective perception of risks (Chinco et al., 2022). We highlight the value of survey-based personality traits by demonstrating how they enrich our understanding of investment decisions.

2. Big Five personality traits and investment decisions

2.1. Definitions and measurements

The Big Five model of personality traits arises from the factor analysis of statements people use to describe themselves.⁶ Across numerous studies that vary in survey questions, languages, and cultures, a stable structure of five traits emerges as a parsimonious way to organize individual differences that can be articulated in natural languages. This finding is surprising,

since the theories of personality have been remarkably diverse and the questionnaires designed to operationalize them show little resemblance to each other (McCrae and John, 1992). Below, we explain these five traits and the standard measurement methodology adopted in this paper.

Openness Openness (to experience) refers to the tendency to be open to new aesthetic, cultural, or intellectual experiences. People who are open to experience are intellectually curious, open to emotion, sensitive to beauty, and willing to try new things. They tend to be more creative and more aware of their feelings. They are also more likely to entertain unconventional ideas.⁷

We use the 20-item form from the SAPA Personality Inventory (Condon and Revelle, 2015), which measures each personality trait by four questions. To measure Openness, we ask respondents self-evaluate, on a scale of 1 to 6, whether they are “full of ideas,” are “able to come up with new and different ideas,” are “original thinkers,” and “love to think up new ways of doing things.”

Conscientiousness Conscientiousness refers to the tendency to be organized, responsible, and hardworking. Conscientious people display self-discipline, have a strong sense of duty and responsibility, and strive for achievement against outside expectations. Accordingly, the psychology literature has found that Conscientiousness is a strong predictor for job performance and is half as important as IQ (Almlund et al., 2011). To measure Conscientiousness, our survey asks the respondents to self-evaluate whether they “like order,” “start tasks right away,” “work hard,” and “neglect duties.”

Extraversion Extraversion refers to an orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experiences; it is often characterized by positive affect and sociability. Extraverts are enthusiastic, action-oriented people who enjoy interacting with people, possess high group visibility, and tend to assert themselves. To measure Extraversion, our survey asks whether the respondents “usually like to spend free time with people,” “like going out a lot,” “avoid company,” and “dislike being the center of attention.”

Agreeableness Agreeableness refers to the tendency to act in a cooperative unselfish manner. Agreeable individuals are more considerate, kind, generous, helpful, trustworthy, and altruistic. For Agreeableness, we ask respondents to self-evaluate whether they are “concerned about others,” “sympathize with others' feelings,” are “sensitive to the needs of others,” and “use others for own ends.”

Neuroticism Neuroticism refers to a chronic level of emotional instability and proneness to psychological distress. More neurotic people are less predictable and less consistent in their emotional reactions. They tend to be flippant in the way they express emotion and are more likely to interpret ordinary situations as threatening and minor frustrations as difficult. To measure Neuroticism, our survey asks respondents to self-evaluate whether they “get overwhelmed by emotions,” are “worriers,” “worry about things,” and “panic easily.”

Some may argue that the personality traits we study are statistical in nature and may not have biological foundations. However, recent research in psychology has provided some evidence that supports the opposite view. According to the Handbook of Personality: Theory and Research (John and Robins, 2021), personality traits (1) have measurable manifestations in mood, temperament, and pathology, (2) have neural underpinnings in specific neurotransmitters, hormones, brain structures, regions, and networks, and (3) have genetic foundations. The

personality traits can also be traced throughout a person's development stages across the life course, with significant manifestations from middle childhood.

While the Big Five model has become an important tool for understanding personalities, several limitations should be noted. First, while the Big Five model represents the highest hierarchical level of dispositional traits, it omits more granular variations across individuals.⁸ Second, personality surveys ask respondents to rate themselves on a 5- or 6-point continuum with respect to certain statements, such as "I am a cheerful optimist." Responses are meaningful only if people mean the same thing when they refer to a cheerful optimist. Third, measures of personality traits are context-free, which should be interpreted as "psychology of the stranger" that provides information about persons that one would need to know when one knows nothing else about them (McAdams, 1992). Despite these limitations, the Big Five model provides an efficient and high-level summary of individual differences from a psychological perspective, and can potentially shed new light on investors' heterogeneity.

2.2. Conceptual framework

The Big Five model has strong predictive power for life outcomes, including divergent thinking abilities (McCrae, 1987), marital adjustment and divorce (Kelly and Conley, 1987), health outcomes such as coronary disease (Dembroski et al., 1989), spending behavior (Weston et al., 2019), job performance (Barrick and Mount, 1991), and corporate decisions (Gow et al., 2016). Given that many of these life outcomes concern economic decisions, it is natural to expect personality traits to also affect financial decisions. However, the exact nature of these effects is unclear as the literature offers limited guidance. In this section, we use a simple framework of investment decisions to provide some guidance on our subsequent analysis.

In a standard framework, financial decisions are determined by an investor's preferences and beliefs over asset returns. Many existing studies, however, show that financial decisions are also driven by other, non-pecuniary factors. For example, Hong et al. (2004) shows that households invest in the stock market, not just because they derive utility from asset returns, but also because they enjoy the social aspect of discussing stocks with their friends. Gao and Lin (2015) provides evidence that retail investors appear to treat trading stocks as a fun and exciting gambling activity. More recently, the rise of ESG investment suggests that people invest in ESG-related stocks not just because they believe these stocks will outperform, but also because of ethical and environmental concerns (Pástor et al., 2021). Therefore, in order to fully understand the implications of personality traits for investment decisions, we need to also consider non-pecuniary factors. For instance, Extraverts may enjoy the interactions with people more and have a stronger tendency to follow their friends.

To incorporate both pecuniary and non-pecuniary factors, we consider the following simple framework. The market has two assets: a risk-free asset with an interest rate of zero and a stock with a stochastic return r . We use

to denote the portfolio share allocated to the stock by investor i , who makes her decision based on two considerations. The first is the standard mean-variance utility maximization. Under this consideration, personality traits are related to investment decisions through standard channels of beliefs and risk preferences. The second consideration is meant to capture the non-pecuniary factors, such as the above-mentioned social and ethical concerns. To this end, we use

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to denote investor i 's allocation to the stock if her decision is entirely determined by the second consideration. We refer to this portfolio as the "target portfolio." For instance,

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is higher for investors who derive more utility from the social aspect of stock trading. Under this second consideration, personality traits are related to portfolio choice through the target portfolio. We choose to leave the target portfolio unspecified. Given the exploratory nature of our study, the goal of this framework is to organize our empirical analysis with an agnostic prior with minimal restrictions.

Investor i 's decision is determined by the following objective function

(1)

*

where the first term captures standard mean-variance maximization:

is the coefficient of risk aversion, and

and

are the subjective mean and variance of stock returns. The second term, with a quadratic formulation, is a simple parameterization that penalizes deviation from the target portfolio.

Finally, parameter α , with

, represents the weight that the investor allocates to the non-pecuniary factors.

Objective function (1) implies that the optimal portfolio is given by:

(2)

*

The above equation illustrates that an investor's decision is determined by not only her belief (i.e.,

and

) and preference (i.e.,

) but also other factors that are summarized by

*

. In one extreme case of

, the decision is determined by the traditional mean variance optimization

. In the other extreme case of

, the investor's decision is

*

and hence is completely guided by factors other than the traditional utility maximization.

We argue that personality traits can affect investment decisions through two separate channels.

First, they can be related to asset allocations through their effects on the expected return

, the perceived risk

, or the risk aversion

. For instance, if investors high in Neuroticism are likely to be pessimistic (i.e., have lower expected return

), they would hold less risky assets. Second, personality traits may carry additional explanatory power for investment decisions beyond their correlation with beliefs and preferences, through their effects on the target portfolio share

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. In the example above, traders who are more social will have higher target shares

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and hence higher allocations to the risky asset.

Instead of specifying a particular functional form relating personality traits to the key ingredients in this model (

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, and

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), we take an agnostic approach and let the data speak out. Our goal is to examine empirically the relevance of both channels that link investors' personality traits to their financial decisions. It is worth noting that the framework also offers a natural explanation of the "low sensitivity" phenomenon documented in Giglio et al. (2021) and Liu et al. (2022). These studies find that although investors' portfolios respond to their reported expectation of future returns, the sensitivity appears to be excessively low relative to the implication from a standard utility maximization framework. While this phenomenon can be driven by transaction costs or investor inertia, our framework offers an additional simple interpretation. An investor's financial decisions are partly driven by non-utility maximization factors, as summarized by the target portfolio share

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. In fact, the sensitivity of the stock allocation to the expected stock return decreases in α and approaches zero when α approaches one.

3. Survey description

We design and administer a nationwide survey through the American Association of Individual Investors (AAII), a nonprofit organization of about 150,000 members. The main purpose of AAII is to assist "individuals in becoming effective managers of their own assets through programs of education, information and research." Previously, survey expectations from AAII members have been used to study the formation of investor expectations over time. For example, Greenwood and Shleifer (2014) show that the expectations based on the AAII surveys are highly correlated with those based on other surveys such as the Gallup investor survey and Graham-Harvey CFO survey.

AAII distributed the survey on our behalf via email to its members on November 22, 2019. Members were given two weeks to complete the survey, and a reminder was sent out on November 29. We obtain 3,325 valid responses after filtering, yielding a 2% response rate out of roughly 150,000 AAII members.⁹

3.1. Survey design

The survey, attached in the Appendix, has four sections. When administering the survey, we randomize the order of the first three sections, which represent the core of the survey and aim to collect three distinct sets of information.

Personality The first section draws upon the well-established questionnaire approach to measure the Big Five personality traits. In particular, we use the 20-item form from the SAPA Personality Inventory (Condon and Revelle, 2015) and randomize the order of these items.¹⁰ Each item is a brief and concise description of a person, such as "I usually like to spend my free time with people." The respondent is asked to evaluate if the item is an accurate description of himself or herself by choosing a score from 1 to 6, where 1 represents "Very Inaccurate" and 6 represents "Very Accurate." Each big-five personality trait is then derived from the equal-weighted average of the respondents' scores for the four questions corresponding to this

trait. For example, “I usually like to spend my free time with people” is one of the four questions corresponding to Extraversion. A respondent’s score for this trait will be the average of his or her responses (1 to 6) for this question and three other questions.

Belief and preference parameters The second section elicits a set of parameters that are central ingredients in standard models of portfolio decision-making. First, we ask respondents to report their expectations about the stock market return, GDP growth, and inflation rate in the following year. To capture beliefs about tail events, we ask them to assign probabilities to the tail events that the stock return will be above 20% or below -20% in the following year. To capture extrapolative and contrarian beliefs, we ask them if they believe stock price trends will continue or reverse in the future, conditional on a past gain or loss. Second, we follow Van Rooij et al. (2011) and elicit investors’ risk attitude by asking them to choose between a job with a stable income and a job with a risky but higher expected income. Third, to capture the “social interaction” dimension of investment decisions, we ask how the respondents typically react when a new financial product becomes popular among people around them.

Equity allocation The third section asks about the allocation of financial assets, our key outcome variables of portfolio choice. Specifically, we ask the correspondents to evaluate, in their retirement and non-retirement accounts, how much money they have invested and what fraction of the investment is in equities. Combining these questions gives the fraction of investment in risky shares.

Demographics The last section includes standard questions on demographics, including age, gender, race, income, wealth, location, education.

3.2. Summary statistics of personality traits and demographics

Table 1(a) reports summary statistics. Our respondents are predominantly white males older than 60 and around 80% fall into this category. Relative to the general population, they are more educated and wealthier: 90% of them have a college degree, more than 80% have wealth over 1 million dollars, and about one third of them have an annual income greater than \$200,000.

Fig. 1 reports the histograms of selected demographic variables and confirms these patterns. Although the AAII sample is skewed in demographics by over-representing white males older in age, these individuals are also the ones more actively invested in the stock market, making it rather relevant for the study of retail behavior.

Table 1. Summary statistics.

Panel (a) Demographics and personality traits

	Mean	Std Dev	10 Pct	50 Pct	90 Pct	Skewness
Male	0.93	0.25	1.00	1.00	1.00	-3.51
White	0.91	0.29	1.00	1.00	1.00	-2.83
Age	68.23	8.50	55.00	75.00	75.00	-1.43
Income (in \$1000)			233.29	369.41	125.00	350.00
Wealth (in \$1000)			12.97	3271.95	2353.79	750.00
College					3500.00	7500.00
Agreeableness						0.76
Conscientiousness						
Neuroticism	3.39	0.97	2.00	3.50	4.75	-0.06
Extraversion	2.59	1.04	1.25	2.50	4.00	0.39

Openness	4.48	0.92	3.25	4.50	5.65	-0.63
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Panel (b) Correlation matrix

Agreeableness	Conscientiousness	Neuroticism	Extraversion	Openness
Agreeableness	1.00	0.21	0.01	0.14
Conscientiousness	0.21	1.00	-0.07	0.12
Neuroticism	0.01	-0.07	1.00	-0.14
Extraversion	0.14	0.12	-0.14	1.00
Openness	0.18	0.24	-0.11	0.16

Panel (c) Beliefs and preferences

Mean	Std Dev	10 Pct	50 Pct	90 Pct	Skewness	
Expected Stock Return		5.57	9.51	-10.00	7.00	14.00 -1.23
Stock Rise by >20%	18.49	16.25	1.00	15.00	40.00	1.54
Stock Fall by >20%	25.09	18.41	5.00	24.00	50.00	1.02
GDP Growth	1.97	1.31	1.00	2.00	3.00	-0.88
Inflation	2.05	1.03	1.00	2.00	3.00	0.30
Pick Risky Job 1	0.60	0.49	0.00	1.00	1.00	-0.42
Pick Risky Job 2	0.27	0.44	0.00	0.00	1.00	1.03
Pick Risky Job 3	0.06	0.23	0.00	0.00	0.00	3.77

Panel (a) reports the summary statistics of personality traits and demographic variables. “Male” is the dummy variable which is 1 if the respondent is a male. “White” is the dummy variable which is 1 if the respondent's self-identified race is white. “College” is the dummy variable which is 1 if the respondent has a bachelor's degree or above. There are 3,325 respondents in total.

Fig. 1

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Fig. 1. Distribution of demographic variables in the AAll survey.

The five personality traits have different means but similar standard deviations, suggesting that variations in their magnitudes are comparable. While Openness and Extraversion exhibit little skewness, the other three are negatively skewed. These distributions are visualized in Fig. 2, which reports the histograms of personality traits.

Fig. 2

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Fig. 2. Distribution of personality traits in the AAll survey.

Table 1(b) reports the pairwise correlation between personality traits. While the Big-Five traits are designed to capture different sources of variation across people, their empirical measures appear to be mildly correlated. For example, people who are more agreeable tend to be more open and conscientious, whereas people who are more neurotic tend to be less conscientious. We therefore, in the following analysis, include all five personality traits as regressors to examine the effect of independent variation in a given trait. As a cross-validation check, our correlation coefficients in Table 1(b) are similar to those reported in Almlund et al. (2011).

Personality traits are also correlated with some demographic characteristics. In early and middle adulthood, it is well documented that as people get older, they tend to become more agreeable and conscientious (e.g., Srivastava et al., 2003). In comparison, people in our sample are significantly older. Table 2 reports the results when we regress personality traits on demographic variables. We find that female respondents tend to have higher Agreeableness and higher Neuroticism, while older respondents tend to have higher Agreeableness, lower Conscientiousness, lower Neuroticism, higher Extraversion and lower Openness. Overall, the explanatory power of the demographic variables is small: the R-squared is 3% to 5%. We include these demographic variables as controls in subsequent regressions.

Table 2. Personality traits and investor characteristics.

Empty Cell	(1)	(2)	(3)	(4)	(5)	
Agreeableness		Conscientiousness		Neuroticism	Extraversion	Openness
Female	0.29***	-0.02	0.25**	0.06	-0.04	
	(0.07)	(0.07)	(0.11)	(0.10)	(0.09)	
Age	0.01***	-0.01***		-0.01**	0.01***	-0.01**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	
Log Income	0.03	0.09***	-0.08**	0.09***	0.05	
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	
Log Wealth	-0.04*	0.04**	-0.03	0.02	0.01	
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	
College	0.05	-0.03	0.03	-0.08	0.07	
	(0.05)	(0.05)	(0.07)	(0.07)	(0.06)	
Race F.E.	Y	Y	Y	Y	Y	
State F.E.	Y	Y	Y	Y	Y	
Observations	2,607	2,607	2,607	2,607	2,607	
R2	0.04	0.05	0.04	0.05	0.03	
Adjusted R2	0.01	0.02	0.01	0.02	0.002	

We regress each personality trait on demographic variables. In these regressions, we use the subsample of the AAII respondents who indicate they are either male or female, and provide their income and wealth information. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.3. Summary statistics of beliefs and preferences

Table 1(c) reports the summary statistics of beliefs and preferences. The average expected one-year stock market return is 5.57%. There is substantial heterogeneity across respondents in the expected return. Respondents at the 10th percentile of the distribution report a one-year expected stock return of

, while respondents at the 90th percentile expect a one-year return of 14%. The cross-respondents standard deviation of the one-year expected return is 9.51%. Similarly, the average probabilities of the extreme events that the stock market rises or falls by more than 20% are 18.49% and 25.09%, respectively, with large heterogeneity across respondents. The average expected one-year GDP growth and the average expected inflation rate are both about 2%, with the 10th-90th percentile bounds around 1% to 3%.

Following Van Rooij et al. (2011), we ask respondents three questions to elicit their risk aversion. Each question asks the respondents to decide between a safe job and a risky job. In the first question, the risky job has a 50% chance to double the income and a 50% chance to cut the income by 20%. In the second question, the risky job has a 50% chance to double the income and a 50% chance to cut the income by 33%. In the third question, the risky job has a 50% chance to double the income and a 50% chance to cut the income by 50%.

The risky jobs in these three questions are increasingly riskier and require higher levels of risk appetite. Consistent with this property, we find that 60% of the respondents pick the risky job in the first question, 27% pick the risky job in the second question, and 6% pick it in the third question. If the respondent prefers more to less and answers these questions in a self-consistent way, picking the risky job in the second question should imply picking the risky job in the first question, and picking the risky job in the third question should imply picking the risky job in the second question. Out of the 3,385 respondents who completed the survey, only 56 are not self-consistent and are excluded from subsequent analysis.

We conclude this section by discussing two more appeals of our AAII survey. First, our survey was distributed by AAII to its members, many of whom had been AAII members for years and had a strong sense of affiliation. Indeed, AAII provides a variety of services to its members, including providing regular newsletters and organizing annual conferences on investing.

Therefore, compared to respondents from other survey platforms such as MTurk or Prolific, our respondents were able to complete the survey with more patience and care, ensuring the high data quality in our survey. Second, we are interested in not only examining the link between personality traits and investment choices, but also shedding light on the underlying mechanism. Compared to other surveys with a personality module, our AAII survey is designed to collect responses on beliefs, risk preference, and social interactions, making it possible to examine the underlying mechanism more directly.

4. Linking personality traits with beliefs, preferences, and social tendencies

4.1. Expectation

In this section, we link personality traits with investor beliefs and preferences. We start with the questions about return expectations. Although our survey only captures one cross-section of return expectations, previous research has documented that belief variation is mostly summarized by individual fixed effects (Giglio et al., 2021). In other words, investors tend to have very large and persistent differences in their views. Therefore, this first exercise aims to attribute investor-level expectations about future stock market performance and economic outcomes to personality traits.

In Table 3, Column (1) reports the results of regressing expected market returns on the five personality traits while controlling for demographic variables. Investors with high Neuroticism are more pessimistic in their expectations: a one-point increase in Neuroticism is associated with a 79-basis-point drop in the forecast of future one-year market return. In contrast, investors high in Conscientiousness and Extraversion are more optimistic in their forecasts: a one-point increase in Conscientiousness (Extraversion) is associated with a 66-basis-point (82-basis-point) increase in the forecast of future one-year market return.

Table 3. Personality traits and investor beliefs.

Panel (a) Benchmark results

(1)	(2)	(3)	(4)	(5)	
Stock Return	GDP Growth	Inflation			
Mean	Prob(>20%)	Prob(<-20%)	Mean	Mean	
Agreeableness	-0.10	-0.34	-0.09	-0.01	0.002
(0.24) (0.40) (0.46) (0.03) (0.03)					
Conscientiousness	0.66***	-0.07	-0.99**	0.04	-0.07***
(0.24) (0.40) (0.46) (0.03) (0.03)					
Neuroticism	-0.79***	-0.21	1.02***	-0.07***	0.05***
(0.16) (0.28) (0.32) (0.02) (0.02)					
Extraversion	0.82***	1.27***	-1.07***	0.09***	-0.02
(0.18) (0.30) (0.34) (0.02) (0.02)					
Openness	0.04	1.49***	0.92**	-0.003	0.01
(0.19) (0.32) (0.37) (0.03) (0.02)					
Demographics F.E.	Y	Y	Y	Y	Y
Observations	3,325	3,325	3,325	3,325	3,325
R2	0.06	0.06	0.04	0.04	0.04
Adjusted R2	0.03	0.04	0.01	0.02	0.01

Panel (b) Adjusted R2 under alternative specifications of explanatory variables

Personality Traits Only 0.02 0.01 0.01 0.01 0.005

Demographics F.E. Only 0.01 0.02 0.01 0.01 0.01

Panel (a) reports the regressions of investor beliefs on personality traits. Each cell in Panel (b) reports the adjusted R-squared of a regression, with personality traits only or with demographics fixed effects only. Dependent variables are (1) the expected stock return, (2) the probability that the stock market rises by more than 20%, (3) the probability that the stock market falls by more than 20%, (4) the expected GDP growth rate, and (5) the expected inflation. Demographics fixed effects include gender, age, income, wealth, education and location. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Columns (2) and (3) are concerned with the tails in the distribution of beliefs about stock market returns. While investors high in Neuroticism do not exhibit any difference in their assessed probability of an extreme upside, they are much more concerned with the downside risk: a one-point increase in Neuroticism is associated with a 102-basis-point increase in the predicted probability of a 20% market crash within the next year. In comparison, investors with high Extraversion and Conscientiousness expect a lower probability of a market crash.

A distinct pattern for Openness is worth noting. While Openness is uncorrelated with average beliefs, higher Openness leads to a higher estimated probability for both the upside and the downside. Intuitively, people with higher Openness are more willing to entertain the possibility of extreme events, which may explain why they assign greater probabilities to both tails at the same time.

How much explanatory power do personality traits have? Table 3(b) runs the regression separately using personality traits and other demographic variables. The five personality traits turn out to have explanatory power similar to that of all the demographic fixed effects combined, including gender, age, income, wealth, education and location. The adjusted R-squared is comparable across the two specifications, which suggests that personality traits may help explain why some people are persistently optimistic while others are persistently pessimistic.

This result is especially interesting, given that the persistent heterogeneity in investor belief has been shown to be difficult to explain (Giglio et al., 2021).

We also find that personality traits shape how investors forecast other macroeconomic variables. Columns (4) and (5) report regression results using expected GDP growth and expected inflation as dependent variables. Higher Neuroticism is associated with a more pessimistic forecast while higher Extraversion with a more optimistic forecast. Moreover, higher Neuroticism is associated with a higher inflation forecast. Panel (b) shows that the explanatory power of personality traits for GDP growth and inflation expectations is also similar to that of all demographic variables combined.

Overall, the results so far consistently highlight Neuroticism as a key determinant in cross-sectional variation in beliefs: neurotic investors are more pessimistic about market returns and economic growth, assign a greater probability to a market crash, and expect future inflation to be higher. While Conscientiousness and Extraversion are also correlated with investors' beliefs, Neuroticism is the only trait that is correlated with beliefs about stock returns, GDP growth, and inflation.

One concern about these results is that an investor's expected stock return and her personality traits are both affected by her recent experiences. We believe this is unlikely to fully explain our results because the five personality traits are context-free constructs. In fact, the psychology literature notes that the Big Five model is designed to capture unconditional differences in personality traits, which abstract away from the contextual and conditional nature of human experiences (McAdams, 1992). Moreover, the five personality traits are stable for an individual, and intra-individual changes are found to be generally unrelated to adverse life events (Cobb-Clark and Schurer, 2012; Anusic and Schimmack, 2016).

To demonstrate the robustness of personality traits' explanatory power, we run a separate survey among a representative sample of Chinese retail investors and find similar results: specifically, the explanatory power of personality traits and of Neuroticism and Openness in particular for the variations in investor belief is similar to that of a large set of demographic fixed effects. We describe our method and results in Appendix B.

We also probe how personality traits affect an investor's belief-formation process. Two of the simplest, most explored belief-formation processes in the literature are extrapolative beliefs and mean-reverting beliefs. In the survey, we ask respondents if they believe a stock will rise, fall, remain the same over the next year if it has risen or fallen a lot over the last year. Based on their answers, we assign each respondent an extrapolation score ranging from -100 to 100, where a higher score indicates more extrapolative and less mean-reverting beliefs. Table 4 reports the results when regressing the extrapolation score on personality traits. Neuroticism and Openness again stand out: higher Neuroticism is associated with less extrapolative and more mean-reverting beliefs while higher Openness is associated with more extrapolative and less mean-reverting beliefs. Therefore, personality traits not only affect the level of beliefs, but also the perception of trends and streaks. In general, the belief in mean-reversion or continuation in stock returns is not necessarily irrational. However, our evidence shows that the tendency of the belief in mean-reversion or continuation depends on personality traits, highlighting their important role in belief formation.

Table 4. Personality traits and belief formation.

Empty Cell	(1)
Extrapolation score	
Agreeableness	0.89
(0.86)	
Conscientiousness	-0.38
(0.87)	
Neuroticism	-1.30**
(0.59)	
Extraversion	-0.10
(0.64)	
Openness	1.55**
(0.69)	
Demographics F.E.	Y
Observations	3,325
R2	0.03
Adjusted R2	0.01

This table reports results from an OLS regression, in which the dependent variable is a respondent's "extrapolation score" that is constructed based on her responses to the following two questions. 1) "If a stock's price has risen a lot over the last year, its price over the next year will..." 2) "If a stock's price has fallen a lot over the last year, its price over the next year will..." For the first question, a respondent receives a score of 100 if her answer is "Continue to rise;" a score of -100 if her answer is "Start to fall;" or a score of 0 if her answer is "Remain the same" or "Cannot say." Similarly, for the second question, a respondent receives a score of 100 if her answer is "Continue to fall;" a score of -100 if her answer is "Start to rise;" or a score of 0 if her answer is "Remain the same" or "Cannot say." A respondent's extrapolation score is the average of her scores for these two questions. Demographics fixed effects include gender, age, income, wealth, education and location. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.2. Risk aversion

Similarly, we regress our measures of risk aversion on personality traits and demographic controls. In Table 5, Columns (1) to (3), the dependent variables are the dummy variables indicating whether the respondent is willing to take a particular bet. In Column (4), the dependent variable is the implied risk aversion parameter.¹¹ This risk aversion parameter is uncorrelated with the respondent's expected stock return, which suggests that it captures a different aspect of the investment decision-making process.

Table 5. Personality traits and risk aversion.

Empty Cell	(1)	(2)	(3)	(4)
Bet 1	Bet 2	Bet 3	Risk aversion	
Agreeableness	-0.03***	-0.04***	-0.01**	0.09***
(0.01) (0.01) (0.01) (0.02)				
Conscientiousness	-0.01	-0.01	0.002	0.02
(0.01) (0.01) (0.01) (0.02)				
Neuroticism	-0.01	-0.02**	-0.002	0.03*

(0.01)	(0.01)	(0.004)	(0.02)	
Extraversion	0.03***	0.03***	0.01	-0.06***
(0.01)	(0.01)	(0.004)	(0.02)	
Openness	0.03***	0.03***	0.02***	-0.08***
(0.01)	(0.01)	(0.005)	(0.02)	
Demographics F.E.	Y	Y	Y	Y
Observations	3,325	3,325	3,325	3,325
R2	0.06	0.05	0.03	0.06
Adjusted R2	0.04	0.02	0.003	0.04

In Columns (1)–(3), we regress the dummy variables indicating whether the respondent is willing to take each bet on personality traits and controls. In Column (4), the dependent variable is the implied risk aversion parameter from the survey responses. Demographics fixed effects include gender, age, income, wealth, education, and location. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

These regression results suggest that Openness, Agreeableness, and Extraversion are strongly correlated with risk aversion. An investor is more risk-averse if she is low in Openness, high in Agreeableness, or low in Extraversion. The connection between Openness and risk aversion is quite intuitive: an investor with higher Openness tends to be more open to taking risks, whereas an investor with lower Openness tends to be more conservative. Similarly, an investor with higher Extraversion enjoys social interaction and tends to be more excitement-seeking (McCrae and Costa Jr., 1997). However, the association between Agreeableness and risk aversion seems less obvious.

Conceptually, the results in Sections 4.1 and 4.2 suggest that personality traits can provide deeper psychological foundations for the origins of individual differences in beliefs and preferences (see McAdams, 2015, for a review). A related literature specifically examines how a particular genetic variation explains financial decisions through its effects on Neuroticism (Kuhnen et al., 2013, among others). Therefore, this could open up a new line of research that relates the origins of heterogeneous risk preference to personality traits, the biological and experiential foundations of which have been studied extensively in psychology and behavioral sciences.

4.3. Social interaction tendencies

A recent literature begins to investigate how social interactions contribute to financial decision-making (e.g., Bailey et al., 2018; Han et al., 2022; Hirshleifer, 2020). To capture this social aspect, we include the following question: “Upon seeing a new type of investment becoming popular among people around you, would you consider investing in it as well?” This captures a scenario that many investors face regularly—e.g., how to respond when Bitcoin became a popular investment amongst the general public—and the resulting measure can be interpreted as a measure of social “herding.” The options range from “Definitely No” to “Definitely Yes,” coded as scores from 1 to 5.

Table 6 reports results when regressing measures of social interactions on personality traits. The dependent variable in Column (1) is the score from 1 to 5 and, in Column (2), is a dummy variable that equals one for “Yes” or “Definitely Yes.” In both specifications, Neuroticism and Extraversion are associated with a higher degree of social “herding.” It is intuitive why Extraversion matters here: an extravert derives utility (and pleasure) from interacting with others

and tends to copy their investment decisions after such social interactions. The positive coefficient on Neuroticism is also worth noting. One possible explanation is that more neurotic investors have more fear of missing out (FOMO), and therefore tend to follow the crowd.

Table 6. Personality traits and social influence.

Empty Cell	(1)	(2)
Score Yes or definitely yes		
Agreeableness	0.01	0.001
(0.02) (0.01)		
Conscientiousness	0.01	-0.003
(0.02) (0.01)		
Neuroticism	0.04*** 0.01**	
(0.01) (0.004)		
Extraversion	0.04*** 0.01***	
(0.01) (0.004)		
Openness	0.02*	-0.002
(0.01) (0.004)		
Demographics F.E.	Y	Y
Observations	3,325	3,325
R2	0.03	0.04
Adjusted R2	0.005	0.01

Column (1) reports the result from an OLS regression, in which the dependent variable is the score from 1 (Definitely No) to 5 (Definitely Yes) assigned by respondents to the question, “upon seeing a new type of investment becoming popular among people around you, would you consider investing in it as well?” In Column (2), we replace the dependent variable by the dummy variable indicating if the score is 4 (Yes) or 5 (Definitely Yes). Demographics fixed effects include gender, age, income, wealth, education and location. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The results above suggest that, to fully incorporate personality traits into a financial-decision framework, we need to go beyond the standard framework of beliefs and preferences by accommodating social interaction tendencies. In particular, personality traits may affect how investment strategies (Han et al., 2022; Hirshleifer, 2020) and expectations (Bailey et al., 2018) transmit in the population, an aspect that has often been ignored in traditional finance models but has recently received growing attention.

5. Personality traits and asset allocation

In this section, we examine the relationship between personality traits and asset allocation decisions. We start with our main data set, the AAII survey, which covers a cross-section of American investors. To further establish robustness in panel data and in an international setting, we conduct similar analysis using two household panels for the Australian and German populations.

5.1. AAII survey

We obtain in our AAII survey each respondent's overall equity share as a fraction of financial wealth, and regress it on the five personality traits, controlling for gender, age, state, and education fixed effects. Table 7 reports the results. As shown in Column (1), both high

Neuroticism and low Openness are associated with low equity shares. However, these two effects appear to operate through different channels. Specifically, as shown in Table 3, Table 5, high Neuroticism is associated with low expected returns and high crash risks, but has no meaningful correlation with risk aversion. Hence, the effect of Neuroticism on equity allocation is likely through the belief channel. In contrast, high Openness is associated with low risk aversion, and high perceived risks, but has no significant correlation with expected returns. That is, this effect is dominated by the preference channel: investors with high Openness have low risk aversion and hence high equity allocation, despite their high perceived risks.

Table 7. Personality traits and equity allocation: AAII data.

Empty Cell	(1)	(2)	(3)	(4)	(5)	(6)	
Total	Retirement	Non-Retirement		Total	Retirement	Non-Retirement	
Agreeableness	-0.46 (0.57)	-0.02 (0.57)	-0.70 (0.56)	-0.39 (0.56)	0.12 (0.72)	-0.61 (0.72)	
Conscientiousness	-1.32** (0.58)	-0.66 (0.58)	-1.00 (0.58)	-1.51*** (0.57)		-0.84 (0.72)	-1.17 (0.72)
Neuroticism	-1.74*** (0.40)		-2.55*** (0.39)		-0.80 (0.39)	-1.44*** (0.49)	-2.23*** (0.49)
Extraversion	-0.33 (0.43)	0.14 (0.43)	-0.05 (0.53)	-0.65 (0.43)	-0.30 (0.42)	-0.31 (0.54)	
Openness	0.94** (0.46)	1.50*** (0.46)	1.15** (0.57)	0.95** (0.46)	1.40*** (0.45)	1.14** (0.58)	
Expected Return				0.23*** (0.05)	0.24*** (0.05)	0.22*** (0.06)	
Up Tail		-0.01 (0.03)	0.04 (0.03)	-0.02 (0.04)			
Down Tail			-0.08*** (0.02)		-0.09*** (0.02)		-0.05 (0.03)
Risk Aversion				-1.17*** (0.44)		-1.44*** (0.44)	-0.90 (0.56)
Demographic F.E.	Y	Y	Y	Y	Y	Y	
Observations	2,807	3,285	3,281	2,807	3,285	3,281	
R2	0.08	0.07	0.09	0.10	0.10	0.10	
Adjusted R2	0.05	0.05	0.07	0.07	0.07	0.08	

Regression results based on our AAII survey. We regress each investor's equity-to-wealth ratio on personality traits and controls. Demographics fixed effects include gender, age, income, wealth, education, and location. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

We then separately analyze the equity shares in retirement and non-retirement savings. In our sample, retirement savings and non-retirement savings are of similar magnitude. In Column (2) of Table 7, we repeat the regression but use the equity share of the retirement saving as the dependent variable. Results are consistent with the evidence in Column (1): high Openness and low Neuroticism are associated with higher equity shares.

In Column (3), we repeat the regression but use the equity share of the assets outside of retirement saving as the dependent variable. The coefficient associated with Openness is consistent with that in Columns (1) and (2), but the coefficient associated with Neuroticism is no longer significant. We suspect that the data in non-retirement savings are more noisy, because they may include alternative investments such as private equity and hedge funds that are risky but not counted in the equity share.¹²

In Columns (4) to (6), we additionally control for the respondents' belief and risk preferences from the survey. While the respondents' expected equity return, belief about tail risks in the stock market, and risk aversion can explain their equity shares, the explanatory power of Openness and Neuroticism remains robust. This suggests that personality traits carry additional explanatory power for investment decisions beyond the traditional framework of beliefs and preferences. There are at least two interpretations for this result. First, under the traditional mean-variance framework in which portfolio choice is pinned down completely by risk preference and expectations, our result suggests that personality traits provide measures of risk preferences and expectations that are complementary to measures commonly used in surveys. Second, if we are willing to deviate from the traditional framework, the above results suggest that personality traits are related to nonstandard preferences, nonstandard beliefs, or other frictions, captured by the "target portfolio." Therefore, there is a need to extend standard models of portfolio choice by considering alternative forces, such as social interactions and non-pecuniary preferences.

One concern about the above specification is omitted variables affecting both sides of the equation. This concern, however, is largely mitigated by the fact that measures of personality traits are highly persistent in time-series (Costa Jr. and McCrae, 1994; Parise and Peijnenburg, 2019). It is also important to note that personality traits are increasingly stable with age (Roberts and DelVecchio, 2000). This feature, combined with the AAII sample's overrepresentation of older individuals, suggests that the measured personality traits in our sample are likely to represent persistent—not transitory—individual characteristics.¹³ Therefore, it is unlikely that the correlation between personality traits and equity allocations is due to concurrent omitted variables, since personality traits have been mostly determined before the realizations of concurrent variables.

5.2. The HILDA survey

One concern, inherent in our cross-sectional setting, is that the effects of personality traits on investment decisions are time-varying and our results only capture one snapshot at a time. For instance, perhaps Neuroticism leads to more pessimistic investment only after a long bull market, if Neurotic investors worry more about a reversion after a long boom. Since the AAII survey data do not allow us to directly address this issue, we resort to a different dataset to examine the robustness of our results in a panel setting.

We bring additional data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Survey is a household-based panel study that collects information about economic and personal well-being, labour market dynamics, and family life. It covers the period from 2001 to 2017. The personality data were collected in 2005, 2009, 2013, and 2017. The investment data were collected in 2002, 2006, 2010, and 2014. We merged these data in adjacent years (for example, the 2005 personality data are merged with the 2006 investment data), obtaining three measurements (2005–2006, 2009–2010, and 2013–2014).¹⁴

We choose this dataset for complementary analysis for the following reasons. First, with a panel structure, the HILDA Survey allows us to track a given household's portfolio decisions and personality traits over time. Second, the HILDA sample has much more balanced demographics. For example, the numbers of female and male respondents are close and the distribution across age brackets is smooth. Third, the HILDA Survey concerns a sample from the population of a different country, Australia, with comparable institutional features. Therefore, it provides an "out-of-sample" test of the results of the AAII survey.

We perform similar analysis using the data from the HILDA Survey. Specifically, we regress the equity share as a fraction of the financial assets on the five personality traits, controlling for the demographic variables including gender, age, income, wealth, and income. To avoid potential data errors, we drop observations where the equity wealth is above financial wealth. Since this data cover multiple years, we also control for year fixed effects.

Because the HILDA data contain household investments and individual personality traits, we consider two specifications. In Column (1) of Table 8, we restrict the HILDA data to the subsample of one-person households, allowing us to perfectly match a person's personality traits with her portfolio holdings. In Column (2), we use the subsample of respondents who claim to be "always" or "usually" the one who makes the households' savings, investment, and borrowing decisions. It is reassuring that these results further validate our previous analysis: both Neuroticism and Openness are significantly correlated with the equity shares in household portfolios.

Table 8. Personality traits and equity allocation: Australian HILDA data.

Empty Cell	One-person household	Decision maker in the household
(1)	(2)	
Agreeableness	0.04 (0.30)	-0.17 (0.23)
Conscientiousness	-0.39 (0.27)	-0.35* (0.20)
Neuroticism	-0.56** (0.27)	-0.46** (0.20)
Extraversion	0.13 (0.24)	-0.26 (0.18)
Openness	0.81*** (0.25)	0.63*** (0.20)
Demographic F.E.	Y	Y
Year F.E.	Y	Y
Observations	5,542	8,924
R2	0.17	0.16
Adjusted R2	0.17	0.16

Regression results based on the HILDA survey, which has a panel structure. The dependent variable is the share of stock assets in households' total financial wealth, which is between 0 and 100. In Column (1), we use the subsample of one-person households. In Column (2), we use the subsample of respondents who claim to "always" or "usually" be the one who makes the household's savings, investment and borrowing decisions. Demographics fixed effects include

gender, age, income, wealth, and location. We also control for year fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5.3. The GSOEP survey

We further test our main result using the German Socio-Economic Panel (GSOEP) Survey. This survey is also a household-based panel study. The personality and investment data were collected in 2005, 2009, 2012, 2013, and 2017. This survey allows us to test our main result in a different language and cultural setting. However, the survey only provides a dummy variable for stock market participation. Hence, the analysis is restricted to the extensive margin. With this limitation in mind, we run the regression in Table 8, using this dummy variable (multiplied by 100) as the dependent variable.

Table 9 reports the results. In order to relate the person-level personality data to the household-level financial data, we restrict the data to the subsample of one-person households, or the subsample of respondents who claim to be the “head” of the household. Similar to the results on the intensive margin in the U.S. and Australian samples, the coefficient associated with Neuroticism is significantly negative and the coefficient associated with Openness is significantly positive, whereas Agreeableness is insignificant on the extensive margin in this German sample. Moreover, Conscientiousness and Extraversion are correlated with stock market participation in this German data.

Table 9. Personality traits and equity allocation: German GSOEP data.

Empty Cell	One-person household	Decision maker in the household
(1)	(2)	
Agreeableness	0.30 (0.40)	-0.73 (0.45)
Conscientiousness	-2.06*** (0.61)	-1.97*** (0.56)
Neuroticism	-1.07** (0.38)	-0.94*** (0.28)
Extraversion	-1.16** (0.41)	-1.11* (0.54)
Openness	1.11*** (0.25)	1.27*** (0.35)
Demographic F.E.	Y	Y
Year F.E.	Y	Y
Observations	10,250	10,781
R2	0.15	0.16
Adjusted R2	0.15	0.15

Regression results based on the GSOEP survey, which has a panel structure. The dependent variable is stock market participation, which is 0 if the person holds no stock assets and 100 if the person holds any stock assets. In Column (1), we use the subsample of one-person households. In Column (2), we use the subsample of respondents who claim to be the head of household. Demographics fixed effects include gender, age, income, wealth, and location. We also control for year fixed effects. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

6. Discussion

6.1. Result synthesis

Our results show that the two personality traits—Neuroticism and Openness—can explain cross-investor variations in belief, risk aversion, tendencies of social interaction, and portfolio allocation. Hence, the two personality traits can potentially provide a unified account for different aspects of investor behaviors. That is, some of the common component of investor heterogeneity in beliefs, preferences, social interaction tendencies, and investment decisions can be traced to these two traits.

To explore this idea, we first sort our survey respondents into 10 groups based on either their Neuroticism or Openness scores. Within each group, we compute the mean of each of the seven characteristic that we examined earlier: expected stock return, risk aversion score, perceived (left and right) tail risks in the stock market, extrapolation score, tendency for social interaction, and equity allocation. We plot these mean characteristics against the mean Neuroticism or Openness scores across the 10 groups in Panels (a)–(g) of Fig. 3. These figures recast our earlier results: investors sorted by either Neuroticism or Openness exhibit clear differences in these characteristics.

Fig. 3

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Fig. 3

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Fig. 3. Investor characteristics vs. neuroticism and openness.

We then rescale each of the seven characteristics to unit variance and conduct a principal component analysis (PCA). The first and second principal components (PC1 and PC2) explain 22% and 18% of the total variance, respectively. For comparison, if those characteristics share no common variations, each principal component should explain of the variance. In other words, there is a modest amount of commonality across those seven characteristics.

The loadings of these two principal components on those key characteristics are quite intuitive. For example, a higher PC1 is associated with a higher expected return, a higher probability of an up tail event in the stock market, and a lower probability of a down tail event in the stock market. These characteristics are consistent with those of a more optimistic investor. A higher PC2 is associated with higher probabilities of both up and down tail events, a lower risk aversion, and a higher tendency of social interaction. These characteristics are consistent with those of an investor who expects more extreme events. Hence, at the intuitive level, PC1 and PC2 reflect the two personality traits, Neuroticism and Openness. To see that, we plot the average PC1 or PC2 score against the average Neuroticism or Openness score for each group sorted by either Neuroticism or Openness scores in the last two panels of Fig. 3. We find that a higher PC1 is related to a lower Neuroticism and a higher Openness, while a higher PC2 is related to a higher Neuroticism and a higher Openness. These results suggest that the investor heterogeneity in those seven key characteristics has a common component that can be traced to the heterogeneity in investors' Neuroticism and Openness. Therefore, the two personality

traits Neuroticism and Openness provide a useful tool for dimension reduction in the context of investor behaviors—in the sense that they provide useful information for organizing a wide range of investor characteristics.

6.2. Implications for future research

Motivated by a simple conceptual framework, we documented a set of correlations between personality traits and beliefs as well as asset allocations. Although our evidence does not establish causal relations, it does suggest a potential role for personality traits in belief formation and investment decisions, and invites further investigations on the nature of these correlations.¹⁵

In the context of our conceptual framework in Section 2.2, the Big Five personality traits can explain investor behavior through two distinct channels. First, they covary with investors' beliefs and preferences, which affect investment decisions through the traditional risk-return trade off. Therefore, this could open up a new line of research that relates the origins of heterogeneous risk preferences and beliefs to personality traits, the biological and experiential foundations of which have been studied extensively in psychology and behavioral sciences. Second, they may operate through non-standard channels, such as social interactions, as illustrated by the target portfolio in a reduced form. This suggests a need to extend standard models of portfolio choice by considering alternative forces, such as social interactions and non-pecuniary preferences. On the empirical side, future research can develop in several important directions. First, while we have presented suggestive evidence on the underlying mechanisms for the roles of personality traits in financial decision-making, the specific channels remain inconclusive. Our evidence suggests that the mechanism can go beyond traditional channels of beliefs and preferences. Further exploration would be fruitful. Second, if one takes the interpretation that personality traits are proxies for fixed characteristics, our evidence suggests that those characteristics need to be domain-specific. For instance, the characteristics proxied by Neuroticism and Openness should be relevant for our financial setting but not in the same manner in other economic settings (e.g., wage bargaining) in the prior literature. Finally, given that personality traits can be determined by both nature and nurture, it is also interesting to compare these two components on their explanatory power for investment decisions. One ongoing data effort that makes this differentiation possible is the increasing amount of data collected on genetic information. For example, the National Longitudinal Study of Adolescent to Adult Health (“Add Health”) contains genetic markers that can be potentially related to the genetic component of personality traits.

7. Conclusion

We conduct a nationwide survey among affluent American individual investors to study the implications of personality traits for investment decisions. Our evidence suggests that personality traits may affect investment decisions via three distinct channels: beliefs, preferences, and social interaction tendencies. Two traits, Neuroticism and Openness, are particularly important for explaining equity investment, through two different channels: Neuroticism through beliefs while Openness through preferences. We discuss how to incorporate personality traits into future frameworks of financial decision-making and advocate the need to consider social interactions in such frameworks.

CRediT authorship contribution statement

Zhengyang Jiang: Conceptualization, Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. Cameron Peng: Conceptualization, Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. Hongjun Yan: Conceptualization, Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Survey questions

Our survey has 4 sections.

A.1. Section I

In this section, you will see a number of different phrases and sentences. Please use the response options to indicate how accurately each phrase or sentence describes you.

1.

Usually like to spend my free time with people.

2.

Get overwhelmed by emotions.

3.

Like order.

4.

Am concerned about others.

5.

Am full of ideas.

6.

Like going out a lot.

7.

Am a worrier.

8.

Start tasks right away.

9.

Sympathize with others' feelings.

10.

Am able to come up with new and different ideas.

11.

Avoid company.

12.

Worry about things.

13.

Work hard.

14.

Am sensitive to the needs of others.

15.

Am an original thinker.

16.

Dislike being the center of attention.

17.

Panic easily.

18.

Neglect my duties.

19.

Use others for my own ends.

20.

Love to think up new ways of doing things.

Answer options for each question above are the same:

•

Very Inaccurate

•

Moderately Inaccurate

•

Slightly Inaccurate

•

Slightly Accurate

•

Moderately Accurate

•

Very Accurate

A.2. Section II

This section asks your opinion about financial markets and the economy in general.

We start with three questions that ask how you make financial decisions under various hypothetical financial situations.

1.

First, in your opinion, if a stock's price has risen a lot over the last year, its price over the next year will

•

Continue to rise

•

Start to fall

•

Remain the same

•

Cannot say

2.

Second, in your opinion, if a stock's price has fallen a lot over the last year, its price over the next year will

•

Continue to fall

•

Start to rise

- Remain the same

- Cannot say

3.

Third, upon seeing a new type of investment becoming popular among people around you, would you consider investing in it as well?

- Definitely yes

- Yes

-

Maybe

-

No

-

Definitely no

4.

We next ask you to make various predictions about the U.S. economy in 2020. First, what do you think the return would be for the S&P 500 Index in 2020? (Note: the S&P 500 Index is one of the best representations of the U.S. stock market.)

- A slide bar between -50 and 50 for S&P 500 Index Return (%).

5.

Second, in your opinion, what is the probability that the S&P 500 Index will rise by more than 20% in 2020? (An answer of 0% means that it cannot happen, an answer of 100% means it is sure to happen.)

- A slide bar between 0 and 100 for Probability (%).

6.

Third, in your opinion, what is the probability that the S&P 500 Index will fall by more than 20% in 2020? (An answer of 0% means that it cannot happen, an answer of 100% means it is sure to happen.)

- A slide bar between 0 and 100 for Probability (%).

7.

We move on to other economic indicators. What do you think the GDP growth rate would be for the U.S. in 2020?

- A slide bar between -10 and 10 for US GDP Growth (%).

8.

How much inflation do you expect for the U.S. in 2020? (Note: inflation rate is the rate at which prices for goods and services increase.)

-

A slide bar between -10 and 10 for Inflation Rate (%).

9.

Finally, we ask about how you perceive risks. Suppose you are the only income earner in the family, and you already have a good job guaranteed to give you your current income every year for life. You are given the opportunity to take a new, equally good job. With a 50% chance it will double your income, and with a 50% chance, it will cut your income by 20%. Would you take the new job?

•

Yes.

•

No.

10.

Suppose the chances were 50% that it would double your income and 50% that it would cut your income by 33%. Would you take the new job?

•

Yes.

•

No.

11.

Suppose the chances were 50% that it would double your income and 50% that it would cut your income by 50%. Would you take the new job?

•

Yes.

•

No.

A.3. Section III

This section asks about your financial decisions.

1.

How many years have you been investing in the stock market (including stocks, mutual funds, ETF, etc.)?

•

Less than 5 years

•

5 to 10 years

•

11 to 20 years

•

21 to 30 years

•

More than 30 years

In the next four questions, we will ask about your asset allocation within and outside of your retirement plan.

2.

First, how much money have you saved in your retirement accounts (such as 401(K)s, IRAs, and Keogh accounts)?

- Less than \$50,000
- \$50,000 - \$199,999
- \$200,000 - \$499,999
- \$500,000 - \$1 million
- \$1 million - \$2 million
- \$2 million - \$5 million
- More than \$5 million
- Prefer not to answer

3.

Second, within your retirement accounts, what percentage is currently invested in equities? Equities include not only individual stocks, but also mutual funds and exchange-traded funds (ETFs) that mainly hold equities. Equities do not include ordinary bonds, preferred stocks, convertible bonds, and various money market funds.

- Less than 10%
- 10% - 20%
- 20% - 30%
- 30% - 40%
- 40% - 50%
- 50% - 60%
- 60% - 70%
- 70% - 80%
- 80% - 90%
- More than 90%
-

Prefer not to answer

4.

Third, outside of your retirement accounts, what is your total financial wealth? Your financial wealth typically includes: cash, stocks, mutual funds, ETFs, bank deposits, etc.

•

Less than \$50,000

•

\$50,000 - \$199,999

•

\$200,000 - \$499,999

•

\$500,000 - \$1 million

•

\$1 million - \$2 million

•

\$2 million - \$5 million

•

More than \$5 million

•

Prefer not to answer

5.

Finally, outside of your retirement accounts, what percentage of your financial wealth is invested in equities? Equities include not only individual stocks, but also mutual funds and exchange-traded funds (ETFs) that mainly hold equities. Equities do not include ordinary bonds, preferred stocks, convertible bonds, and various money market funds.

•

Less than 10%

•

10% - 20%

•

20% - 30%

•

30% - 40%

•

40% - 50%

•

50% - 60%

•

60% - 70%

•

70% - 80%

•

80% - 90%

•

More than 90%

-
- Prefer not to answer

A.4. Section IV

Lastly, we have some questions about your demographic information. (Answer options omitted.)

1.

What is your gender?

2.

What is your age?

3.

In which state do you currently reside?

4.

What is the highest level of school you have completed or the highest degree you have received?

5.

Choose one or more races that you consider yourself to be.

6.

What was your total household income before taxes during the past 12 months?

7.

What is your total household wealth (including real estate, financial assets, pension plans, etc.)?

Appendix B. Additional empirical results on investor belief

In this appendix, we describe the additional survey we ran among Chinese retail investors. We administered the survey through the Investor Education Center of the Shenzhen Stock Exchange (SZSE). The same setting has been used in Jiang et al. (2022), which includes more institutional details. In a nutshell, we randomized across branch offices of China's 60 largest brokers. Specifically, we selected 2,993 branch offices across 30 provinces (and regions) and required each branch office to collect at least 10 valid responses.

The survey took place between November 29, 2021, and January 6, 2022, and respondents were given two weeks. A valid response had to be completed within 30 minutes. Respondents could open the survey using their personal computers or on their smartphones; the vast majority completed on their phones. After applying basic filters, we collected an initial sample of around 17,324 respondents. By design, respondents are evenly distributed across the 60 brokers, with only slight variation. In terms of geographic variation, areas that are more financially developed (e.g., Guangdong, Zhejiang, Jiangsu, and Shanghai) are more represented. Overall, the sample is young, well-educated, and affluent: the median age is around 35, the majority have a bachelor degree, and a substantial fraction have a wealth above 1 million RMB.

In the survey, we implemented the same 20-item personality questionnaire that we translated into Chinese. We also asked the respondents about their expectations of the stock market's performance in the next 30 days and in the next year, as well as their expectations of their own stock portfolio's performance in the next 30 days and in the next year. We also collected additional variables, including age, gender, level of education, total wealth, and total income, which we refer to below as the demographic variables.

We regress investor beliefs of future performance on either demographic variables or personality traits, as in Table 3. We report the adjusted R-squared in Table A1. In the first row,

we use the demographic variables as the explanatory variables. Specifically, we use 89 age dummies, 8 education dummies, 9 wealth dummies and 10 income dummies. In the second row, we use the five personality traits. In the third row, we specifically use the two personality traits that stand out in the main text: Neuroticism and Openness. We note that, the explanatory power of the personality traits is comparable to that of the demographic dummies, which is consistent with our finding in the main text. Also, while the adjusted R-squared is relatively low across specifications, Neuroticism and Openness remain significant predictors of the respondents' expectations.

Table A1. Explanatory power of different variables for investor belief.

(1)	(2)	(3)	(4)
Market 30 Day	Market 1 Year	Self 30 Day	Self 1 Year
Demographics F.E. Only	0.008	0.027	0.029
Personality Traits Only	0.015	0.027	0.020
Neuroticism and Openness Only	0.012	0.019	0.020
			0.019

We regress investor beliefs on either demographic variables or personality traits. Each cell reports the adjusted R-squared of a regression. The dependent variable is the expected market return in the next 30 days or the next year, or the expected return of the investor's own portfolio in the next 30 days or the next year, in columns (1) through (4), respectively. The independent variables are demographics fixed effects (including gender, age, income, wealth, and education) in the first row, the Big Five personality traits in the second row, and traits Neuroticism and Openness in the third row.

Investing for beginners

Those new to investing can find it daunting. But is it truly as intimidating as it seems?

JAN 09, 2024

By

Ramon Vicente Berenguer

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The concept and practice of investing can be a daunting subject, especially for the beginning investor. Apart from its complex nature, advancements in technology (like the internet) have made the investment landscape even more dynamic and complicated.

Thanks to the internet, new investments have sprouted up, transactions have sped up, and the way people can do business has changed forever.

With so many more investment opportunities and ways to invest, it's even more difficult nowadays to advise your clients where they should invest their money. Although the added investments offer more opportunities for higher returns, they also come with higher levels of risk.

Another major challenge of investing is market volatility. Financial markets where everyone from beginning investors to savvy veterans are likely to invest in are inherently volatile and often unpredictable. The volatility can be due to several factors like government regulations, geopolitical conditions, and investor sentiment. So how does a beginning investor know what to do and where to invest?

In this article, InvestmentNews offers some fundamental tips for beginning investors to navigate the complicated field of investing.

Know the investor's risk appetite

The important first step in investing is to know what the investor's acceptable level of risk is. This is also known as their "risk appetite" or risk tolerance. Few investment concepts are as important as risk appetite. This can heavily influence you or your clients' investment strategies and decisions.

An investor's risk appetite is not a specific amount. It's how willing an investor is to bear a financial risk, hoping to earn a potential profit.

Another similar but crucial metric is risk capacity. This is the amount that an investor is willing and able to bear given their current financial situation. One way to determine an investor's risk capacity is to ask what percentage of their investment they would be comfortable to write off as a loss, should the investment project fail.

A reasonably acceptable loss would be at a level higher than the current prevailing inflation rate. As of November of 2023, the inflation rate in the U.S. is at 3.1%.

Factors that influence risk appetite

These are the most common factors that can have a significant impact on investors' risk appetite:

Age

Younger investors would be less risk-averse and more tolerant of risky investments, since they still have a lot of time. Should they incur any losses, they have the time to manage their investment portfolios and adjust their strategy.

Older investors simply don't have the same luxury, and it's uncertain if they'll have enough time to mitigate losses.

Investment goals

The cost and nature of investors' investment goals can likewise influence their risk appetite. The more important the investment goal, the more risk-averse or avoidant the investor will be.

For example, if an investor started putting money into an investment to put up a college fund for their children, then they would be less tolerant of risky investments.

Conversely, if their investment goal was more trivial like raising money for a summer cottage, then they would be more tolerant of risk in their investments.

Time horizon

This is the "deadline" for achieving a financial goal. Financial goals with long time horizons, like raising funds for retirement, can mean a more flexible risk appetite. A financial goal like this could make investors choose riskier investments like a combination of individual stocks and mutual funds.

On the other hand, a financial goal with a shorter time horizon would make investors choose lower-risk, more liquid investments. Some examples are money market mutual funds or high-yield savings accounts.

Different types of risk tolerance

Every investment has its own level of risk, and investors who are aware of their degree of risk can better plan their portfolios. Investors themselves may be classified according to their risk tolerance:

investors with aggressive risk tolerance: this type of investor is more familiar with the markets. They're not afraid to lose money in the pursuit of potentially bigger and better returns. Their knowledge and experience allow them to better understand the volatility of assets like securities and apply strategies that give better results.

investors with moderate risk tolerance: the moderate-risk investor is concerned with growing their money without losing too much of it. This type of investor usually applies what's called a balanced strategy. Most moderate investors put together a portfolio made up of a mix of stocks and bonds in either a 60/40 ratio, or in an even 50-50 split.

investors with conservative risk tolerance: the conservative type of investor tolerates minimal to no volatility in their investments. Investors who are close to retirement or are already retired make up this category. They often adopt short-term investment strategies to preserve a principal asset or investment.

Setting up investment goals

Another important step in investing is for the investor to decide on their reasons for making the investments. There are three common investment goal types:

1. short-term – these are goals that can enhance one's lifestyle, such as taking a holiday or buying a car

2. medium-term – goals like these include more serious purchases like paying for college tuition or buying new property

3. long-term – this includes goals with a long time horizon and can have a lasting impact on investors' lives, such as planning for retirement or for financial independence

Steps in financial goal planning

Complex tasks like investing can be more manageable when done step by step. Here's what advisors can suggest to their clients to make the investment process more efficient and practicable.

1. Consider your goals for investing

Investors should think about why they need to invest. Is it for a short-, medium-, or long-term goal?

If the investment is for retirement, paying off debt, or purchasing an asset, then the investor should be prepared to make a significant time commitment, with a minimum of five years. But if the investment goal is to reap financial rewards sooner, then saving – not investing – is more appropriate.

2. Consider the financial risk and plan accordingly

Beginning investors should realize early that the value of their investments can rise and fall. Their investment goals will largely depend on their appetite and capacity for risk.

Investors should give serious thought to which risks they can take, and which they cannot. For instance, investors who are close to retirement should avoid riskier investments like stocks. Younger investors can probably afford to take on investments with bigger risks, as they have a longer period of time to recoup losses.

3. Decide for how long you want to invest

Beginning investors should decide on their time horizon. The longer the money is invested, the more chances it has of growing over time and reaching its target amount.

How long they decide to invest their money will depend on how much they want to earn from it. Investors should take note of the time horizons of each type of financial goal and decide how long they want to invest.

short-term goals: 5 years or less

medium-term goals: 5 to 10 years

long-term goals: over 10 years

4. Make an investment plan

After investors have decided on their financial needs and goals, considered the risks, and decided on their time horizon, it's time to consider investment options.

For beginning investors, have a financial plan composed of simple, low-risk investments like short-term certificates of deposit. More low- and moderate-risk investments can be added to the portfolio later on.

5. Diversify your portfolio

As your confidence builds and your funds grow, you can slowly put together a more diversified portfolio of increasingly complex investments. Doing this gives investors the benefit of protecting against the ups and downs of the market, while expanding their experience and knowledge.

What is a balanced investment strategy?

The balanced investment strategy is one where the goal is to find a balance of maximizing growth while preserving capital. This strategy is usually employed by investors who have a moderate risk tolerance. Oftentimes they apply this type of investment strategy by cobbling together a mix of stocks and bonds. The asset allocation for implementing this strategy can be 60/40 or an equal 50/50 split.

The Risk-Reward Principle

Also called the risk-return tradeoff, this is an investment principle that states that the higher the risk of an investment, the higher its potential returns. Conversely, the lower the risk, the lower the potential returns.

This is a crucial guiding principle in investing, and it is what savvy investors use when considering potential risks and rewards of an investment. This principle is particularly useful when weighing investment decisions.

Common investing mistakes to avoid

Knowing your client's risk appetite, financial goals, and risk capacity goes hand in hand with coming up with an investment plan. But it's important to also know some of the most common investment mistakes beginners make and avoid them.

1. not knowing anything about an investment – while you don't need to know all the ins and outs of an investment, it's important to know something about it. Don't invest in companies with business models that are difficult to understand. As you build your portfolio, start investing in mutual funds and exchange-traded funds (ETFs) to be on the safe side.
2. not being patient – Rome wasn't built in a day, so don't expect to build a financial empire overnight. When it comes to investing, slow and steady wins the race.
3. trying to time the market – trying to predict patterns in the market is next to impossible. Even the most experienced institutional investors fail at this. A study entitled "Determinants of Portfolio Performance" showed that most of a portfolio's return is due to asset allocation decisions, and not by timing or choosing the "right" securities.

4. not diversifying your portfolio – as a general rule, never allocate more than 5-10% to any single investment. Beginning investors are advised to make their portfolios as diversified as possible.

5. investing with your feelings – emotions are the number one killer of investing and getting decent investment returns. The adage that “fear and greed rule the market” still holds true. Sensible investors do not allow either of these destructive emotions to control their decisions. Instead, they look at the bigger picture.

Remember that in some investments, like the stock market, returns can swing wildly over the short term. But in the long term, investors who remain patient and calm reap the benefits.

Start out simply, sensibly, and sustainably

Those new to investing should start with simple investments and expand their portfolios in manageable increments. Mutual funds or Exchange Traded Funds (ETFs) are excellent starting choices before trying real estate, stocks, and other investments.

It's not advisable for beginners to monitor their portfolios daily. A better strategy is to begin with index funds that mirror the market. When starting out, invest in at least three types of index funds. Invest in funds on the U.S. equity market, one in international equities, and finally, take on a bond index.

Here's an insightful video on investing for beginners. There's a lot of good advice on where to start investing, such as in mutual funds and the S&P500. The video goes on to say that investing does not have to be as complicated as most people think:

<https://www.youtube.com/watch?v=hmcDbvGXA6U>

If investors choose to be more hands-on with their investments, they should create a portfolio with an asset mix suited to their risk appetite, time horizon, and financial goals. When in doubt, they can always consult other more experienced financial professionals. Better yet, they should watch this space to know more about investing!

Stay updated on the latest in financial planning and investing. Subscribe to InvestmentNews for access to news stories, reports, and opinion pieces from experts in the industry.

Conservative:

KEY TAKEAWAYS

- Conservative investing emphasizes capital preservation with low-risk securities like blue-chip stocks and Treasury bills.
- This strategy prioritizes stable returns and lower risk, often suiting older investors nearing retirement.

- A defensive approach may be adopted temporarily when market conditions appear unfavorable.
- Alternatives to conservative investing, like a growth portfolio, aim for higher returns through riskier assets.
- Conservative funds may include inflation-adjusted investments to protect purchasing power over time.

What Is Conservative Investing?

Conservative investing focuses on [preserving capital](#) by allocating most funds to low-risk assets like bonds, Treasury bills, and [cash equivalents](#).

Unlike [aggressive strategies](#) that chase higher returns, it emphasizes stability and steady income, making it suitable for retirees or risk-averse investors. However, its safety often comes at the cost of lower potential returns.

Exploring the Principles of Conservative Investing

Conservative investors have [risk tolerances](#) ranging from low to moderate. As such, a conservative investment portfolio will have a larger proportion of low-risk, fixed-income investments and a smaller smattering of high-quality stocks or funds. A conservative strategy necessitates investment in the safest short-term instruments, such as Treasury bills and [certificates of deposit](#).

Although a conservative investing strategy may protect against [inflation](#), it may not earn significant returns over time when compared to more aggressive strategies. Investors are often encouraged to turn to conservative investing [as they near retirement](#) age, regardless of individual risk tolerance.

Designing a Conservative Investment Portfolio

Preservation of capital and [current income](#) are popular conservative investing strategies. Capital preservation focuses on keeping current capital levels and preventing losses. This strategy uses safe, short-term instruments like [Treasury bills \(T-bills\)](#) and [certificates of deposit \(CDs\)](#). A capital preservation strategy could be appropriate for an older investor looking to maximize her current financial assets without significant risks.

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A current income strategy can be appropriate for older investors with a lower risk tolerance, who are looking for a way to continue to earn a steady flow of money post-retirement and without their usual salary. Current income strategies work to identify investments that pay above-average distributions, such as [dividends](#) and interest. Current income strategies, while relatively steady overall, can be included in a range of allocation decisions across the spectrum of risk. Strategies focused on income could be appropriate for an investor interested in

established entities that pay consistently (i.e. without risk of default or missing a dividend payment deadline), such as [large-cap](#) or blue chip equities.

Sometimes, investors who are otherwise more aggressive will temporarily adopt a conservative strategy if they feel that the markets will take a negative turn. This could be due to over-heating asset prices or indicators of an economic recession on the horizon. In such instances, this shift to safer assets is called a [defensive strategy](#), designed to deliver protection first and modest growth second. After the market has adjusted, they may adopt a more offensive or aggressive strategy once again.

TIP

Conservative investors can look to inflation-adjusted investments, such as [Treasury inflation-protected securities \(TIPS\)](#), which are issued by the U.S. government, to mitigate the effects of inflation on low-risk, low-return investments.

Comparing Conservative Investing With Other Strategies

Conservative investing strategies generally have lower returns than more aggressive strategies, such as a growth portfolio. For example, a [capital growth strategy](#) seeks to maximize capital appreciation or the increase in a portfolio's value over the long term. Such a portfolio could invest in high-risk [small-cap](#) stocks, such as new technology companies, junk or below-investment-grade bonds, international equities in emerging markets, and derivatives.

In general, a capital growth portfolio will contain approximately 65-70% equities, 20-25% fixed-income securities, and the remainder in cash or money market securities. Although growth-oriented strategies seek high returns by definition, the mixture still somewhat protects the investor against severe losses. Investors who are familiar with the market and stock research can also find success in a value investing portfolio heavy on stocks or even a passively invested [exchange traded fund \(ETF\)](#) portfolio mixing stock and bond funds.

The Bottom Line

Conservative investing aims to preserve capital through low-risk assets like bonds, cash equivalents, and TIPS. It appeals to risk-averse investors or those nearing retirement, offering stability but lower returns. Many also adopt this approach temporarily during uncertain or overvalued markets.

Key Takeaways

- Conservative investing prioritizes the preservation of principal while minimizing risk.
- A successful conservative investment approach requires understanding both what a conservative investment is and how to identify it.
- Conservative investments are characterized by robust safety features, skilled management, and strong business fundamentals.
- Prominent examples of conservative investments include companies like Coca-Cola, Walmart, and Johnson & Johnson.
- Effective conservative investing involves a detailed evaluation of the competitive landscape and potential regulatory hurdles.

Understanding Conservative Investments

[Conservative investing](#), when understood and applied properly, is not a low-risk, low-return strategy. Investors must understand two definitions to appreciate the appropriate means by which to invest conservatively.

A **conservative investment** is one that carries the greatest likelihood of preserving the [purchasing power](#) of one's capital with the least amount of risk.

Conservative investing is the understanding of what a conservative investment is, and then following a specific course of action needed to properly determine whether or not particular investments are indeed conservative investments.

Where many investors falter in attempting to invest conservatively is blindly assuming that, by purchasing any [security](#) that qualifies as a conservative investment, they are, in fact, conservative investors. In other words, such investors simply focus on the first definition.

Such a viewpoint is limited and costly. A successful conservative investment approach requires not only an understanding of what a conservative investment is, but—more importantly—the correct approach to take in order to identify what truly qualifies as a conservative investment.

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Key Traits of Conservative Investments

If, based on the first definition, investors already know what qualifies as a conservative investment, they need to know which characteristics define a conservative investment, which is where the second definition comes into play. There are three broad categories that investors can use to identify a conservative investment.

The Safety Factor

Clearly, any conservative investment should be able to weather market storms better than the rest. In order to do this, certain characteristics must stand out. First, a business should have a low cost of production. Being a [low-cost producer](#) has the principal advantage that, when a bad

year hits the industry, the chance of still churning out a [profit](#) or reporting a smaller [net loss](#) is available. Second, a business should have a strong research and [marketing](#) department. A company that cannot compete by staying abreast of market changes and trends is doomed in the long run. Finally, management should possess financial skills. In doing so, it will be well-versed in things such as the [per-unit cost](#) of production, maximizing [return on investment capital](#), and other essential elements of business success.

The People Factor

This is a rather self-explanatory qualification for a conservative investment. But take notice that excellent people can only be beneficial after a business has demonstrated the signs of the above-mentioned quality. Take note of [Warren Buffett's](#) advice: "When a management team with a reputation for brilliance tackles a business with a reputation for bad [economics](#), it is the reputation of the business that remains intact." A small company can succeed on the heels of one or two exceptionally-talented people. But as a business grows, people throughout the organization must be counted if the company is to succeed and remain a conservative investment.

Characteristics of the Business

This third quality requires a little more work for investors, but it is well worth the effort. Here, the goal is to determine what advantages (or disadvantages) may prevent the business from growing and earning more profits, despite satisfying the first two conditions. One important thing to consider is the competitive landscape of the industry; the existence of many competitors or the relative ease with which new competition can enter can affect the best of companies. The potential for excessive regulation could also be a [game-changer](#).

Even when a company satisfies the obvious conditions of being a conservative investment, you should always remember to consider this third condition.

Examples of Successful and Unsuccessful Investments

Great examples of those businesses that pass the test include names such as Coca-Cola ([KO](#)), Walmart ([WMT](#)) and Johnson & Johnson ([JNJ](#)). These companies have demonstrated time and time again the strengths of their [franchises](#). Even more importantly, these companies will likely continue to have very favorable future prospects. Coke essentially competes with Pepsi and no one else. What's more, it's unlikely that [entrepreneurs](#) are sitting in garages thinking about creating the next great soft drink company.

The existence and continued success of Walmart should raise a [red flag](#) for most other retailers, save for Target. Remember Circuit City, which used to be number two in electronics stores? It's now [bankrupt](#), in no small part due to Walmart. Of course, once a passing company has been identified, the stock price only matters in determining the [value](#) gained.

The Bottom Line

Investing conservatively is not about simply identifying large, well-known businesses, but also going through a process that identifies why a particular company qualifies as a conservative investment. And as you can see from the names of conservative investment companies above, being a conservative investor can lead to some of the most dependable and respectable [returns](#) in the market

While it is impossible to entirely eradicate risk from a portfolio, even low-risk assets such as treasury bills, corporate bonds, and precious metals like silver and gold, inherently carry some risk. Nevertheless, there are proactive measures one can adopt to mitigate exposure to price volatility, counterparty risks, and market cycles.

Being a conservative investor involves prioritizing security and consistency over high returns, thus protecting your hard-earned capital during economic downturns and market fluctuations. For those seeking capital preservation and minimized risk, adopting a conservative investment philosophy is a sagacious decision.

This article elucidates how to adjust your portfolio to embody a more conservative investment approach.

1. Embrace Asset Class Diversification

A cardinal tenet of conservative investing is diversification. Diversifying your portfolio across various asset classes, including:

- Defensive equities (e.g., water, gas, and electric utilities)
- Bonds
- Real estate
- Cash and cash-like equivalents
- Physical precious metals

Different asset classes possess distinct risk profiles, and when some underperform, others may excel. This equilibrium can attenuate the overall risk of your portfolio by dispersing it across various asset types.

For instance, during the global financial crisis, the S&P 500 Index plummeted by 20.1% from October 2007 to October 2010, whereas gold prices surged by 78.9%. By investing in a mix of non-correlated assets, such as precious metals and stocks, rather than exclusively in one type, you can counterbalance some or all losses from any single asset class. However, it is essential not to overcommit to any single asset type, instead, allocate a reasonable percentage of your wealth to each class.

2. Opt for Prudent Asset Allocation

Asset allocation involves deciding how much of your portfolio to assign to different asset classes. Conservative investors generally favor a higher allocation to less volatile assets, such as bonds, commodities, and cash, and a lower allocation to riskier assets like stocks.

Your asset allocation should align with your financial objectives, risk tolerance, and investment horizon. Here are examples of asset allocations suitable for conservative investors:

Mid-Term Conservative Investor (Age 45 and Above)

This strategy suits individuals with a longer time horizon and a lower appetite for risk, typically those aged 45 and above. The aim is to preserve capital while achieving moderate growth over the long term.

- Stocks: 40%
- Bonds (Including Treasury Bonds and Corporate Bonds): 40%
- Cash or Cash Equivalents (e.g., Money Market Funds): 10%
- Precious Metals (e.g., Gold and Silver): 10%

Rationale: This allocation strives to provide growth potential through moderate exposure to stocks while maintaining significant bond allocation for income and stability. The allocation to precious metals serves as a hedge against economic uncertainty and inflation.

Long-Term Conservative Investor (Age 30-45)

This strategy is designed for investors aged 30 to 45, who have a somewhat longer time horizon but still prioritize capital preservation with moderate growth potential.

- Stocks: 45%
- Bonds (Including Treasury Bonds and Corporate Bonds): 35%
- Cash or Cash Equivalents (e.g., Money Market Funds): 10%
- Precious Metals (e.g., Gold and Silver): 10%

Rationale: This allocation increases stock exposure slightly compared to the mid-term strategy, placing greater emphasis on bonds for stability and income generation. The 10% allocation to precious metals maintains a conservative approach.

Short-Term Conservative Investor (Age 60 and Above)

For investors aged 60 and above, capital preservation becomes paramount as they may rely on their investments for retirement income. This allocation minimizes risk and volatility while providing stable income.

- Stocks: 15%
- Bonds (Including Treasury Bonds and Corporate Bonds): 60%
- Cash or Cash Equivalents (e.g., Money Market Funds): 10%
- Precious Metals (e.g., Gold and Silver): 15%

Rationale: This is the most conservative allocation, with reduced stock exposure and increased bonds and cash allocation. The higher allocation to precious metals provides an additional stability layer, particularly during economic downturns.

It is crucial to recognize that these asset allocation strategies are general guidelines. Individual circumstances may necessitate adjustments. Conservative investors should regularly review and rebalance their portfolios to ensure alignment with specific financial goals, in collaboration with a licensed financial advisor.

3. Prioritize Quality Investments

Conservative investors often opt for high-quality, well-established investments. This may entail investing in large-cap stocks with a history of stability, investment-grade bonds, or well-managed real estate properties. Quality investments are generally less susceptible to extreme value fluctuations, aiding in wealth preservation during recessions and other adverse conditions.

4. Seek Income-Generating Investments

Consider investments that provide a consistent income stream, such as dividend-paying stocks and bonds. These income-generating assets can provide a buffer during market downturns, helping you meet financial needs even when your portfolio's capital value is not appreciating significantly.

Another example of an income-generating investment is rental property. While real estate markets are known to periodically crash, dedicating a minority percentage of your net worth to income-generating real estate can help you achieve cash flow positivity while diversifying your investment holdings.

5. Regularly Rebalance Your Portfolio

The weighting in your portfolio will naturally shift over time as market values fluctuate. To maintain your desired asset allocation and risk level, it is essential to periodically rebalance your portfolio.

Rebalancing involves selling assets that have performed well and buying assets that may have underperformed. This practice ensures that you do not become overly exposed to a single asset class. Explore this guide to learn more about portfolio rebalancing.

6. Employ Risk Management with Stop-Loss Orders

If you invest in individual stocks or exchange-traded funds (ETFs), consider using stop-loss orders. A stop-loss order sets a predetermined price at which your investment will be sold automatically, helping to limit potential losses during market downturns.

In essence, a stop-loss order allows you to purchase or liquidate assets at predetermined prices. Using these tools can help you avoid holding onto assets that have fallen below your acceptable risk threshold. Although stop-loss orders are more commonly used by stock and options traders, conservative investors can and should utilize them too.

7. Maintain an Emergency Fund

Having an emergency fund outside of your investment portfolio is crucial for conservative investors. Despite more than 20% of Americans lacking emergency savings, an emergency fund provides a safety net for unexpected expenses and prevents the need to sell investments at unfavorable times.

There is no clear consensus on how much wealth to allocate to an emergency fund. However, leading investors, investment companies, and financial educators suggest the following:

- Vanguard Investments: 3 to 6 months' worth of expenses
- Dave Ramsey: At least \$1,000 cash
- The Motley Fool: 6 times your monthly budget
- MoneyHelper: 3 months' living expenses

An emergency fund's significant benefit is that it prevents reliance on high-interest credit for unexpected expenses, potentially saving thousands in interest payments over time.

8. Diligently Monitor Your Investments

Stay informed about your investments and keep an eye on market conditions. Conservative investors should be more risk-averse, so monitoring your portfolio's performance and making necessary adjustments is essential to maintaining a conservative approach.

As a rule, consider checking your portfolio's performance at least weekly. If your portfolio is losing value over multiple consecutive quarters, consult a qualified financial advisor.

9. Seek Professional Advice

If you're unsure about creating and managing a conservative investment portfolio, do not hesitate to seek professional advice. A financial advisor can help tailor your investments to your specific financial goals and risk tolerances. If you're actively preparing for retirement, outside guidance is even more critical.

Conclusion: A Conservative Investor is a Principled Investor

Becoming a more conservative investor involves deliberate choices to prioritize safety and stability in your investment portfolio. By diversifying, wisely allocating assets, focusing on quality investments, and implementing risk management strategies, you can protect your wealth while pursuing your financial goals.

Remember that conservative investing may not provide the highest returns but can offer peace of mind and financial security, which are invaluable in the long run. To enhance your portfolio while managing risk, consider opening a self-directed retirement account with one of America's top gold investment companies.

Their risk tolerance is low and they tend to make emotional errors. Being worriers, they tend to place great emphasis on financial security and preserving wealth, and to obsess over short-term performance. They also are slow to make investment decisions because they are uncomfortable with change and uncertainty. Their behavioral-bias orientation is emotional:

Loss aversion: Feeling the pain of losses (especially realized losses) more than the pleasure of gains, they tend to hold onto losing investments too long.

Status quo: They feel safe keeping things the same, even if they are not working optimally.

Endowment: They assign greater value to an asset they already own than to a prospective purchase.

Anchoring: They tend to cling to investments, anchoring on a specific price (such as the purchase price, or a historic high).

Mental accounting: Treating different pockets of assets differently, they tend to use a “bucket” approach instead of evaluating the portfolio as a whole.

Moderate:

Executive Summary

This study investigates the relationship between self-reported financial risk tolerance and actual investment behaviors.

Data were collected via an online Qualtrics survey using participants from the Precision Sample research panel in mid-2023. The sample was intentionally designed to include individuals actively managing their household investments, with targeted weighting to overrepresent high-earning households (combined incomes of \$200,000–\$300,000) and high-net-worth investors (net worth exceeding \$1 million, excluding primary residences and associated loans). General linear model analyses demonstrated that risk tolerance, as measured by the Survey of Consumer Finances (SCF) risk-tolerance scale, was a significant descriptor of portfolio allocation composition and portfolio risk, independent of wealth, education, age, and other demographic covariates.

Investors reporting higher risk tolerance held a broader set of investments and constructed riskier portfolios, with a clear progression across SCF categories. Net worth and educational attainment were also significantly associated with portfolio outcomes, whereas other demographics showed mixed effects.

Findings underscore the dual role of financial capacity and psychological willingness to take risks in describing investment behavior. Implications for financial advisory practice, client segmentation, and investor protection policies are presented.

Dr. John Grable, CFP®, is a University of Georgia professor and leading scholar in topics related to financial risk tolerance and personal finance. Dr. Grable has authored more than 150 papers, co-edited major journals, and published several field textbooks.

Dr. Swarn Chatterjee, a professor at the University of Georgia, conducts research that examines financial planning performance, the link between financial well-being and health across populations, and factors that enhance financial decision-making among young adults and older households.

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Understanding how an investor's risk tolerance, defined as a person's willingness to engage in a behavior where the outcome is uncertain and potentially negative (Rabbani and Nobre 2022), translates into actual risk-taking behavior is a central concern for those who provide financial advice at the individual and household level. Understanding the association between someone's risk attitude and their investment choices is also of interest to policymakers and regulators.

Traditional investment allocation models assume that financial capacity proxies (e.g., wealth, income, and education) are the primary determinants of investment choices at the household level (Borrelli and Villanova 2025; Crockett and Friend 1967; Makarov and Schornick 2010), but growing evidence suggests that a person's willingness to take risk, independent of risk-taking capacity, also plays an important role in describing portfolio composition (Aggarwal 2025; Corter and Chen 2006; Heo et al. 2016). Accurately capturing this attitudinal component of investing is essential for designing suitable investment recommendations, assessing investor accreditation status, and improving theoretical models of portfolio choice.

While it is widely recognized that individuals with greater financial risk tolerance tend to make riskier investment choices, the relationship between self-reported risk tolerance and portfolio allocation composition remains underexplored. Specifically, little is known about how well risk tolerance describes the breadth of investments held in portfolios, while controlling for factors such as wealth, education, and other demographic characteristics. Gaining insight into this association is important because exposure to a variety of investment types is a cornerstone of modern portfolio theory. Through the use of investments with varying degrees of risk and return

tradeoffs, it is possible to achieve greater risk-adjusted returns (Modigliani and Leah 1997). Mismatches between risk tolerance and portfolio allocation composition can lead to suboptimal portfolio construction, which can heighten vulnerability to market downturns and derail an investor's long-term financial goals (Park and Yao 2016). By clarifying the relationship between risk tolerance and investment allocation decisions, financial advisers can provide more tailored, client-centered recommendations. In this regard, the purpose of this paper is to document whether an association between financial risk tolerance and portfolio allocation composition exists in practice. The study also provides evidence to the extent to which self-reported financial risk tolerance describes the overall riskiness of investor portfolios, as well as the degree to which demographic and socioeconomic factors (e.g., age, net worth, educational attainment) are associated with risk tolerance in describing investment choices.

Literature Review

Securities regulators worldwide (e.g., Securities and Exchange Commission (SEC), the Financial Industry Regulatory Authority (FINRA), the Securities Industry and Financial Markets Association (SIFMA), the Canadian Investment Regulatory Organization (CIRO), the Financial Conduct Authority (FCA) in the United Kingdom, and the European Securities and Markets Authority (ESMA)) require financial advisers to assess the financial risk tolerance of clients before making financial and investment recommendations. Standards of practice fall under general Know Your Client (KYC) frameworks. Nearly all financial advisers and firms use some type of risk-tolerance questionnaire or test to meet KYC requirements (Tahvildari 2025). Subjective client assessments are popular because they meet regulatory guidelines. SIFMA, for example, encourages the use of structured, repeatable processes, such as psychometric tools and data-driven platforms that align with the design of questionnaires (Varley 2007).

A complicating factor in the required regulatory risk-tolerance assessment process is that the SEC (and some other regulators) allows financial firms and advisers to bypass the use of risk-tolerance assessments as a portfolio risk constraint when working with some clients. This applies particularly to security-offering firms and financial advisers who provide access to highly speculative investment markets (i.e., private placements). This loophole in U.S. regulations falls under accredited investor rules, which allow some investors to purchase private placements without regard to their risk tolerance. Accredited investor rules are based on an investor's risk capacity rather than risk tolerance (Lee 2011), where risk capacity refers to the objective financial ability of a financial decision-maker to absorb losses without jeopardizing their financial objectives (Cordell 2002; Kwak and Grable 2024). Capacity can be assessed using objective measures such as income and wealth (Aggarwal 2025).

Under current rules, an accredited investor is someone who (1) has earned income that exceeded \$200,000 (or \$300,000 together with a spouse or spousal equivalent) in each of the prior two years and reasonably expects the same for the current year; (2) has a net worth over \$1 million, either alone or together with a spouse or spousal equivalent (excluding the value of the person's primary residence and any loans secured by the residence (up to the value of the residence)); or (3) is a broker or other financial professional holding certain certifications, designations, or credentials in good standing, including a Series 7, 65, or 82 license (SEC n.d.).

Regulators assume that someone with sufficient financial capacity can deal with financial losses, understand the nature of illiquidity in relation to subsequent selling, and be willing to accept investment risk with limited financial disclosures. Whether risk capacity, risk tolerance, or a combination of the two is more appropriate as a precursor to providing investment advice is one outcome associated with this study.

Assessing Financial Risk Tolerance

Two approaches dominate the way in which financial risk tolerance is typically assessed (Grable et al. 2020). The first is the use of stated-preference items that ask an investor to subjectively indicate their willingness to take a risk. Stated-preference tests can range from as simple as a single item to as complicated as multi-item questionnaires. The alternative approach is to gauge past and current investing behavior as an indicator of future action. This is referred to as a revealed-preference test or outcome measure.

One of the most commonly used stated-preference items was introduced in the 2016 SCF. Since its introduction, the single-item SCF question has been used hundreds of times in published studies. Although some have criticized the item and other similarly worded assessments, stated-preference items (like the SCF question) tend to perform satisfactorily when subjected to validity tests (Grable and Schumm 2010). Answers to the SCF question do reasonably well in describing a person's willingness to take financial risks (Kim et al. 2021).

Ideally, a stated-preference test score should correlate highly with a revealed-preference outcome. For example, someone who reports being very willing to take financial risks should, in fact, take greater portfolio risk compared to others. This is what Grable and Lytton (2001), Cوتر and Chen (2006), Nosita et al. (2020), and Yao and Rabbani (2021) have observed in practice.

Surprisingly, little is known about the direct relationship between risk tolerance and the composition of portfolio allocations. What is known matches what Goetzmann and Kumar (2008) and Sages and Grable (2010) reported. Specifically, U.S. investors tend to be under-diversified. The lack of broad investment allocation is particularly strong among younger, lower-income, less educated, and less sophisticated investors. Statman (2004) also noted that the portfolios of a large portion of the investing public lack broad allocation composition. Statman explained the tendency to concentrate portfolios on factors like overconfidence, emotional attachment to assets, feelings of control, and market constraints.

Portfolio allocation decisions may also be related to an investor's risk tolerance. As described in modern portfolio theory, rational investors should seek to either maximize expected returns while maintaining a constrained level of risk or minimize risk while targeting a specific expected return. Investors do this by constructing efficient portfolios along the efficient frontier by combining assets with low or negative correlations. Adding more investments across sectors to a portfolio typically reduces total risk without proportionally sacrificing returns, assuming imperfect correlations (Wagner and Lau 1971). Pursuing pure return maximization, absent risk

constraints, may lead to concentrated positions in high-expected-return assets; however, this approach exposes investors to unnecessary unsystematic risk, which deviates from theoretical efficiency. For example, an investor with a low tolerance for risk might diversify across a narrow set of low-volatility assets (e.g., bonds and cash equivalents) to minimize overall portfolio volatility. In contrast, an investor with high risk tolerance might strive for greater exposure to different types of investments, especially high-risk assets (e.g., equities, commodities, and investment alternatives), as a way to optimize the risk-return tradeoff (i.e., attempt to maximize expected returns while minimizing idiosyncratic risks through correlational associations). To date, this and other portfolio allocation composition possibilities associated with financial risk tolerance have been underexplored.

Factors Associated with Financial Risk Tolerance

In this study, a broad set of demographic and socioeconomic characteristics was examined as potential correlates of portfolio allocation composition and portfolio risk. These variables (i.e., age, gender, marital status, race/ethnicity, education, income, net worth, and employment status) were selected because they align with those most commonly used as controls in empirical research on financial risk tolerance (Gondaliya and Dhinaiya 2016).

Prior research has identified several consistent patterns in the associations between the demographic and socioeconomic variables used in this study and financial risk tolerance and risk-taking behavior, although some findings remain context dependent. For example, gender effects are relatively uniform, with men, on average, reporting a greater willingness to take financial risk compared with women (Anbar and Eker 2010; Chavali and Mohanraj 2016; Grable and Roszkowski 2007; Hallahan et al. 2004; Larkin et al. 2013). The age relationship is more nuanced. Brooks et al. (2019), Gibson et al. (2013), Hallahan et al. (2004), Sung and Hanna (1996), and Yao et al. (2011) documented a positive relationship between risk tolerance and age, which contrasts with the common assumption that risk tolerance declines over the life cycle (Kuzniak and Grable 2017).

The literature on marital status presents more nuanced conclusions (Heo et al. 2016). Some studies suggest that being married enhances household risk capacity by allowing potential losses to be absorbed across two individuals (Brooks et al. 2019). Others argue that single individuals exhibit higher risk tolerance precisely because losses do not directly affect another household member (Hallahan et al. 2004; Wong 2011). Racial and ethnic differences in risk tolerance have also been observed, with some evidence indicating that identifying as non-Hispanic White is positively associated with risk-taking behavior (Ferreira and Dickason-Koekemoer 2020; Fisher 2019). However, the direction and magnitude of racial/ethnic effects vary across studies, suggesting that the relationship may be moderated by other factors such as socioeconomic context.

Socioeconomic indicators, including education, household income, and net worth, are among the most consistently reported positive correlates of risk tolerance (Hallahan et al. 2004; Kruger et al. 2017; Pinjisakikool 2017; Wong 2011). Higher education and wealth are believed to

enhance an investor's ability to bear financial risk, thereby fostering a greater willingness to assume financial risks. Employment status functions similarly. Full-time employment, in particular, is associated with stronger household risk capacity, which may translate into riskier portfolio holdings (Anbar and Eker 2010; Chang et al. 2004; Gondaliya and Dhinaiya 2016; Grable 2000).

The remainder of this paper focuses on providing information about the dataset, sample characteristics, and the methodological approach employed to determine the relationship between financial risk tolerance, portfolio allocation composition, and portfolio risk. The paper concludes with a discussion of the results.

Methods

Data and Sample

The data utilized in this study were obtained through a structured online survey administered via the Qualtrics platform. Recruitment was conducted through the Precision Sample research panel, a nationally recognized provider of targeted survey participants. Data collection occurred over a five-week period in mid-2023. The sampling strategy was deliberately designed to capture a population of individuals who were actively engaged in the management of their household investment portfolios at the time of participation. This focus ensured that participants possessed relevant financial decision-making experience and were likely to provide informed responses regarding investment behaviors and preferences.

To enhance the relevance of the findings for high-net-worth and high-income investor segments, the sample was purposefully weighted to include a disproportionate representation of individuals meeting accredited investor financial criteria. Specifically, some participants were selected to reflect (1) high-income households, defined as those with annual incomes ranging from \$200,000 to \$300,000 (this threshold included both individual and combined household incomes (e.g., with a spouse or partner)); and (2) high-net-worth individuals, defined as those with a net worth exceeding \$1 million. Importantly, net worth calculations excluded the value of primary residences and any mortgage or loan obligations secured by those residences, up to the appraised value of the property. This exclusion was intended to isolate investable assets and provide a more accurate representation of financial capacity. Others in the sample represented traditional household financial decision-makers. All variables included in the analysis were fully populated, with no missing data.

Variables

Two outcome variables were evaluated in this study: portfolio allocation composition and portfolio risk. Allocation composition was measured using a summed index based on whether a participant indicated owning one or more of the following nine assets (yes/no): (1) bonds, (2) stocks, (3) exchange-traded funds (ETFs), (4) mutual funds, (5) hedge funds, (6) private placements, (7) commodities, (8) cryptocurrencies, and (9) other, including non-tangible assets, art, commercial real estate, etc. The default investment category was cash and cash

equivalents. The number of holdings owned ranged from zero to eight. Table 1 shows the distribution of asset ownership across the sample.

distribution of asset holdings

The portfolio risk variable was estimated in three ways using various investment risk-scoring methodologies, including volatility metrics and online portfolio risk frameworks.¹ With the first estimate, a weight was assigned to each of the assets shown in table 2, ranging from 0 (very low risk, very low return) to 9 (high risk, high return). Table 2 shows the scoring system. Scores ranged from 0 to 36. The mean, median, and standard deviation scores were 10.78, 8.00, and 8.76, respectively.

portfolio risk scoring

The scoring system presented in table 2 incorporated expert judgment and known risk factors derived from academic studies and institutional practices.² The scoring methodology used insights from Markowitz (1952), Pedersen et al. (2014), and Bruder et al. (2022). Specifically, the scoring system was created based on the notion that risk can be proxied by price volatility and that illiquid and opaque investments carry additional risk beyond volatility. The scoring system also assumed that assets with high skewness, kurtosis, or downside uncertainty are riskier.³

The scoring system (0 = very low risk to 9 = high risk) aligns well with established financial principles and models, particularly the “investment risk pyramid” and the “risk ladder,” which categorize assets from the safest to the most speculative. The risk pyramid is widely used by financial educators and planners to guide asset allocation decisions based on volatility, liquidity, historical returns, and potential for loss (Grable and Palmer 2024; Investopedia 2023). To maintain comparability, each score was chosen to represent a step change based on volatility, liquidity, complexity, tail risk, and regulatory risk. Portfolio risk scores were estimated as follows:

$$\text{Portfolio Risk Score} = \sum (\text{Ownership Indicator } i \times \text{Risk Score } i) \text{ for } i = 0 \text{ to } 9,$$

where Ownership Indicator $i = 1$ if the participant owned the i -th investment type, 0 otherwise, and Risk Score i = the predefined risk level for that investment (e.g., 1 for bonds, ..., 9 for Other, like NFTs/art/collectibles). For example, if someone owned ETFs (2), individual stocks (4), and cryptocurrencies (8), but nothing else, the score would be $(0 \times 0) + (0 \times 1) + (1 \times 2) + (0 \times 3) + (1 \times 4) + (0 \times 5) + (0 \times 6) + (0 \times 7) + (1 \times 8) + (0 \times 9) = 2 + 4 + 8 = 14$. Using this scoring framework, higher scores represent portfolios with greater risk.

The second scoring procedure used in this study corresponds to one used by Cوتر and Chen (2006). An ordinal score (i.e., weight) was matched to three investments from table 2: bonds, stocks, and cryptocurrencies. These weights were used to compute a composite portfolio risk score for each participant, with the score representing the overall riskiness of their portfolio.

Bonds (low risk, low return) were coded 1. Stocks (medium risk, medium return) were coded 2. Cryptocurrencies (high risk, high return) were coded 3. A revised portfolio risk score was estimated as follows:

$$\text{Revised Portfolio Risk Score} = \sum (\text{Ownership Indicator } i \times \text{Risk Score } i) \text{ for } i = 1, 2, \text{ or } 3,$$

where Ownership Indicator $i = 1$ if the participant owned bonds, $i = 2$ if the participant owned stocks, and $i = 3$ if the participant owned cryptocurrencies. Scores ranged from 0 to 6. The mean, median, and standard deviation for the scores were 2.55, 2.00, and 2.09, respectively.

The third scoring method used a modified Herfindahl-Hirschman Index (HHI). HHI values account for the degree of concentration in a portfolio (Brezina et al. 2016). Specifically, HHI scores quantify the concentration of a portfolio across its holdings (Woerheide and Persson 1992). HHI was used in this study to reduce the subjective nature of the previous scoring systems. HHI was calculated as $\text{HHI} = 1/N$, where N represents portfolio allocation composition from table 2. The HHI estimate was then adjusted using the following formula:

$$\text{HHI Adjusted Risk Score} = \text{Original Risk Score (from the first estimation)} \times (1 - \text{HHI})$$

HHI scores ranged from 0 to 31.50. The mean, median, and standard deviation scores were 6.85, 4.67, and 8.15, respectively.

The primary independent variable was financial risk tolerance (FRT). FRT was assessed using a question from the 2016 SCF. The item was presented to participants as follows:

On a scale from zero to 10, where zero is not at all willing to take risks and 10 is very willing to take risks, what number would you (and your {husband/wife/partner}) be on the scale?

Given the response categories, participant scores could range from 0 to 10. The mean, median, and standard deviation scores for the item were 7.11, 7.00, and 2.44, respectively.

Model covariates included age, gender, marital status, race/ethnicity, education, household income, net worth, and employment status. Age was measured as a continuous variable in years. The valid range in the sample was 18 to 99, with a mean of 43.81 (SD = 13.75). Gender

was a dichotomous variable, coded 0 for female and 1 for male. Marital status was also a dichotomous variable coded 0 = Not married and 1 = Married, as was race/ethnicity, where participants were coded 0 = Non-White or other race/ethnicity and 1 = Non-Hispanic White. Educational attainment was a dichotomous variable indicating whether a participant held a bachelor's degree or higher, coded 0 = No and 1 = Yes.

Household income was an ordinal variable with eight categories: 1 = Less than \$50,000, 2 = \$50,000–\$74,999, 3 = \$75,000–\$99,999, 4 = \$100,000–\$149,999, 5 = \$150,000–\$199,999, 6 = \$200,000–\$249,999, 7 = \$250,000–\$299,999, and 8 = \$300,000 or more. The variable was used to categorize household financial capacity. Similarly, net worth was an ordinal variable with 10 categories: 1 = Less than \$0 (negative), 2 = \$0–\$5,000, 3 = \$5,001–\$10,000, 4 = \$10,001–\$25,000, 5 = \$25,001–\$50,000, 6 = \$50,001–\$100,000, 7 = \$100,001–\$250,000, 8 = \$250,001–\$500,000,

9 = \$500,001–\$1,000,000, and 10 = More than \$1 million. Net worth calculations excluded the value of primary residences and associated mortgages up to the value of the home.

Employment status was a dichotomous variable indicating whether the participant worked full-time, coded 0 = No and 1 = Yes.

Data Analysis

A general linear model (GLM) framework was employed to investigate the relationships between self-reported FRT and investment behaviors. GLM is a flexible extension of traditional ANOVA and regression techniques that allows for the simultaneous modeling of continuous dependent variables as a function of categorical and continuous predictors. In this study, several GLM analyses were conducted: one with portfolio allocation composition as the dependent variable and three with the estimates of portfolio risk as the dependent variable.

The primary fixed factor in all the models was the 11-point SCF FRT scale, which represents intervals of self-reported willingness to take financial risks. Covariates included the following demographic and socioeconomic characteristics: age, gender, marital status, race/ethnicity, educational attainment, household income, net worth, and full-time employment status. These covariates were included to control for differences in financial capacity and sociodemographic factors that may be independently associated with investing behaviors.

For each GLM, the Type III sums of squares method was used to estimate the unique contribution of each independent variable after adjusting for the other variables in the model. This approach enabled an assessment of the independent effect of risk tolerance on portfolio outcomes, while controlling for potential confounders. Model fit was evaluated using F-tests for each effect and overall model significance. Effect sizes were interpreted in terms of explained variance (R^2 and adjusted R^2). Post hoc inspection of descriptive statistics and estimated marginal means supported the interpretation of the direction and magnitude of differences in portfolio allocation composition and risk across SCF risk tolerance categories.

Results

Sample and Variables

The profile of participants was diverse. The mean age was 43.81 years (SD = 13.75). Slightly more than 60 percent of the sample consisted of males, with nearly 74 percent of participants indicating that they were married at the time of the survey. The majority of participants were non-Hispanic White (71 percent). Educational attainment was coded as bachelor's degree or higher, with approximately 76 percent of participants meeting this criterion. Household income was categorized into eight brackets, with most participants falling into the \$200,000 or higher range. Net worth was classified into 10 categories, ranging from a negative net worth to over \$1 million, with approximately 20 percent of participants reporting a net worth exceeding \$1 million. Employment status was coded dichotomously as full-time work, with 73.1 percent of participants reporting full-time employment.

Table 3 presents the non-parametric correlations across the covariates used in this study. This analysis provided a preliminary assessment of the relationships between the demographic and socioeconomic factors prior to their inclusion in the multivariate models. As expected, correlations were significant in the majority of cases, but the effects were small to modest in size.

non-parametric correlation coefficients between the covariates

Table 4 presents the Pearson correlation coefficients between FRT and allocation composition, as well as the three portfolio risk estimates. This analysis offered an initial bivariate perspective on the strength and direction of variable associations. The relationships between FRT and portfolio allocation composition, as well as portfolio risk, were positive and statistically significant.

Correlation coefficients between FRT, allocation composition, portfolio risks

Portfolio Allocation Composition

Table 5 shows the results from the first GLM. The model shows that portfolio allocation composition, operationalized as the summed count of "yes" responses to holding various investments, varied significantly by responses to the SCF risk-tolerance question, even after controlling for demographic and socioeconomic covariates. The model was statistically significant, $F_{18, 2016} = 16.81$, $p < .001$, with an R^2 of .147 (adjusted $R^2 = .140$), indicating that approximately 14 percent of the variance in allocation composition was explained by the fixed factor (FRT) and the covariates.

test of between-subjects (GLM) effects for portfolio allocation composition

Descriptive patterns showed a clear, monotonic relationship between self-reported risk tolerance and portfolio allocation composition. As shown in table 6, participants with the fewest investment holdings had the lowest FRT scores, whereas those holding more types of investments had higher FRT scores.

monotonic relationship between portfolio allocation composition and FRT

Among the covariates, educational attainment (i.e., bachelor's degree or higher) and net worth emerged as significant descriptors of allocation composition. Holding a bachelor's degree or higher level of education was associated with holding a greater breadth of investments, $F_1, 2016 = 28.74$, $p < .001$. This finding aligns with what has generally been reported in the literature, namely that financial literacy and human capital facilitate more complex investment strategies (Thomas and Spataro 2018). Net worth was the strongest factor in the model, $F_1, 2016 = 97.54$, $p < .001$. This finding highlights the importance of financial capacity when describing allocation composition. The other demographic controls were not significant after accounting for education, net worth, and risk tolerance.

The main effect of FRT was statistically significant, $F_{10}, 2016 = 9.46$, $p < .001$. This finding confirms that an investor's FRT is independently associated with allocation composition above and beyond socioeconomic resources. These results reinforce the conceptual distinction between FRT (a psychological willingness to bear risk) and risk capacity (financial ability to take risk). In this model, both dimensions contributed to explaining the number of investments held in portfolios.

Portfolio Risk

Table 7 shows the results from the second GLM estimation related to the initial evaluation of portfolio risk. The model was statistically significant, $F_{18}, 2016 = 20.61$, $p < .001$, explaining 13.4 percent of the variance in portfolio risk ($R^2 = .134$; adjusted $R^2 = .126$). The results indicate that portfolio risk varied systematically across the FRT categories, controlling for demographic and socioeconomic covariates.

test of between-subjects (GLM) effects for portfolio risk

The descriptive model statistics shown in table 8 revealed an increase in portfolio risk that aligned with FRT. The lowest FRT categories reported the least risky portfolios (FRT = 0, $M = 6.66$, $SD = 4.53$), while the two highest FRT categories were associated with substantially higher portfolio risk scores (FRT = 9, $M = 14.53$, $SD = 10.28$ and FRT = 10, $M = 13.07$, $SD = 10.24$, respectively). The upward trend in scores suggests a behavioral alignment between stated willingness to take financial risks and actual portfolio riskiness.

monotonic relationship between portfolio risk and FRT

Among the covariates, net worth emerged as the strongest descriptor of portfolio risk, $F_1, 2016 = 76.96$, $p < .001$, underscoring the notion that financial capacity enables higher-risk allocations. Educational attainment (i.e., holding a bachelor's degree or higher level of education) was also significant, $F_1, 2016 = 13.98$, $p < .001$. This result suggests that human capital does enhance an investor's comfort with, or ability to manage, riskier portfolios. Age was positively associated with portfolio risk, $F_1, 2016 = 15.34$, $p < .001$. The other demographic factors were not significant in the model.

The main effect of FRT was statistically significant, $F_{10}, 2016 = 8.59$, $p < .001$, indicating that risk tolerance is a significant descriptor of portfolio risk, even after accounting for wealth, education, and other demographic characteristics. Similar to what was observed in the

allocation composition model, this insight reinforces the conceptual distinction between FRT and risk capacity. While greater wealth enables someone to increase exposure to risky assets, psychological willingness to bear risk appears to exert its own, separate influence on portfolio riskiness. Taken together, the findings highlight the notion that ability (as measured by net worth and education) and willingness (as measured by FRT) can be used to describe the level of portfolio risk in investor portfolios.

Table 9 shows the GLM estimation results from the second estimate of portfolio risk. In this model, the dependent variable was the weighted score for bonds, stocks, and cryptocurrencies. The model was statistically significant, $F_{18, 2016} = 10.55$, $p < .001$. The model explained approximately 11 percent of the variance in portfolio risk scores ($R^2 = .113$; adjusted $R^2 = .105$). Portfolio risk varied consistently across FRT categories, controlling for demographic and socioeconomic covariates.

test of between-subjects (GLM) effects for portfolio risks (est 2)

Similar to the first portfolio risk model, an upward trend in portfolio risk was observed with FRT. As shown in table 10, those in the lowest FRT group held the least risky portfolios (FRT = 0, $M = 1.09$, $SD = 1.61$). In contrast, those in the two highest FRT groups held riskier portfolios (FRT = 9, $M = 3.19$, $SD = 2.33$ and FRT = 10, $M = 2.94$, $SD = 2.21$, respectively).

monotonic relationship between portfolio risk (est 2) and FRT

In this model, net worth was positively associated with portfolio risk, $F_{1, 2016} = 62.72$, $p < .001$, as was educational attainment, $F_{1, 2016} = 10.92$, $p < .001$. Similarly, household income was positively associated with portfolio risk, $F_{1, 2016} = 13.88$, $p < .001$. Identifying as non-Hispanic White ($F_{1, 2016} = 12.84$, $p < .001$) and working full-time ($F_{1, 2016} = 11.99$, $p < .001$) were also associated with taking more portfolio risk. The other demographic factors were not significant in the model. The main effect of FRT was statistically significant, $F_{10, 2016} = 6.37$, $p < .001$. This finding provides support for the concept that FRT is associated with portfolio risk, even when risk is measured in a constrained manner.

Table 11 shows the final GLM model. The dependent variable represents modified Herfindahl-Hirschman Index (HHI) scores. The model was statistically significant, $F_{18, 2016} = 24.89$, $p < .001$, with an R^2 of .155 (adjusted $R^2 = .148$). As was the case with the other models, portfolio risk varied consistently across FRT categories, controlling for other factors.

test of between-subjects (GLM) effects for portfolio risk (est 3)

Portfolio risk patterns showed an upward monotonic relationship with FRT. As shown in table 12, participants in the lowest FRT categories were observed to hold the least risky portfolios. Those at the two highest levels of FRT held portfolios with the highest risk (FRT = 9, $M = 13.01$, $SD = 11.79$ and FRT = 10, $M = 11.12$, $SD = 11.90$, respectively).

monotonic relationship between portfolio risk (est 3)and FRT

Among the covariates, age was positively associated with portfolio risk, $F_{1, 2016} = 6.16$, $p = .013$. Holding a bachelor's degree or higher level of education was also associated with portfolio

risk, $F_{1, 2016} = 25.29$, $p < .001$, as was working full-time, $F_{1, 2016} = 5.54$, $p = .019$. Similar to the other models, net worth was significant in the model, $F_{1, 2016} = 86.77$, $p < .001$. Taken together, these findings suggest that financial capacity and human capital are useful descriptors of financial risk-taking.

In alignment with the other models, the main effect of FRT was statistically significant, $F_{10, 2016} = 10.07$, $p < .001$. This finding confirms that an investor's FRT is independently associated with the degree of risk taken in their portfolio above and beyond other investor characteristics. As with the allocation composition model, this finding highlights the conceptual distinction between FRT (a person's psychological willingness to bear risk) and risk capacity (the financial ability to take risk). In this model, both dimensions helped to describe portfolio risk.

Discussion

The GLM analyses were used to examine two distinct behavioral investment outcomes (i.e., portfolio allocation composition and portfolio risk) as a function of self-reported risk tolerance, measured using the SCF single-item risk-tolerance scale question. The models controlled for commonly utilized demographic and socioeconomic variables. Across all the models, FRT emerged as a significant and independent descriptor of allocation composition and portfolio risk.

Descriptive patterns revealed a consistent, monotonic relationship between FRT and allocation composition, as well as portfolio risk. When describing the number of different investment vehicles held in portfolios, the mean number increased from 1.25 in the lowest FRT group to over 3.00 in the highest FRT group. For portfolio risk derived from the first estimate, mean scores rose from 7.91 to over 16.00 across the same FRT categories. In the HHI model, those with the lowest FRT scores were found to have the lowest portfolio risk (1.83), whereas those at the upper end of the FRT scale were found to take more risk (11.00+). Findings suggest that a willingness to take investment risks is associated with broader investment exposure and higher portfolio risk levels.

When the models are viewed in combination, findings can be used to answer the research questions presented at the outset of this paper. First, self-reported financial risk tolerance can be used to describe the breadth of portfolio allocation composition, even after controlling for wealth, education, and other demographic factors. Second, FRT is significantly associated with overall portfolio risk, independent of financial capacity and investor characteristics.

Higher-risk-tolerant investors were found to allocate larger proportions of their portfolios to higher-risk assets, resulting in greater overall portfolio risk. This finding confirms that a person's willingness to bear risk has tangible behavioral consequences beyond owning a variety of investments. And third, among the covariates, net worth and educational attainment exert the strongest independent effects on portfolio outcomes. Age, gender, marital status, and income have smaller or non-significant effects. These findings indicate that while financial capacity does describe investment behavior, psychological risk tolerance remains an important descriptor of allocation composition and portfolio risk. Overall, the results of this study indicate that ability (wealth and education) and willingness (risk tolerance) jointly describe investment behavior. The parallel findings for allocation composition and portfolio risk suggest that measuring risk

tolerance with a simple, single-item question may be sufficient to capture someone's general psychological orientation toward risk. In alignment with Kim et al. (2021), the consistent stepwise behavioral differences across FRT categories provide further evidence of validity for the SCF scale and reinforce its utility in research and applied financial planning contexts.

Study Limitations

Despite the significant associations observed between self-reported FRT and portfolio behaviors and outcomes, several limitations warrant consideration. First, the study relied on a cross-sectional design, which precludes causal inferences. While higher self-reported risk tolerance was associated with broader investment holdings, it was not possible to determine whether risk tolerance drives portfolio choices or whether engagement with diverse investment products reinforces perceptions of one's own risk tolerance.

Additionally, the use of a single-item self-reported measure introduced potential biases. Although the SCF FRT scale demonstrated face validity through its graded relationship with portfolio allocation composition, participants may have overstated or understated their willingness to take risks due to social desirability or recall biases (Grable et al. 2009; Jain and Kesari 2022). The item does not capture all aspects of risk attitude. Future research should consider using multidimensional questionnaires and tests for comparison. Similarly, portfolio data were based on a participant's self-report rather than verified brokerage records, which may have affected the accuracy of the outcome. Additionally, the sample was deliberately weighted toward high-income and high-net-worth investors, which limits generalizability to similar investors. While this design approach enabled a detailed analysis of financially sophisticated individuals, the findings may not be applicable to lower-income or less financially experienced populations, which may exhibit different patterns of risk tolerance and portfolio behavior.

Another limitation is that unmeasured factors, such as behavioral biases, financial literacy beyond formal education, and access to professional advisory services, may have influenced portfolio composition independently of risk tolerance, potentially confounding the observed associations (see Pan and Statman 2012). Finally, the categorical coding of investment vehicles and the assignment of risk weights, while conceptually justified, may have oversimplified the actual risk-return characteristics of the financial instruments. Future studies should aim to determine the percentage held in various investment vehicles. Doing so will allow for a more precise estimate of portfolio risk. As a result, it should be understood that the composite portfolio risk scores described in this study provide an approximation rather than a precise measure of portfolio volatility. Future research would benefit from longitudinal designs, verified transaction data, and broader population samples to further validate and extend these findings.

Conclusion and Implications

The results from this study have implications for practice and policy. From a financial advisory standpoint, the results highlight the importance of formally assessing risk tolerance, rather than merely inferring someone's willingness to take risks from wealth or demographic profiles, when constructing portfolios (Sages and Grable 2010). The stepwise increases in the number of investment vehicles held in portfolios and portfolio risk across levels of FRT suggest that

financial advisers who fail to capture a client's psychological willingness to take risk may misalign investment recommendations, either underexposing high-tolerance clients to growth opportunities or overexposing low-tolerance clients to excess volatility. Incorporating validated measures of FRT into the client onboarding process is not only a legal requirement but also a practical way to enhance suitability assessments, improve client–adviser trust, and help document regulatory compliance with KYC standards (Brayman et al. 2017; Grable et al. 2020).

In terms of practice management, the dual effect of risk-taking capacity (i.e., wealth and education) and willingness to take risk (FRT) on investment behaviors highlights the need for more nuanced client segmentation. Financial advisers could use joint profiling by mapping clients along capacity and tolerance dimensions as shown in figure 1. Creating a profiling map could facilitate tailored client communications, portfolio modeling, and educational interventions. For instance, clients with a high willingness but low capacity to take risks may require targeted education on liquidity constraints and risk budgeting. In contrast, those with high capacity but low willingness may benefit from behavioral coaching to reduce underinvestment in growth assets. Such segmentation can also inform resource allocations within a firm, directing more time-intensive planning services toward clients whose risk-taking profiles indicate higher behavioral risk of deviating from agreed-upon strategies (i.e., those at the corner extremes in figure 1).

From a policy perspective, findings contribute to ongoing discussions about the adequacy of current investor profiling systems, such as the way the SEC defines accredited investors (Adler et al. 2021). Results from this study suggest that risk tolerance should be considered along with income and wealth. The fact that risk tolerance was independently associated with allocation composition choices and the riskiness of household portfolios suggests that capacity-based thresholds (i.e., income and net worth) may not fully capture an investor's propensity to engage with complex or high-risk assets. Policymakers should consider integrating behavioral measures of risk tolerance into regulatory frameworks to more precisely identify investors who may require additional protections or disclosures. Additionally, the observed role of education supports initiatives aimed at expanding financial literacy, not only to improve market participation but also to promote portfolio strategies that align with both willingness and capacity to bear risk.

risk-taking profiling map based on risk capacity and financial risk tolerance

Citation

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Endnotes

See

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Moderate Investors

Their risk tolerance is moderate and they tend to make cognitive errors. They often do not have their own firm ideas about investing, instead following the lead of their friends and colleagues. They tend to be comfortable with the latest, most popular investments, often without regard to a long-term plan. In addition, they often overestimate their risk tolerance. Their behavioral-bias orientation tends to result in cognitive biases such as:

Recency: The predisposition to recall and overweight recent events and/or observations and to extrapolate patterns where none may actually exist.

Hindsight: Belief that investment outcomes were predictable.

Framing: The tendency to respond to situations differently depending on the context in which a choice is presented (framed). For example, when questions are worded in a “gain frame” (e.g., an investor is asked to suppose an investment goes up), a risk-taking response is more likely.

When questions are worded in a “loss frame” (e.g., an investor is asked to suppose an investment goes down), risk-averse behavior is the more likely response.

Cognitive dissonance: When a person believes something is true only to find out that it is not, he or she tries to alleviate discomfort by ignoring the truth and/or rationalizing decisions (often ending up throwing good money after bad).

Moderate investors also tend to make the emotional error of regret-aversion bias, which is the fear of taking decisive action because they worry that, in hindsight, whatever course they select will prove unwise. Regret aversion can cause moderate investors to be too timid in their investment choices because of losses they have suffered in the past.

Growth Investors

Their risk tolerance is moderate to high and they tend to make cognitive errors. Growth investors tend to be active investors who are often strong-willed and independent thinkers. They also tend to be self-assured and “trust their gut” when making decisions. However, when they do their own research, they may not be thorough enough with due diligence tasks. They also can be subject to maintaining their views even when those views are not supportable. Some growth investors may appear obsessed with trying to beat the market and may hold

concentrated portfolios. Their behavioral-bias orientation tends to be cognitive and reflect biases such as:

Conservatism: The tendency to cling to a prior view or forecast at the expense of acknowledging new information.

Availability: Estimating the probability of an outcome based on how prevalent that outcome appears to be in one's own life.

Representativeness: Representativeness bias occurs due to a flawed perceptual framework when processing new information. To make new information easier to process, some investors project outcomes that resonate with their own pre-existing ideas.

Self-attribution: The tendency of people to ascribe their successes to their talents and to blame failures on outside influences.

Confirmation: The proclivity actively to seek information that confirms one's claims while ignoring or devaluing evidence that discounts them.

The primary goal of a moderate investment strategy is capital appreciation, but income generation may also be a priority.

Moderate investors typically maintain a diversified asset allocation that consists of both stocks and bonds

Moderate investors must be comfortable with a reasonable degree of risk in the pursuit of building wealth. But many opt for more passive investments in their retirement plan, such as [target date funds](#) that automatically become more conservative as they age.

Aggressive:

In my book, "The Only Guide You'll Ever Need for the Right Financial Plan," there's a detailed discussion on how investors can choose the right asset allocation for them, with the focus being on determining one's ability (capacity), willingness (tolerance) and need (the rate of return required to achieve a goal) to take risk.

To help with issues surrounding the willingness to take risk, risk tolerance questionnaires have become a very popular. Unfortunately, as Joachim Klement showed in his article, "Investor Risk Profiling: An Overview," published in the June 2018 CFA Institute Research Foundation brief "Risk Profiling and Tolerance: Insights for the Private Wealth Manager," the "current standard process of risk profiling through questionnaires is found to be highly unreliable and typically explains less than 15% of the variation in risky assets between investors. The cause is primarily the design of the questionnaires, which focus on socioeconomic variables and hypothetical scenarios to elicit the investor's behavior."

He went on to explain that there are three problems questionnaires typically fail to address: Our genetic predisposition affects our willingness to take on financial risks, the people we interact with shape our views, and the circumstances we experience in our lifetimes—in particular, during the period psychologists call the formative years— influence our outlook.

Being aware of biases at least gives us a chance of addressing them, either on our own or with the help of a financial advisor. Michael Pompian provides guidance on behavioral biases in his article, “Risk Profiling Through a Behavioral Finance Lens,” for the aforementioned CFA Institute Research Foundation brief. (Pompian also is the author of the 2012 book “Behavioral Finance and Wealth Management,” which I recommend for both investors and advisors.)

In his article, Pompian places biases into two broad categories: cognitive and emotional. Cognitive biases have to do with how people think and result from memory errors or faulty reasoning.

He writes: “There are two types of cognitive biases: belief perseverance and information-processing biases. Belief perseverance biases concern people who have a hard time modifying their beliefs even when faced with information to the contrary. It is a very human reaction to feel mentally uncomfortable when new information contradicts information you hold to be true.”

Emotional biases are the result of reasoning that is influenced by feelings, especially during times of stress.

Pompian then analyzes four different investor types—conservative, moderate, growth and aggressive—and reviews the biases likely to be present with each type.

Aggressive Investors

Their tolerance for risk is high and they tend to make emotional errors. They often are the first generation in their family to create wealth. They are even more strong-willed and (over)confident than growth investors, which often leads to chasing high-risk investments. They also tend to change their portfolios as market conditions change, which often creates a drag on investment performance. Finally, they are often “hands on” and want to be involved in the investment decision making. Their behavioral-bias orientation is emotional, tending to exhibit the following biases:

Overconfidence: An overestimation of one’s quality of judgment, often leading to failure to diversify and concentrated positions in risky assets.

Self-control: The tendency to consume today at the expense of saving for tomorrow.

Affinity: The tendency to make irrationally uneconomical consumer choices or investment decisions predicated on how one believes a certain product or service will reflect held values.

Outcome: Focus on the outcome of a process rather than on the process used to attain the outcome, leading to confusing luck with skill.

Illusion of control: Believing that one can control or at least influence investment outcomes when, in fact, one cannot. That often leads to persistent “tinkering” with investments.

Summary

Behavioral biases can cause even the most well-developed and well-thought-out investment plans to fail. One reason, as physicist Richard Feynman noted, is that “the first principle is that you must not fool yourself and you are the easiest person to fool.” The best cure for such biases

is to become educated about them so that at least you are aware you can be subject to them. Perhaps you can even learn to overcome them. If you recognize that isn't the case, or don't have sufficient knowledge to invest on your own, you can consider hiring a fiduciary advisor who can help you overcome any particular behavioral biases you might gravitate toward.

For those interested in learning more about behavioral biases, I recommend Nobel Prize-winner Daniel Kahneman's book, "Thinking, Fast and Slow," and my own book, "Investment Mistakes Even Smart Investors Make and How to Avoid Them." The latter covers 77 mistakes, both cognitive and behavioral.

Larry Swedroe is the director of research for The BAM Alliance, a community of more than 140 independent registered investment advisors throughout the country.