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The editor of *Financial Services Review* wishes to thank the Stetson University, School of Business, for its continuing financial and intellectual support of the journal.

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

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From the Editor

This issue contains **Volume 29 - Issue 1** of *Financial Services Review* (*FSR*). I would like to thank the board and members of the Academy of Financial Services for their continued support. I continue to work in broadening the scope of articles, while still focusing on individual financial management and personal financial planning. I encourage authors to reach out when discussing implications of their findings in a more comprehensive way. As such, all articles in the Journal more appropriately relate to financial planning issues.

The lead article "Optimism, Overconfidence, and Insurance Decisions" is coauthored by Jennifer Coatsa and Vickie Bajtelsmit, both at Colorado State University. The authors present experimental evidence regarding overconfidence, optimism and insurance decisions. They distinguish between an individual's optimism bias and overconfidence bias, a contribution particularly important for understanding insurance decisions related to risks beyond the purchaser's control. Their results show that optimistic participants incur a higher total cost of risk and are more likely to underinsure than non-optimistic participants, even when purchasing insurance maximizing expected payoffs. They also find that overconfidence does not significantly affect the decision to insure, participants with higher overall overconfidence show larger differences in insurance behavior when the risk of loss arises from their own mistakes.

The second article "The Impact of Using Financial Technology on Positive Financial Behaviors" is coauthored by Qianwen Bi, Utah Valley University, Lukas R. Dean, Utah Valley University, Tao Guo, William Paterson University, and Xu Sun, Utah Valley University, The authors use the 2013 Survey of Consumer Finances data to explore the impact of financial technologies on households' positive financial behaviors. The authors find that only planning technologies (e.g. direct deposit and computer software) are positively related to households' engagement in positive financial behaviors. They also find that the impact of transaction technologies (e.g. using ATM card, credit card, phone banking, and computer banking) is negative.

The third article, "Using Investor Utility to Determine Portfolio Choice with REITs" is coauthored by Wei Feng, Lynn University, Travis L. Jones, Florida Gulf Coast University, and Marcus T. Allen, Florida Gulf Coast University. The authors examine the decision of individual investors to allocate a portion of their existing investment portfolios to REITs. They derive the risk preferences of investors represented by their benchmark portfolios of stocks and bonds and then use the risk preferences to determine portfolio decisions regarding REITs. Their analysis shows that investors with lower risk aversion tend to have a more

substantial stock component in their benchmark porfolio and will obtain higher risk-return benefits from adding REITs.

The final article, "Demographic and Psychological Differences between Chapter 13 Bankruptcy Filers and Non-Filers" is coauthored by Scott E. Kehiaian, Southern New Hampshire University, Albert A. Williams, Nova Southeastern University, and Carolyn L. Bird, North Carolina State University. In this article the authors find financial, demographic, and psychological differences between Chapter 13 filers and non-filers. They also show that financial training reduces the likelihood of filing for personal bankruptcy and males are twice as likely as females to be filers. A single person is less likely to file than a married person and homeowners are more likely than renters to be filers. Increases in education, religious commitment, and parents' income reduce the likelihood of filing. Increases in the psychological factors, self-efficacy, locus of control, and self-control, reduce the likelihood of filing for Chapter 13 bankruptcies.

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

Please consider submission to the Financial Services Review and rely on the style information provided to ease readability and streamline the review process. The Journal welcomes articles over the range of areas that comprise personal financial planning. While FSR articles are certainly diverse in terms of topic, data, and method, they are focused in terms of motivation. FSR exists to produce research that addresses issues that matter to individuals. I remain committed to the goal of making Financial Services Review the best academic journal in individual financial management and personal financial planning.

Best regards,
Stuart Michelson
Editor *Financial Services Review*

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Optimism, overconfidence, and insurance decisions

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Abstract

We report experimental evidence regarding overconfidence, optimism, and insurance decisions. Our design distinguishes between an individual's *optimism bias* and *overconfidence bias*, a contribution particularly important for understanding insurance decisions related to risks beyond the purchaser's control. Results show that optimistic participants incur a higher total cost of risk and are more likely to underinsure than non-optimistic participants, even when purchasing insurance maximizes expected payoffs. In contrast, we find that overconfidence does not significantly affect the decision to insure. However, participants with higher overall overconfidence show larger differences in insurance behavior when the risk of loss arises from their own mistakes. © 2021 Academy of Financial Services. All rights reserved.

Keywords: C9 Design of experiments; C91 Laboratory experiments; D81 Decision-making under uncertainty; Overconfidence; Insurance demand

1. Introduction

Optimism bias, or the tendency to assign higher subjective probabilities to favorable outcomes, is well documented in the psychology and economics literature. In fact, after decades of controlled studies in psychology, the only individuals identified as consistently free from this bias are the clinically depressed (Pyszczynski, Holt, & Greenberg, 1987). Overconfidence, which can be viewed as a special case of optimism, relates to having a biased perception of one's own skills, prospects, or knowledge. Both optimism and overconfidence theoretically affect decision-making under conditions of risk and uncertainty (De Bondt & Thaler, 1985). Although previous studies differ in how these factors are defined and operationalized, the

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conclusions overwhelmingly suggest that underestimation of the risk of negative outcomes has an economically significant effect on individual and societal well-being.[1] General optimism about events outside of one's own control may cause individuals to underestimate their actual risk, which may lead them to make suboptimal financial decisions. For example, underestimation of expected losses may result in reduced demand for insurance (Kunreuther & Pauly, 2004) and optimism about market performance may affect portfolio allocations (Jacobsen, Lee, Marquering, & Zhang, 2014). Similarly, overestimation of one's financial skills may result in excessive and costly financial market trading (Barber & Odean, 2001) or investment in suboptimal business projects (Malmendier & Tate, 2005).[2] In this article, we focus on the degree to which heterogeneous risk perceptions, which may be affected by both optimism and overconfidence, influence insurance and risk management decisions. To the extent that these biases result in underestimation of personal risks, individuals are hypothesized to have reduced demand for insurance and greater total cost of risk.

Although overconfidence and optimism are widely discussed in the psychology and economics literatures, the influence of these behavioral biases on insurance decision-making has received less attention. Information asymmetry in insurance markets, in which applicants for insurance know more about their own risk characteristics than do insurers, is shown theoretically to create the potential for market failure. With heterogeneous risk types, equilibrium solutions result in separating contracts that encourage individuals to select price and coverage policies that are appropriate to their risk type.[3] For example, a high risk individual might prefer a contract that provides relatively full coverage for a higher premium rate, whereas an individual with a lower risk of loss might select a partial-coverage policy for a lower premium rate. Critical to the success of self-selection equilibria models is that individuals can correctly self-identify their risk type. Bajtelsmit and Thistle (2015) develop a model in which noisy or imperfect information about risk types could result in suboptimal insurance and risk management decisions. In this article, we consider information imperfection caused by individual psychological biases that influence an individual's risk perceptions.

Our study uses a novel experimental design which connects, through large monetary incentives, an earnings task, a frequency estimation task, and insurance decisions. Participants develop subjective estimates of their own and others' performance on an earnings task and decide, in light of their subjective probabilities of loss, whether to fully insure against loss of earnings. In this article, we first focus on the origins of subjective probability estimation, as it depends on task performance, and then develop measures to distinguish between optimism and overconfidence biases in the estimation task. Finally, we investigate how the biases affect the risk management decision to fully insure against loss. Our analysis of insurance decisions in this article continues a stream of research from a large experimental design which, as a whole, considers an extensive set of variables shown theoretically to affect risk management and insurance decisions.[4]

The experiment design allows us to distinguish between an individual's *optimism,* or the general tendency to overestimate favorable outcomes ("wishful thinking"), and their *overconfidence,* the tendency to overestimate their own performance or skills ("I think I'm better than I am") and the relationship between these outlooks.[5] We assess optimism with a treatment manipulation in which a participant's expected payoff is independent of their own performance on a task, but positively related to the performance of others on the same task.

Participants' outlooks range from underconfident to highly overconfident in their own performance and from pessimistic to optimistic about others'. Participants who are optimistic about others' performance are generally confident in their own as well. We find that overconfidence bias does not reduce the likelihood of insurance purchase, but that the highly optimistic are less likely to purchase insurance and, controlling for risk preferences, tend to underinsure.

The remainder of the article is organized as follows. Section 2 describes related literature on insurance and overconfidence. Section 3 explains the experimental design and hypotheses. We provide results in Section 4, and discuss conclusions in the final section.

2. Related literature

The empirical link between overconfidence and the purchase of insurance is an important contribution in support of recent theoretical findings (Huang, Liu, & Tzeng, 2010; Spinnewijn, 2013) and leads to policy implications applicable to insurance contract design and government policy interventions. Huang et al. (2010) show theoretically that hidden overconfidence can lead to insurance market equilibria that are consistent with observed anomalies in insurance markets. They suggest that insurers could use an overconfidence proxy to screen prospective policyholders so as to achieve an advantageous selection equilibrium and that regulators might need to intervene in markets that are operating imperfectly as a result of this type of asymmetric information.[6]

In recent years, researchers have distinguished several different categories of overconfidence bias. However, overconfidence, as a subset of optimism bias, has often remained confounded with a general optimistic outlook. The optimism bias leads individuals to underweight the probability of negative outcomes that are beyond their control, such as an airline crash or a wildfire, and overweight the probability of positive outcomes that are beyond their control, such as winning a lottery. Spinnewijn (2013) refers to this phenomenon as "baseline optimism." For example, Landry and Jahan-Parvar (2011) suggest that failure to purchase flood insurance may be related to residents' reliance on community protection policies (seawalls, beach replenishment, etc.). If the households are overly optimistic regarding the success of the communities' risk management efforts, then they may underinsure against loss.

In addition to a baseline level of optimism, individuals may be overconfident with respect to their influence and/or abilities, which then leads to unrealistic optimism about outcomes, a quality Spinnewijn (2013) terms "control optimism." Royal and Tasoff (2017) show theoretically that overconfident agents are likely to reduce their payoffs by investing too much in capital that complements their ability and too little in capital that substitutes for their own ability. Their experimental results support the theoretical predictions. In the insurance context, this could lead an individual to underinsure if they unrealistically believe they can reduce the frequency or severity of loss through their own actions. A large literature in behavioral economics distinguishes further between different types of control optimism. "Absolute overconfidence" is a term applied to individuals who overestimate their own knowledge, ability, or performance against a given benchmark, such as the prediction that

they will perform better on a test or run faster than they actually do (Moore & Healy, 2008). Perhaps the most well-known type of overconfidence is the "better-than-average effect," also termed "over-placement," which refers to overestimation of one's relative performance in a group. An important quality of over-placement is "reference group neglect" in which individuals rank their placement equally high among groups of self-selected members and groups of exogenously assigned members (Camerer & Lovallo, 1999; Moore & Healy, 2008). Other types of control optimism include the "illusion of control," which refers to the case in which individuals erroneously perceive their actions to influence independent events, and "calibration-based overconfidence," or overconfidence in the precision of knowledge.[7] Fellner and Krugel (2012) find evidence that overconfidence assessed with different methods actually reflects separate and distinct biases.

Several recent studies suggest that heterogeneity of risk perceptions (Spinnewijn, 2013) or risk preferences (De Meza & Webb, 2001) can explain the negative correlation between risk and insurance coverage found in some markets.[8] For example, as modeled in Sandroni and Squintani (2007), differences in risk perceptions may lead some high-risk types to believe that they are low-risk types, which can decrease investment in precaution and/or reduce demand for insurance at offered prices. Huang et al. (2010) model optimistic individuals who have subjective loss probabilities that are lower than their objective loss probabilities and "rational" individuals who assess their loss probability correctly. In their model, higher optimism leads to lower likelihood of insurance purchase. Arad (2014) presents a study in which participants are aware of objective probabilities but may assign a higher or lower likelihood due to their own personal motivations that are unrelated to the random event. Arad labels this phenomenon "magical thinking" and notes that beliefs about one's own good or bad luck, regardless of probability distribution can also lead to suboptimal insurance decisions. Honl, Meissner, and Wulf (2017) develop a model in which individual risk-taking behavior depends on cognitive processing of outcomes and probabilities, affect in judgment and decision-making, and upon contextual factors. To the extent that insurance purchasers do not know the objective likelihood of a loss event, it is important to consider biases in estimating risk, and insurance decisions in light of subjective probability estimation.

While our experiment is not motivated as a study of gender effects or risk preferences per se, extant studies suggest that it is important to control for both factors in the analysis. Recent studies designed to investigate gender differences in decision-making find that optimism about conditions or others' performance varies across men and women. In an analysis of survey data that includes several different indicators of optimism, Jacobsen et al. (2014) find men to be more optimistic than women in their expectations about the general economic outlook. In a study spanning three years, Foster and Frijters (2014) find that male university students are more consistently overconfident than females about their future grades. In an experiment task where payoffs depend on team performance, Kuhn and Villeval (2015) find that both men and women expect to outperform others on their team, although women are more optimistic than men about their team members' performance.

Laboratory experiments designed to model insurance decisions offer the opportunity to measure and control for beliefs, risk attitudes, and the set of risk management alternatives. For example, Harrison and Ng (2016) find that, after measuring and controlling for risk

preferences, experimental participants tend to make welfare-reducing insurance decisions. In another controlled laboratory experiment, Jaspersen and Aseervatham (2017) find that insurance demand decisions are often driven by biases and the use of heuristics. Laury and McInnes (2003) find that information provided by actuarially fair insurance prices can reduce experimental participants' reliance on heuristics and improve decisions. When experiment participants are allowed to insure against losses that depend on relative performance, Hales and Kachelmeier (2008) show that insurance decisions are affected by biases in performance estimation. For a comprehensive survey on the experimental literature on insurance demand, see Jaspersen (2016) who concludes that the decision context, decision task, and the use of salient incentives all heavily influence experimental results. In this article, we present the results of an experimental study in which we first elicit participants' beliefs about risk perceptions, and then investigate their subsequent decisions in laboratory insurance decision tasks.

3. Experiment procedures and design and hypotheses

In this section, we first describe the design and procedures used in this laboratory experiment, and then explain how this design can be used to test various hypotheses related to the effects of overconfidence and optimism on risk management decisions. The experiment is designed with incentive-compatible earnings and risk management tasks. The design also includes an indirectly incentive-compatible frequency estimation task to elicit subjective probabilities for losses that depend on the participants' own ability and losses that are outside of their influence.[9] The reported subjective probabilities allow us to measure participants' overconfidence in their own performance as well as baseline optimism regarding favorable outcomes. We use these to estimate the impact of overconfidence and optimism biases on incentivized insurance purchase decisions under different risk conditions.

3.1. Procedures overview

Students were recruited from business classes at a large university to participate in a paid experiment. All sessions were conducted with Z-tree (Fischbacher, 2007) in a networked computer lab with partitioned stations. We conducted six sessions, each with ten participants, between June and October 2013. The experiment proceeded through two stages with steps as summarized in Table 1, including participation payment, earnings task, instructions, estimation task, and risk management task.

After participants were paid $15 up-front in cash (never at risk of loss) and learned the experiment procedures, they earned $60 for correctly answering at least eight questions on a quiz comprised of twenty questions drawn from previous driver licensing exams for the state in which their university was located.[10,11] For each question, participants were asked to indicate whether they were sure they had answered it correctly. To incentivize participants to carefully make these assessments, the instructions clearly explained the relationship between their quiz performance, others' quiz performance, the probability of loss, and their expected earnings from the experiment. After participants demonstrated their understanding of these

Table 1 Experimental procedures

First stage	
Step 1 Participation payment and procedures overview	• $15 in cash immediately upon entering lab. • Agenda for earnings and risk management tasks.
Step 2 Earnings task	• Twenty multiple choice driving quiz questions distributed on paper. • Monetary incentives to answer correctly. • Indicate whether sure of answer.
Step 3 Instructions	• Risk management task instructions distributed and read aloud. • Relation between earnings, estimation, and risk management tasks explained with examples. • Instructions assessment and review.
Step 4 Estimation task	• Enter driving quiz final answers and whether sure of each. • Enter estimate of own score. • Enter estimate of average score earned by other participants.
Second stage	
Step 1 Risk management tasks	• No Mistakes, Own Mistakes, and Others' Mistakes treatments. • Precaution, insurance, and initial probability of loss treatment manipulations presented in random order.
Step 2 Review all decisions	• Complete all decisions, then review each, one at a time. • Must actively confirm or revise each individual decision.
Step 3 Selection of a treatment for payoff	• Random draw by a participant determines treatment applied for session payment. • Participants are each paid according to their decision in the drawn treatment.

relationships, we proceeded with the estimation task in which they recorded an estimate of the number of questions they had answered correctly and an estimate of the average number correct for the other participants in the session.

In the second stage, participants made risk management and insurance decisions in several treatments. Participants finalized their choices in the program only after experiencing all decisions for the experiment, and no losses or outcomes were realized until after confirmation of all decisions. A random draw at the end of the experiment was used to select the treatment used to determine payoff.

3.2. Treatment design

We use a within-subjects design with 60 participants each completing 8 treatments.[12] This results in 480 participant-treatment observations, some of which are used in the primary analyses, and some of which are used only to check participant rationality or as controls. To minimize order effects, treatment manipulations are randomized across participants in each session.

In each treatment, participants are exposed to a risk of losing $45 from their $60 earnings. Treatment manipulations include the initial loss probability (10% or 32%), and the determinants of overall loss probability. For each initial loss probability, three treatment manipulations that differ in the way that quiz performance determines the overall probability of loss as follows:

- No Mistakes: The risk of loss is implemented as a computer-generated random number—explained with the analogy of a random draw from 100 white and orange ping-pong balls. The risk of loss is expressed as a percentage (10% or 32% orange balls) and also described in terms of number of orange and white balls, respectively. Participants are told that, if an orange ball is drawn, they lose $45.
- Own Mistakes: As in the No Mistakes treatments, there is a draw from a known distribution of orange and white ping-pong balls (10% or 32% orange). Participants are told that they lose $45 if an orange ball is drawn but, if a white ball is drawn, there is a random draw from their own driving quiz questions. If they answered the drawn question correctly, they do not lose any money, but if they answered it incorrectly, they lose $45.
- Others' Mistakes: As in the Own Mistakes treatments, there is a draw from a known distribution of orange and white ping-pong balls (10% or 32% orange). Participants are told that they lose $45 if an orange ball is drawn but, if a white ball is drawn, there is a random draw from a different participant's driving quiz questions. If the other participant answered it incorrectly, they lose $45.

Before learning about whether they experienced a loss, participants made risk management (insurance or precaution) decisions described as the option to pay a dollar cost from their earnings to replace orange balls with white balls. In each case, they were presented with a menu of incremental options as in the example in the Appendix. Consistent with Jasperson and Aseervatham (2015), who emphasize the importance of a choice frame in laboratory experiments of insurance decisions, the insurance and precaution decisions are framed as choice tasks rather than elicitations of willingness to pay for insurance. The cost

Table 2 Probability of losing $45 before risk management decisions in different treatments

Treatments	Initial probability of loss	
	Low (10%)	High (32%)
Own Mistakes: Dependent on own performance	$0.10 + 0.90 * \frac{(20 - Own\ Quiz\ Score)}{20}$	$0.32 + 0.68 * \frac{(20 - Own\ Quiz\ Score)}{20}$
Others' Mistakes: Dependent on others' performance	$0.10 + 0.90 * \frac{(20 - Others'\ Avg.\ Score)}{20}$	$0.32 + 0.68 * \frac{(20 - Others'\ Avg.\ Score)}{20}$
No Mistakes: Independent of performance	0.10	0.32

of insurance is $14.50 and, if purchased in any treatment, it reduces their probability of loss to zero. Each $1.50 spent on precaution reduces the probability of loss by one percentage point in the low probability of loss treatments and by four percentage points in the high probability of loss treatments.[13] In the No Mistakes treatments, participants could reduce their initial probability of loss to zero through buying the maximum level of precaution, making this choice equivalent to full insurance. Buying full precaution is more expensive than insuring in the low probability treatments, but less expensive in the high probability treatments. Our within-participants design allows us to observe that participants who wish to reduce risk to zero make rational choices between precaution and insurance. In the Mistakes treatments where the probability of loss depends on quiz performance, insurance is the only option for reducing risk to zero, because even with the purchase of full precaution (replacing all orange balls with white balls), the risk of loss from mistakes remains.

In the No Mistakes treatments, participants know their risk of loss with certainty whereas, in the Mistakes treatments, they must make subjective assessments over the risk of quiz mistakes to determine their probability of loss. Table 2 summarizes the way in which participants' estimates of quiz scores impact estimates of the probability of loss prior to any investments in risk mitigation.

Table 3 summarizes the optimal insurance decisions for a risk-neutral participant in each of the treatments used in this study.[14] The treatments that do not provide an insurance option are used to categorize and control for participants' risk preferences but are not otherwise included in the primary analysis. The No Mistakes low probability treatment provides a check of participant rationality but is not included in the primary analysis.

Several treatments allow for the possibility of underinsurance by risk-neutral (or risk-averse) participants. In all of the High (32%) Initial Probability of Loss treatments, purchasing insurance is optimal for risk-neutral (or risk-averse) participants in that it results in the highest expected payoff. In the Low (10%) Initial Probability treatments with loss probability independent of performance, the highest expected payoff results from not purchasing any risk mitigation. However, in the treatments where loss probability depends on performance, purchasing insurance is optimal for risk-neutral or risk-averse participants who performed poorly on the quiz. Participants maximize expected payoffs by purchasing insurance if less

Table 3 Optimal risk management decisions to minimize expected loss in each treatment

Treatments	Initial probability of loss	
	Low (10%)	High (32%)
Own Mistakes: Risk depends on own performance	Insure if quiz score < 76% No risk mitigation if > 76%	Insure
Others' Mistakes: Risk depends on others' performance	Insure if quiz score < 76% No risk mitigation if > 76%	Insure
No Mistakes: Risk is independent		
Risk mitigation-precaution and insurance	*No risk mitigation*	Full precaution[a]
Risk mitigation-precaution only[b]	*No risk mitigation*	*Full precaution*

[a] Participants pay to reduce the initial probability of loss before a mistake is drawn in increments of 10 percentage points. In the No Mistakes treatments, the purchase of full precaution reduces the probability of loss to zero and is, therefore, the risk mitigation equivalent to buying insurance in this design. Full precaution is the more efficient means to reduce risk to zero in the high probability treatments, while insurance is the more efficient means in low probability treatments.

[b] Precaution is the only risk management tool. These treatments are used only to categorize and control for risk attitudes.

than 76% of quiz questions are answered correctly. Therefore, overestimation of performance can lead to underinsurance.

3.3. The incentive for accurate estimation in this experiment design

In addition to the show-up fee paid at the beginning of Stage 1, participants received a payment at the end of Stage 2 (in private and in cash) based upon their performance, risk management decisions, and chance. Monetary incentives connect the earnings, estimation, and risk management tasks across the two stages. A higher score on the driving quiz decreases the probability of loss in the Own Mistakes treatments in the same way that loss event probability estimation and insurance decisions correspond to expected wealth effects in practice. That is, the estimation task facilitates comparison by the participants between their expected payoff without insurance versus their payoff with insurance. More accurate score estimates improve a participant's ability to make an optimal insurance decision. In summary, higher scores on the quiz reduce the risk of loss in the mistakes treatments, but *overestimation* of scores could lead to suboptimal insurance decisions and lower expected payoffs, and this correspondence rewards participants for accuracy in their estimation.[15] For example, a risk-neutral participant with an initial 10% probability of loss who estimates scoring 90% correct on the driving quiz in the Own Mistakes treatment (expected loss of $8.55) is better off not purchasing insurance for $14.50. However, if the participant's actual performance on the driving quiz is 60% (expected loss of $20.70), the expected payoff is higher *with* insurance. Participants recorded their estimated scores only after they had received all the instructions and passed the instructions assessment, demonstrating they understood how both the probability of mistakes on the quiz and the cost of insurance affected their expected payoffs. At that point, participants were aware of how their quiz

scores and score estimation accuracy combined with their risk management and insurance decisions to affect their earnings in the experiment.

As in actual insurance purchase decisions, a participant in the experiment who chooses not to insure based on an optimistic or overconfident estimate of loss probability faces a larger total cost of risk compared with insurance decisions based on more accurate assessments. All responses were completely anonymous. There were no financial or risk management incentives to report higher or lower scores than estimated, and optimal decisions depended on using best estimates. Therefore, participants had incentives to accurately estimate their risk of loss and faced no incentive to inaccurately report their estimates.[16] Consequently, the earnings task is directly incentive-compatible, and the corresponding estimation task is indirectly incentive-compatible, with respect to maximizing final payoffs in the experiment.

Participants completed all decisions before receiving their earnings from the estimation and risk management task. After all decisions were completed, reviewed, and confirmed, a public random draw of a numbered ping-pong ball by a participant determined the treatment used to pay out earnings. Each participant's individual earnings for the chosen treatment depended on a computer-generated random number representing either an orange ball or white ball, and if applicable, random selection of quiz question.

3.4. Hypotheses

In this section, we draw on the existing literature to categorize participants as optimistic or overconfident based on decisions made in the experiment and develop hypotheses about the expected impact of optimism and overconfidence on participants' insurance decisions.

Participants who overestimate their own quiz scores are classified as overconfident in their own knowledge or abilities. We measure a participant's overconfidence as the percentage by which they overestimate (or underestimate) their own score and we call this measure the *gross overconfidence bias*.[17] Gross overconfidence bias ranges from negative (under confident) to positive (overconfident) so that results closer to zero reflect smaller biases.

We measure a participant's general level of optimism (or pessimism) about an unknown probability of loss outside of his or her own control, as the percentage by which they overestimate (or underestimate) the average score of other participants. Our measure of *optimism bias* also ranges from negative (pessimistic) to positive (optimistic), with measures closer to zero reflecting smaller biases. Because an individual may be generally optimistic or pessimistic about outcomes that beyond their control, the accuracy of the participant's estimate of others' average score is used as a proxy for a general tendency to underestimate or overestimate the risk of loss in the experiment, independent of their own knowledge or ability. Participants who overestimate others' scores are classified as optimistic because overestimation of scores corresponds to underestimating the probability of loss due to errors that are beyond their own control.

An optimistic outlook that causes participants to underestimate the chance of loss in general may also influence participants' estimation of their own scores. In other words, a participant's overestimation of their own score may be attributable to overconfidence in their own abilities, a general optimistic outlook, or a combination of the two biases. Therefore, we also measure *net overconfidence bias* as the difference between the errors in estimates of own and others' scores.

Again, there is no compensation associated with relative performance, or reward for above average performance in this experiment. The larger the positive bias in a participant's own estimate compared with the bias in estimating others' average score, the higher that participant's net overconfidence bias. Participants who overestimate their own performance by the same or smaller percentage than they overestimate others' do not exhibit the net overconfidence bias.

Based on the theoretical literature on insurance demand, and the literature on optimism and overconfidence, we develop the following hypotheses to be tested using the experiment design described in the previous section:

Hypothesis 1: Individual biases

A. *Gross Overconfidence Bias:* Participants will exhibit gross overconfidence bias and will, therefore, overestimate their own performance. This measure of bias includes the possibly confounded effects of general optimism and overconfidence in their own ability to minimize the risk of loss.
B. *Optimism Bias:* Participants will exhibit optimism bias and will, therefore, overestimate others' average performance.
C. *Net Overconfidence Bias:* Participants will exhibit net overconfidence bias and will overestimate their own performance to a larger extent than they overestimate others' performance. After adjusting for general optimism about overall performance, participants' estimates of their own performance will reflect a positive bias.

Hypothesis 2: Effect of biases on decision-making

By causing individuals to underestimate the risk of loss, optimism and overconfidence biases will lead to underinsurance against losses. We define underinsurance as declining to insure when the expected payoff is higher with insurance than without it.[18]

A. Gross overconfidence bias will increase the likelihood of underinsurance. Our measure of gross overconfidence bias directly reflects an underestimate of the probability of loss in the Own Mistakes treatments. Therefore, the gross overconfidence bias will be more likely to increase underinsurance against a loss depending on a participant's own performance, than a loss depending on others' mistakes.
B. Optimism bias will increase the likelihood of underinsurance. Errors in assessing risk due to general optimism do not depend on the source of loss. However, our measure of optimism bias directly reflects an underestimate of the probability of loss in the Others' Mistakes treatments. Therefore, the optimism bias will be more likely to increase underinsurance against a loss resulting from others' mistakes than a participant's own mistakes.
C. Net overconfidence bias should not affect the probability of underinsurance in this design because the estimated probability of loss does not depend on relative performance in any way.

Hypothesis 3: Effect of biases on the total cost of risk

In this experiment, participants can spend money on partial risk mitigation and insurance. Participants who do not either insure or purchase precaution face expected losses that depend on their quiz performance, while those who insure incur the known cost of the insurance premium. Therefore, our measure of the total cost of risk is the sum of the expected loss resulting from the risk event and the known amount spent on precaution or insurance. If the overconfident or optimistic choose to pay for precaution rather than fully insuring, they may actually increase their total cost of risk. We hypothesize that:

A. Higher gross overconfidence bias will be associated with greater total cost of risk. The increase in the total cost of risk will be higher when the probability of a loss depends on one's own performance (because the overconfidence bias directly measures errors in assessing risk in the Own Mistakes treatment).
B. Higher optimism bias will be associated with greater total cost of risk. The increase in the total cost of risk will be higher when the probability of loss depends on others' performance (because the optimism bias directly measures errors in assessing risk in the Others' Mistakes treatment).
C. Net overconfidence, the difference between a participant's gross overconfidence and optimism, does not inform the estimation of risk in either Mistakes treatment. Therefore, it will not affect participants' total cost of risk.

The next section presents and discusses the outcomes of participant decisions. Then it introduces controls used in the analysis and presents tests of these hypotheses.

4. Results and analysis

4.1. Summary statistics

Table 4 presents summary statistics for the participants' performance on the earnings and estimation tasks, and summarizes the definitions used for participants' optimism, gross and net overconfidence biases. The summary statistics show that participants overestimate their own performance to a greater extent (9.26%) than they overestimate others' performance (2.10%) and that there is a great deal of within-sample variation in these bias measures.

Given our experiment parameters ($45 loss, $14.50 insurance premium, and precaution alternatives), risk-neutral and risk-averse participants are predicted to purchase insurance (or the full precaution equivalent) for all high initial probability treatments. If they do not purchase insurance, their expected payoff decreases with lower quiz scores in the Mistakes treatments. However, risk-seeking participants in the 32% initial probability No Mistakes treatments may prefer not to purchase insurance in the Mistakes treatments as well. Under the low initial probability of loss, the expected loss is $4.50 in the No Mistakes treatments, and a risk-neutral participant should not purchase insurance. However, in the low initial probability Mistakes treatments, any participant who answers 76% or fewer quiz questions

Table 4 Summary statistics: driving quiz, estimation task, and biases, $N = 60$ participants

	Mean	Minimum	Maximum	Standard deviation
Estimated own quiz score (out of 20)	16.4	11	19	2.06
Percent correct	*82%*	*55%*	*95%*	
Estimated others' quiz score (out of 20)	15.4	10	18	1.94
Percent correct	*77%*	*50%*	*90%*	
Actual quiz score (out of 20)	15.1	12	18	1.50
Percent correct	*75%*	*60%*	*90%*	
$GOC\,bias = \frac{Own\,estimate - own\,score}{Own\,score}$	9.26%***	−18.75%	41.67%	15.80%
$Optimism\,bias = \frac{Estimated\,others'score - others'\,score}{Others'score}$	2.10%	−33.86%	19.46%	12.89%
NOC bias = Overconfidence Bias – Optimism Bias	7.16%***	−23.83%	39.65%	14.72%

***Significantly different from zero at the 99% confidence level, according to the t test and nonparametric signed rank test. GOC and NOC denote gross and net overconfidence, respectively.

correctly has higher expected payoffs from purchasing insurance, making insurance the optimal choice for risk averse and risk neutral participants. As discussed above, overconfidence and/or optimism regarding quiz scores could lead participants to underestimate their risk of loss, which could lead to underinsurance in light of their risk preferences.

While Table 4 shows the average levels of the biases, Table 5 categorizes participants in terms of which biases they exhibit. The table illustrates that participants are relatively unlikely to exhibit one of these biases and not the other. They are more likely to have gross overconfidence and optimism bias or show neither bias. Results in Tables 4 and 5 reveal that while 50% of participants exhibit some degree of optimism, the average level of optimism does not differ significantly from zero. However, 60% of participants exhibit gross overconfidence, and the average level of gross overconfidence is significantly above zero. It follows that their average net overconfidence bias is also significant. In fact, 60% of participants exhibit the net overconfidence bias. In summary, we find descriptive evidence in support of parts A (gross overconfidence bias) and C (net overconfidence bias) of Hypothesis 1, but not part B (optimism bias).

We summarize the insurance and precaution purchase decisions in Table 6. In the No Mistakes treatments, most participants insure against loss, all purchase some form of risk mitigation in the initial 32% probability of loss treatments, and most purchase some risk mitigation in the initial 10% probability of loss treatments. Participants insure against loss more frequently under the Others' Mistakes treatment than the Own Mistakes treatment. Some participants purchase precaution to reduce their risk of loss. For example, in the No Mistakes 32% initial probability treatment, those participants who do not insure, purchase

Table 5 Classification of participants by optimism and gross overconfidence

	Not overconfident	Overconfident (gross overconfidence)
Not optimistic	33%	17%
Optimistic	7%	43%

Differences in proportions are significant at the 99% level in a χ^2 test.

Table 6 Percentages choosing each risk mitigation alternative, by treatment

Mistakes treatment	No Mistakes		Own Mistakes		Others' Mistakes	
Initial probability of loss	32%	10%	32%	10%	32%	10%
Buy insurance or full precaution[a]	65%	43%	57%	55%	68%	67%
Buy partial precaution (average reduction in initial probability)[b]	35% (−20%)	38% (−5%)	43% (−22%)	23% (−5%)	32% (−21%)	17% (−3%)
No risk mitigation	0%	19%	0%	22%	0%	16%

[a] The purchase of full precaution reduces the probability of loss to zero and is, therefore, the equivalent to buying insurance in this design (although not the same cost).

[b] Participants pay to reduce the initial probability of loss before a mistake is drawn in increments of 10 percentage points. The numbers in parentheses show the average percentage point reduction in initial probability. For example, in the No Mistakes 32% initial probability treatment, 35% of participants reduce their probability of loss by an average of 20%.

sufficient precaution to reduce the initial risk from 32% to 12% on average. In the No Mistakes 10% initial probability treatments, participants who buy precaution instead of insurance reduce the risk of loss from 10% to 5% on average.

4.2. Risk attitudes and gender controls

The primary purpose of this research is to analyze the relationship between overconfidence, optimism, and insurance purchase. However, participants make insurance and precaution decisions in light of their estimation of the risk of loss *and* their attitudes about accepting different levels of risk. Previous literature suggests that overconfidence bias (that affects estimation of risk) may vary systematically with gender. At the same time, optimal insurance purchase decisions will differ based on risk attitudes. This subsection discusses summary statistics particular to the risk attitude and gender control variables included in the analysis.

Risk-neutral or risk-averse participants should purchase insurance whenever the expected loss exceeds the insurance premium. All else equal, risk-seeking participants would be less likely to purchase insurance. We use the Precaution Only No Mistakes treatments to provide information about participants' risk attitudes. The within-subject design allows us to observe individual participants' choices across each different treatment. In the Precaution Only No Mistakes treatments, full precaution provides equivalent risk mitigation to insurance. Under an initial probability of loss of 10%, expected payoff is decreasing in precaution, and full precaution (the equivalent of insurance) costs roughly three times the expected loss. Under an initial probability of loss of 32%, expected payoff is increasing in precaution, and the cost of full precaution is only 83% of the expected loss. Therefore, we can identify participants whose behavior is consistent with risk-seeking preferences in the 32% probability of loss treatments, and those who make choices consistent with risk aversion in the 10% probability of loss treatments.

We analyze each participant's choices across No Mistakes Precaution Only treatments to broadly classify risk attitudes. We classify participants as risk averse if they purchase any precaution in the 10% initial probability treatment and also purchase full precaution in the 32% initial probability treatment. Participants who exhibit risk-averse behavior under the 10% initial probability treatment, but risk-seeking behavior under the 32% initial probability treatment are considered to be "reflexive."[19]

We classify participants as risk-seeking if they purchase less than full precaution in the 32% initial probability treatment and also do not purchase any precaution in the 10% initial probability treatment. The risk-seeking classification also controls for an interpretation of optimism in which some participants are optimistic about their "luck" in the outcome of a random draw with a known distribution, even if they are realistic about the distribution itself. Because risk-seekers could optimally choose to remain uninsured in cases where purchasing insurance is optimal for risk-neutral or risk-averse individuals, we control for evidence of risk-seeking behavior in our analysis of the relationship between optimism, overconfidence, and insurance purchase. To avoid multicollinearity problems between this control variable and others, we use the participants' decisions in the Precaution Only No Mistakes treatments

Table 7 Classification of risk attitudes, optimism, and overconfidence

	Percent of participants	Percent of females	Percent of males
Risk seeking	17%	17%	17%
Optimism	50%	50%	50%
Gross Overconfidence	60%	54%	64%
Net overconfidence	67%	63%	69%

(that are not included in the main regressions) only to estimate risk attitudes of the participants.

Table 7 presents the classification of participant risk attitudes, optimism, and overconfidence. Risk-seeking behavior is evident in 17% of the sample. As discussed above, participants who overestimate others' average score are classified as optimistic and Table 4 showed no statistically significant optimism bias in the sample (though this is conservative given the small sample size). However, Table 7 reveals that half of the participants do not overestimate others' scores. (The participants who overestimate others' scores have an average error of 11.74%, while those who underestimate others' scores have an average error of only 7.5%.) We classify participants who overestimate their own score as exhibiting gross overconfidence in their own knowledge or abilities; but some or all of that overconfidence may be due to general optimism. Therefore, we also report the participants classified as exhibiting net overconfidence bias. Comparing these metrics by gender, we find that a larger percentage of men are overconfident, both before and after adjusting for general optimism.

Results in Tables 5, 6, and 7 confirm the presence of optimism and overconfidence. Table 8 summarizes the respective sample correlations of these measures, along with the categorical variables Risk-Seeking and Male. Correlations with the categorical variable Male in Table 8 show that there are no significant gender differences on average in gross overconfidence or optimism biases. However, women's average optimism is slightly higher and gross overconfidence slightly lower than men's. When these effects are combined, the difference-in-differences between men and women is significant for net overconfidence bias. Men exhibit a larger difference between gross overconfidence in their own quiz performance and optimism about others' quiz performance, compared with women. These results are consistent with those reported in Kuhn and Villeval (2015), although the earnings tasks in the two experiments are very different.

Table 8 Biases, risk attitude, and gender correlations

	Gross overconfidence	Optimism	Net overconfidence	Risk seeking	Male
Gross overconfidence	1				
Optimism	0.49***	1			
Net overconfidence	0.65***	−0.35***	1		
Risk seeking	0.08	0.02	0.06	1	
Male	0.19	−0.14	0.33***	0	1

***Significant at the 99% level.

4.3. The effect of overconfidence and optimism on the decision to insure

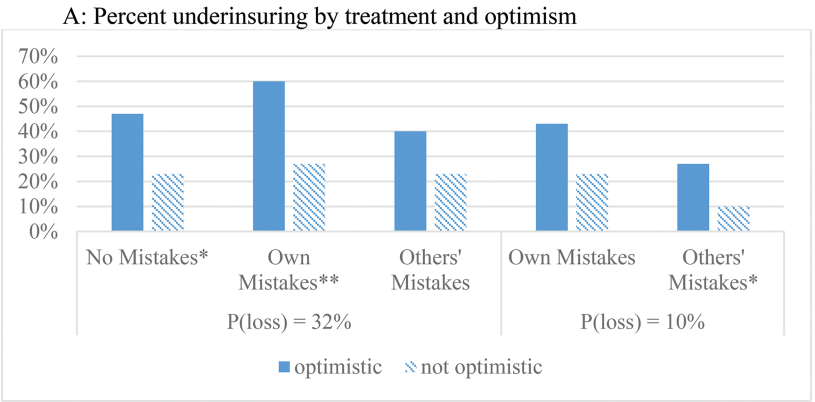
We now turn our attention to the second set of hypotheses, which considers the effects of the biases on the decision to insure and on the total cost of risk. Because full precaution is equivalent to insurance in the No Mistakes treatments, participants who purchase either of those options in the No Mistakes treatments are counted as buying insurance.

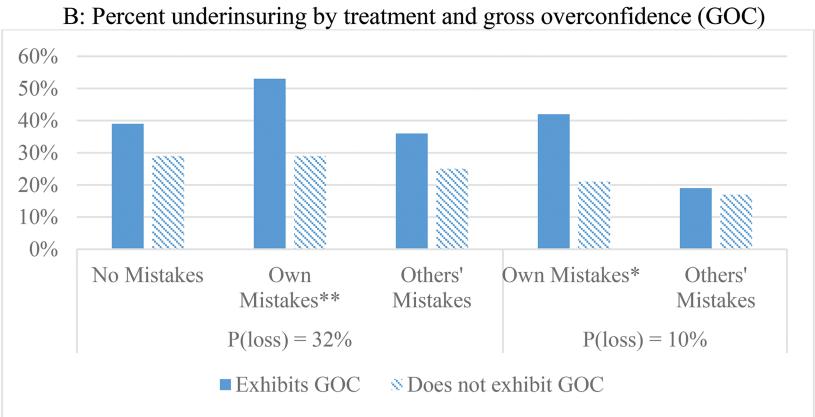
Although some participants purchase partial precaution rather than insurance in the Mistakes treatments, this decision results in their being underinsured when the probability of loss is 32% or higher (unless they are risk-seeking). Participants who are overconfident in their own quiz performance or precaution decisions, or optimistic with respect to others' quiz performance, will underestimate this probability and therefore could make suboptimal insurance decisions in the Mistakes treatments. Hypothesis 2 predicts that the likelihood of underinsurance in the Others' Mistakes treatment will increase with higher levels of optimism bias. It also predicts that insurance decisions in the Own Mistakes treatments will depend on the gross overconfidence bias, which as discussed above, may also include general optimism. We expect both the optimism bias and the gross overconfidence bias to increase the likelihood of underinsurance in the Own Mistakes treatment.

Fig. 1 presents the incidence of underinsurance (from a risk-neutral perspective) for participants in each treatment, according to whether they exhibit optimism (Panel A), gross overconfidence (Panel B), or net overconfidence (Panel C). The optimism bias is associated with underinsurance in the Others' Mistakes low probability treatment, but also in the No Mistakes and Own Mistakes high probability treatments. We find that, as expected, the gross overconfidence bias is associated with underinsurance when payoffs depend on one's own performance, but not others' performance, and the net overconfidence bias has an insignificant impact on underinsurance in this experiment.

We further analyze the effect of the biases on underinsurance through logit regressions presented in Table 9, in which the dependent variable is a dummy variable where Underinsurance =1 indicates underinsurance from a risk-neutral perspective. Categorical independent variables include gender (female is the omitted category), risk treatment type (10% initial probability is the omitted category), and risk-seeking attitude (no evidence of risk seeking is the omitted category).[20] Regression coefficients are presented in terms of log odds. Due to the strong relationship between the biases, we run separate regression models, including different bias measures as independent variables in each.

The top panel of Table 9 presents analysis of the Mistakes treatments ($N = 240$ decisions, with 60 standard error clusters). Conceptually, we would expect optimism and gross overconfidence (that encompasses optimism) to influence insurance decisions in both Mistakes treatments. At the same time, our measure of optimism directly informs subjective probability of loss in the Others' Mistakes treatment and our measure of gross overconfidence directly informs subjective probability of loss in the Own Mistakes treatment. Therefore, we are especially interested in the significance of interaction terms for the biases and Mistakes treatment. In particular, we would expect the gross overconfidence measure to have a more significant impact on underinsurance in the Own Mistakes treatments and general optimism to be more influential in the Others' Mistakes treatments.





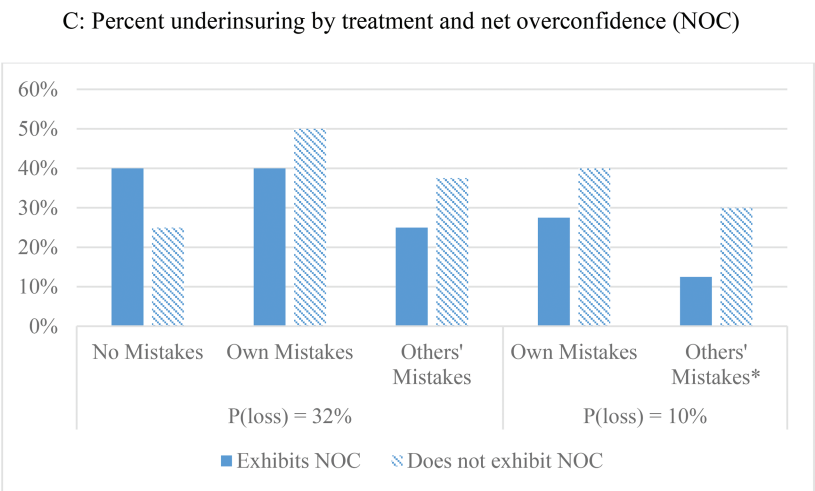


Fig. 1. Panel A: Percent underinsuring by treatment and optimism. Panel B: Percent underinsuring by treatment and gross overconfidence (GOC). Panel C: Percent underinsuring by treatment and net overconfidence (NOC) *Notes:* Differences in proportions are significant at the 90% level (*) based on a χ^2 test. P(loss) represents the initial probability 32% and 10% treatments; No Mistakes, Own Mistakes, and Others' Mistakes denote No Mistakes, Own Mistakes and Others' Mistakes treatments, respectively.

Table 9 Determinants of underinsurance, logit regression coefficient estimates and (standard errors)

	Mistakes treatments, N =240, standard errors clustered by participant					
	Model 1: Gross overconfidence		Model 2: Optimism		Model 3: Net overconfidence	
	Main effects	Interaction effects	Main effects	Interaction effects	Main effects	Interaction effects
Intercept	−1.5050*** (0.3972)	−1.6089*** (0.4104)	−1.7894*** (0.4095)	−1.8065*** (0.4121)	−1.4986*** (0.4248)	−1.5706*** (0.4357)
Others' Mistakes	−0.7122*** (0.2393)	−0.4965* (0.2507)	−0.7607*** (0.2532)	−0.7202*** (0.2369)	−0.7332*** (0.2419)	−0.6055** (0.2600)
GOC bias	0.7388 (1.5140)	1.7013 (1.6054)				
GOC × Others' Mistakes		−2.1804* (1.2481)				
Optimism bias			5.0281*** (1.5427)	5.4407*** (1.6508)		
Optimism × Others' Mistakes				−0.9332 (1.7860)		
NOC bias					−3.1288* (1.7988)	−2.1298 (1.7532)
NOC × Others' Mistakes						−2.4306 (1.5311)
Male	0.5600 (0.4644)	0.5647 (0.4672)	0.8271* (0.4439)	0.8287* (0.4460)	0.9287* (0.4915)	0.9361* (0.4924)
Initial probability = 32%	0.6243* (0.2716)	0.6285** (0.2743)	0.6669** (0.2908)	0.6677** (0.2919)	0.6428** (0.4915)	0.6449** (0.2849)
Risk-seeking	1.6746*** (0.3876)	1.6890*** (0.3977)	1.8039*** (0.4439)	1.8057*** (0.3682)	1.8305*** (1.7988)	1.8599*** (0.3959)
	No Mistakes p(loss) = 32% treatment, N = 60					
	Model 1: Gross overconfidence		Model 2: Optimism		Model 3: Net overconfidence	
Intercept	−1.1615 (0.5205)		−1.2197** (0.4953)		−1.0912** (0.4818)	
GOC bias	1.0152 (1.8618)					
Optimism bias			2.4298 (2.3574)			
NOC bias					−0.7252 (0.6037)	
Male	0.7046 (0.5946)		0.8563 (0.6015)		0.8338 (0.6037)	

Notes: *, **, *** designate significance at the 90%, 95%, and 99% confidence intervals, respectively. The dependent variable is zero if the participant did not underinsure, and 1 if they did. Coefficients are presented in log odds terms. GOC and NOC denote gross and net overconfidence, respectively.

Controlling for the biases, initial probability of loss, and risk-seeking preferences, we find that participants are significantly less likely to underinsure in the Others' Mistakes treatments than in the Own Mistakes treatments. Model 1 shows that gross overconfidence itself is not a significant predictor of underinsurance. However, the interaction effect in the second column reveals that the difference in the probability of underinsuring between the Own and Others' Mistakes treatment does depend on gross overconfidence. As gross overconfidence increases, there is a greater increase in the likelihood of underinsuring in the Own Mistakes compared with the Others' Mistakes treatments. In other words, participants with higher gross overconfidence are even more likely (compared with those who are less overconfident) to make suboptimal insurance decisions when the risk of loss depends on their own performance than when it depends on others' performance. This is somewhat consistent with the Hypothesis 2 predictions about biases.

In Model 2, we find that participants who exhibit higher levels of optimism bias are significantly more likely to underinsure. However, the interaction between Optimism and the Others' Mistakes treatment is not significant, which suggests that the effect of optimism is no more influential in the Others' Mistakes treatment than in the Own Mistakes treatment. Finally, In Model 3, we find that net overconfidence bias has a negative relationship with underinsurance that is weakly significant and independent of the Mistakes treatment. We attribute this result to the fact that net overconfidence is decreasing in optimism, which as discussed above, has a strong positive and significant relationship with the probability of underinsuring across both Mistakes treatments.

The second panel of Table 9 displays results for the No Mistakes condition. In this treatment, participants can only underinsure in the 32% initial probability of loss treatment, because purchasing no risk mitigation is the payoff-maximizing choice in the 10% initial probability treatment. Therefore, we examine underinsurance decisions separately for the No Mistakes, 32% probability of loss treatment ($N = 60$), and find that, as expected, none of the biases have a significant effect.[21] This suggests that participants' bias stems from their beliefs about the probability of loss rather than optimism or pessimism about luck when confronting a known distribution. However, the insignificant effect on the insurance decision may also be attributable to the smaller sample size using only one treatment for this statistical test.

4.4. The effect of overconfidence and optimism on the total cost of risk

As described in Hypothesis 3, the relationship between the total cost of risk (the sum of the expected loss resulting from the risk event and the known amount spent on precaution or insurance) and the biases provides a way to examine the cost of underinsurance, in particular when participants have access to alternative risk mitigation measures instead of insuring. For example, given the experiment parameters in the 10% initial loss probability Own Mistakes treatments, a participant who answers 70% of the quiz questions correctly and insures faces a total cost of \$14.50 (out of their \$60 earnings). If they underinsure by neither purchasing insurance nor precaution, they face an expected loss of \$16.70 in the initial 10% probability treatment. However, if that participant pays for precaution to reduce the initial

probability of loss to 5%, then the total cost of risk, including the cost of precaution, is actually even higher at $22.60. Participants who are overconfident about the effects of precaution increase their total cost of risk when they choose to purchase partial precaution instead of either insuring or doing nothing.

Table 10 presents results of a generalized least squares regression estimating the impact of the biases and control variables on the total cost of risk. As in the previous regressions, we separately analyze the effects of the three types of biases. The results for Model 1 show that gross overconfidence bias is a statistically and economically significant factor increasing the cost of loss in the Own Mistakes treatment. Furthermore, the effect is significantly lower for participants in the Others' Mistakes treatments as compared with the Own Mistakes treatments. Overconfidence in one's own ability is more costly when the expected loss depends on own performance.

In Model 2, we find that optimism bias also increases the total cost of risk, but there is no significant difference in this relationship across mistakes treatments. This too is expected, since errors in assessing risk due to general optimism do not depend on the source of loss. Finally, Model 3 confirms that net overconfidence bias does not significantly increase the total cost of risk. However, as the combined results for gross overconfidence and optimism imply, the impact of net overconfidence on the total cost of risk is lower in the Others' Mistakes treatment than in the Own Mistakes treatment. As in the previous table, the smaller sample size when using only the data from the No Mistakes treatment ($N = 60$) reduces the power of the test but, in this case, we still find the effect of net overconfidence to be marginally significant.

5. Conclusions

This article contributes to the literature by providing experimental evidence regarding the effects of overconfidence and optimism on insurance decisions. In the existing literature, optimism is sometimes confounded with overconfidence, and we contribute an innovative design that distinguishes between overconfidence regarding the likelihood of a favorable outcome resulting from one's own performance versus optimism regarding the likelihood of a favorable outcome outside of one's own influence. We find that these psychological biases have important implications for insurance in that they can cause individuals to underestimate their risk and, therefore, underinsure, resulting in a higher total cost of risk. This effect is stronger for insurance over risks that depend on one's own performance as compared with exogenous risks. Our results contribute to the growing body of literature on the effect of psychological biases on financial decisions and reinforce the importance of careful measurement of overconfidence bias in laboratory experiments. This distinction is particularly important for understanding insurance decisions related to risks outside of the purchaser's control. The relationship between overconfidence and optimism may also help explain the perceived tradeoffs between risk mitigation and insurance decisions.

Our results show that, after controlling for risk-seeking behavior, participants are more likely to make suboptimal insurance decisions when the risk of loss depends on their own

Table 10 Determinants of total cost of risk, generalized least squares regression coefficient estimates and (standard errors)

	Determinants of underinsurance in Mistakes treatments, N =240, standard errors clustered by participant					
	Model 1: Gross overconfidence		Model 2: Optimism		Model 3: Net overconfidence	
	Main effects	Interaction effects	Main effects	Interaction effects	Main effects	Interaction effects
Intercept	14.6311 (0.3988)	14.8373*** (0.4034)	14.5583*** (0.3931)	14.5297*** (0.3922)	14.8056*** (0.4373)	14.6504*** (0.4340)
Others' Mistakes	−0.4847 (0.3302)	0.0320 (0.2900)	−0.4847 (0.3302)	−0.4275 (0.3102)	−0.4847 (0.3302)	−0.1743 (2.6154)
GOC bias	3.2637 (2.0064)	6.0541*** (2.7703)				
GOC × Others' Mistakes		−5.5808*** (0.4352)				
Optimism bias			5.6885*** (1.6254)	7.0494*** (1.9744)		
Optimism × Others' Mistakes				−2.7218 (1.9373)		
NOC bias					−0.4847 (0.3302)	1.4179 (0.5898)
NOC × Others' Mistakes						−4.3369* (2.3555)
Male	0.4099 (0.5369)	0.4099 (0.5381)	0.8170 (0.5159)	0.8170 (0.5170)	0.6780 (0.5401)	0.6780 (0.5413)
Initial probability = 32%	2.1959*** (0.4306)	2.1959*** (0.4315)	1.8272*** (0.4937)	2.1959*** (0.4315)	2.1959 (0.4306)	2.1959*** (0.4315)
Risk-seeking	1.7596*** (0.5186)	1.7596*** (0.5381)		1.8272*** (0.4947)	1.8831*** (0.5408)	1.8831*** (0.5419)
	Determinants of total cost of risk in No Mistakes p(loss) = 32% treatment, N = 60					
	Model 1: Gross overconfidence		Model 2: Optimism		Model 3: Net overconfidence	
Intercept	12.5650*** (0.2367)		12.6446*** (0.2222)		12.58*** (0.2194)	
GOC bias	0.6910 (0.8133)					
Optimism bias			−1.0439 (1.0396)			
NOC bias					1.7385* (0.9780)	
Male	0.0212 (0.9299)		0.0236 (0.2568)		−0.1062 (0.2588)	

Notes: *, **, ***designate significance at the 90%, 95%, and 99% confidence intervals, respectively. GOC and NOC denote gross and net overconfidence, respectively.

performance than others' performance. Optimistic participants are more likely to underinsure than non-optimistic participants. Overconfidence does not have a significant effect on the decision to purchase insurance, although participants with higher overall overconfidence show larger differences in behavior when they are responsible for the risk of loss than when it is beyond their control.

Analysis of the total cost of risk, including both the expected loss and the cost of precaution or insurance, under different treatments provides similar evidence about the influence of these psychological biases. Overconfidence and optimism both significantly increase the total cost of risk. However, overconfidence has a significantly lower effect on total cost when the loss event is triggered by someone else's error. Optimism bias increases the cost by about the same amount regardless of whether the risk depends on one's own actions. These results suggest that general optimism extends to outcomes that depend on one's own ability, but overconfidence in one's own performance does not affect the decision to mitigate risks due to factors outside of one's own control, such as those resulting from nature or from others' errors.

The laboratory evidence reported in this article offers a potential explanation for the underinsurance against catastrophe that has been observed in the market. Beliefs, together with risk tolerance, preferences, or general probability misperceptions may provide alternative explanations for some of the observed insurance decision puzzles. For example, Jacobsen et al. (2015), who study asset allocation decisions under uncertainty, find that optimism about outcomes and optimism about the level of risk are as important as risk aversion in explaining asset allocation. Spinnewijn (2013) notes that, while heterogeneity in beliefs informs insurance policy design, it is very difficult to obtain direct evidence about beliefs. Laboratory results such as ours provide a first step in connecting beliefs to insurance decisions, with more control than surveys or behavioral proxies for perceptions. While convenience samples of students provide for a strong degree of laboratory control, it would interesting to further explore these issues with a more diverse participant population. Future research should also consider in greater detail the influence of these biases on individual perceptions about the effectiveness of different risk mitigation alternatives.

Notes

1 Theoretical explanations in economics and evolutionary biology have also illustrated conditions under which optimism or overconfidence bias can be individually welfare-improving (compared to rational expectations), a second best solution in the presence of other biases, and even a necessary adaptation for species survival. See, for instance Brunnermeier and Parker (2005), Besharov (2004), and Johnson and Fowler (2011).

2 This definition of overconfidence assumes misperceptions rather than a well-calibrated assessment of one's own relative abilities. Well-calibrated confidence does not produce lower results. For example, Fielder (2011) finds that virtual traders who self-report as better than average, in fact earn above average virtual profits.

3 The adverse selection literature in insurance originated with the seminal work of Rothschild and Stiglitz (1976). See Dionne, Fombaron, and Doherty (2013) for a more complete summary of this extensive literature.
4 In Bajtelsmit, Coats, and Thistle (2015), the authors focus on the other considerations addressed by the experiment design, including the effect of ambiguity on risk management decisions and the tradeoff between taking precaution and purchasing insurance, as well as replicability of other researchers' results.
5 We acknowledge that there is a great deal of inconsistency in terminology and trait measurement across the overconfidence literature, both theoretical and empirical. See Clark and Friesen (2009) and Spinnewijn (2013) for more complete reviews of this literature.
6 De Meza and Webb (2001) show that insurers can design contracts that will result in an equilibrium which they term "advantageous selection" in which the risk-averse agent buys insurance and also invests in some precaution. The risk-neutral agent does not take precaution or buy insurance.
7 However, recent research suggests that calibration-based overconfidence observed in confidence interval reporting may be overstated because of the measurement instrument (Blavatskky, 2009; Cesarini, Sandewall, & Johannesson, 2006; Glaser, Langer, & Weber, 2013; Soll & Klayman, 2004).
8 See Chiappori and Salanie (2013) for a review of this literature.
9 Experiments by Cesarini et al (2006), Blavatskyy (2009), and Clark and Friesen (2009) suggest that frequency estimation tasks provide better measures of overconfidence relative to confidence interval estimation tasks because of the improvement in incentive-compatibility, better alignment of accuracy and information, and because framing a forecast as a frequency is a much more natural cognitive task.
10 The earnings, probability estimation, and risk management tasks were explained in a Power Point presentation at the front of the room, with the instructions read aloud. Participants took an instructions assessment to confirm they understood how their earnings would be determined and were able to ask questions.
11 Participants were required to have a valid state driver's license as a condition of participation in the experiment. The driving quiz was designed to include a sufficient number of easy questions such that all participants were expected to be able to achieve the minimum score, but also some more difficult questions to minimize the number who could achieve a perfect 20 out of 20 correct.
12 The within-participants design provides for much greater statistical power than a between-participants design of the same size (see Bellamare, Bissonnette, and Kroger, 2014 and Charness, Gneezy, and Kuhn, 2012). We obtain more participant observations and cluster standard errors at the participant level in our analysis.
13 The return to taking precaution is higher for the high-risk treatments than the low-risk treatments due to the assumption of greater productivity of precaution

under high initial risk. For a theoretical justification, see Bajtelsmit and Thistle (2015).

14 The full design also included four additional treatments, in which the probability of loss depended on own and others' performance under high and low initial probabilities of loss. However, in those treatments, participants could neither reduce loss probability to zero, nor insure against loss and, therefore, we do not include or analyze them in this article. See Bajtelsmit et al. (2015).

15 Although there are other methods of incentivizing participants, such as scoring rules that reward estimates but penalize errors, participant risk preferences have been shown to affect their choices. See, for example, Andersen, Fountain, Harrison, and Rutström (2014) and Harrison, Martinex-Correa and Swarthout, (2014). Other probability elicitation mechanisms depend on independence between agents' actions and the probability of the risky event (Armentier and Treich, 2013) and on the agent having no stake in the risky event (Karni, 2009).

16 *Estimating* one score to use in risk management decision making, but *recording* a different score, while technically possible, would be inconsistent with payoff maximization efforts because it would increase the cognitive difficulty of the risk management task and potentially increase the chance of making a costly risk management error and, therefore, would not be incentive compatible with maximizing experiment payoffs.

17 We thank an anonymous referee for suggesting the "gross overconfidence" and "net overconfidence" labels.

18 Because this definition only applies to risk-averse and risk-neutral participants, we control for risk-seeking behavior in our analysis.

19 This classification is discussed in detail in an earlier article by the authors where the No Mistakes treatments is compared to the alternative to buy insurance against the No Mistakes Precaution Only treatments and show that (1) participants purchase the more efficient means of risk mitigation, and (2) that participants are consistent in their risk mitigation decisions across treatments. Comparison of the Precaution Only Mistakes treatments to the Precaution Only No Mistakes treatments shows that participants respond predictably to the lower effectiveness of precaution by purchasing less precaution in the Mistakes treatments.

20 Identified through behavior in the Precaution Only No Mistakes treatments.

21 The risk-seeking dummy variable is not included because, in the treatments used to determine risk attitudes (Precaution Only No Mistakes), a risk-seeking identification is indistinguishable from underinsurance in the high probability of loss insurance treatments.

Appendix: Examples of choices available in high and low initial probability treatments

Initial high probability of loss example: Choose one of the following options below.

Decision	Up-front cost to replace orange balls	New number of orange balls	New number of white balls	Probability orange ball is drawn
A	$0	32	68	32%
B	$1.50	28	72	28%
C	$3.00	24	76	24%
D	$4.50	20	80	20%
E	$6.00	16	84	16%
F	$7.50	12	88	12%
G	$9.00	8	92	8%
H	$10.50	4	96	4%
I	$12.00	0	100	0
J (Insurance)	$14.50	32	68	N/A

Your decision in Scenario 2: _____

Initial low probability of loss example: Choose one of the following options below.

Decision	Up-front cost to replace orange balls	New number of orange balls	New number of white balls	Probability an orange ball is drawn
A	$0	10	90	10%
B	$1.50	9	91	9%
C	$3.00	8	92	8%
D	$4.50	7	93	7%
E	$6.00	6	94	6%
F	$7.50	5	95	5%
G	$9.00	4	96	5%
H	$10.50	3	97	3%
I	$12.00	2	98	2%
J	$13.50	1	99	1%
K	$15.00	0	100	0
L (Insurance)	$14.50	10	90	N/A

Your decision in Scenario 8: _____

References

Andersen, S., Fountain, J., Harrison, G. W., & Rutström, E. E. (2014). Estimating subjective probabilities. *Journal of Risk and Uncertainty*, *48*, 207–229.

Arad, A. (2014). Avoiding greedy behavior in situations of uncertainty: The role of magical thinking. *Journal of Behavioral and Experimental Economics*, *53*, 17–23.

Armentier, O., & Treich, N. (2013). Eliciting beliefs: Proper scoring rules, incentives, stakes, and hedging. *European Economic Review*, *62*, 17–40.

Bajtelsmit, V., Coats, J., & Thistle, P. (2015). The effect of risk ambiguity on risk management choices: An experimental study. *Journal of Risk and Uncertainty*, *50*, 249–280.

Bajtelsmit, V., & Thistle, P. (2015). Liability, insurance and the incentive to obtain information about risk. *The Geneva Risk and Insurance Review*, *40*, 171–193.

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, *116*, 261–292.

Bellemare, C., Bissonnette, L., & Kroger, S. (2014). *Statistical Power of Within and Between-Subjects Designs in Economic Experiments.* Discussion Paper No. 8583. Germany: Institute for the Study of Labor.

Besharov, G. (2004). Second-best considerations in correcting cognitive biases. *Southern Economic Journal*, *71*, 12–20.

Blavatskyy, P. R. (2009). Betting on own knowledge: Experimental test of overconfidence. *Journal of Risk and Uncertainty*, *38*, 39–49.

Brunnermeier, M., & Parker, J. (2005). Optimal expectations. *American Economic Review*, *95*, 1092–1118.

Camerer, C. F., & Lovallo, D. (1999). Overconfidence and excess entry: an experimental approach. *American Economic Review*, *89*, 306–318.

Cesarini, D., Sandewall, O., & Johannesson, M. (2006). Confidence interval estimation tasks and the economics of overconfidence. *Journal of Economic Behavior & Organization*, *61*, 453–470 .

Charness, G., Gneezy, U., & Kuhn, M. (2012). Experimental Methods: Between-subject and Within-subject Design. *Journal of Economic Behavior and Organization*, *91*, 1–8.

Chiappori, P., & Salanie, B. (2013).Asymmetric information in insurance markets: Predictions and Tests. In G. Dionne (Ed.), *Handbook of Insurance* (pp. 397–422). New York, NY: Springer.

Clark, J., & Friesen, L. (2009). Overconfidence in forecasts of own performance: An experimental study. *The Economic Journal*, *119*, 229–251.

De Bondt, F., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, *40*, 793–805.

De Meza, D., & Webb, D. C. (2001). Advantageous selection in insurance markets. *The Rand Journal of Economics*, *32*, 249–262.

Dionne, G., Fombaron, N., & Doherty, N. (2013).Adverse selection in insurance contracting. In G. Dionne (Ed.), *Handbook of Insurance* (pp. 231–280). New York, NY: Springer

Fellner, G., & Krugel, S. (2012). Judgmental overconfidence: Three measures, one bias? *Journal of Economic Psychology*, *33*, 142–154.

Fiedler, M. (2011). Experience and confidence in an internet based asset market experiment. *Southern Economic Journal*, *78*, 30–52.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for readymade economic experiments. *Experimental Economics*, *10*, 171–178.

Foster, G., & Frijters, P. (2014). The formation of expectations: competing theories and new evidence. *Journal of Behavioral and Experimental Economics*, *53*, 66–81.

Glaser, M., Langer, T., & Weber, M. (2013). True overconfidence in interval estimates: Evidence based on a new measure of miscalibration. *Journal of Behavioral Decision Making*, *2*, 405–417.

Hales, J., & Kachelmeier, S. (2008). Predicting relative performance in economic competition. *Journal of Behavioral Finance*, *9*, 187–192.

Harrison, G., Martinez-Correa, J., & Swarthout, T. (2014). Eliciting subjective probabilities with binary lotteries. *Journal of Economic Behavior & Organization*, *101*, 128–140.

Harrison, G., & Ng, J. (2016). Evaluating the expected welfare gain from insurance. *Journal of Risk and Insurance*, *83*, 91–120.

Honl, H., Meissner, P., & Wulf, T. (2017). Risk attribution theory: An exploratory conceptualization of individual choice under uncertainty. *The Journal of Behavioral and Experimental Economics*, *67*, 20–27.

Huang, R., Liu, Y., & Tzeng, L. (2010). Hidden overconfidence and advantageous selection. *The Geneva Risk and Insurance Review*, *35*, 93–107.

Jacobsen, B., Lee, J., Marquering, W., & Zhang, C. (2014). Gender differences in optimism and asset allocation. *Journal of Economic Behavior & Organization*, *107*, 630–651 .

Jaspersen, J. (2016). Hypothetical surveys and experimental studies of insurance demand: A review. *Journal of Risk and Insurance*, *83*, 217–255.

Jaspersen, J., & Aseervatham, V. (2017). The influence of affect on heuristic thinking in insurance demand. *Journal of Risk and Insurance*, *84*, 239–266.

Johnson, D., & Fowler, J. (2011). The evolution of overconfidence. *Nature*, *477*, 317–320.

Karni, E. (2009). A mechanism for eliciting probabilities. *Econometrica*, *77*, 603–606.

Kuhn, P., & Villeval, M. (2015). Are women more attracted to co-operation than men? *The Economic Journal*, *125*, 115–140.

Kunreuther, H., & Pauly, M. (2004). Neglecting disaster: Why don't people insure against large losses? *Journal of Risk and Uncertainty*, *28*, 5–21.

Landry, C., & Jahan-Parvar, M. (2011). Flood insurance coverage in the coastal zone. *Journal of Risk and Insurance*, *78*, 361–388.

Laury, S., & McInnes, M. (2003). The impact of insurance prices on decision making biases: An experimental analysis. *Journal of Risk & Insurance*, *70*, 219–233.

Malmendier, U., & Tate, G. (2005). Does overconfidence affect corporate investment?: CEO overconfidence measures revisited. *The Journal of Finance*, *11*, 649–659.

Moore, D., & Healy, P. (2008). The trouble with overconfidence. *Psychological Review*, *115*, 502–517.

Pyszczynski, T., Holt, K., & Greenberg, J. (1987). Depression, self-focused attention, and expectancies for positive and negative future life events for self and others. *Journal of Personality and Social Psychology*, *52*, 994–1001.

Rothschild, M., & Stiglitz, J. (1976). Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. *The Quarterly Journal of Economics*, *90*, 629–649.

Royal, A., & Tasoff, J. (2017). When higher productivity hurts: The interaction between overconfidence and capital. *Journal of Behavioral and Experimental Economics*, *67*, 131–142.

Sandroni, A., & Squintani, F. (2007). Overconfidence, insurance, and paternalism. *American Economic Review*, *97*, 1994–2004.

Soll, J., & Klayman, J. (2004). Overconfidence in interval estimates. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *30*, 299–314.

Spinnewijn, J. (2013). Insurance and perceptions: How to screen optimists and pessimists. *The Economic Journal*, *123*, 606–633.

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The impact of using financial technology on positive financial behaviors

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Abstract

This study uses 2013 Survey of Consumer Finances data to explore the impact of financial technologies on households' positive financial behaviors. After controlling for variables on general capitals, financial literacy capitals, and financial resources, we find that only planning technologies (e.g., direct deposit and computer software) are positively related to households' engagement in positive financial behaviors. In contrast, the impact of transaction technologies (e.g., using ATM card, credit card, phone banking, and computer banking) is negative. Policymakers and financial service providers should assist consumers with better financial tools and help them manage financial resources and behaviors. © 2021 Academy of Financial Services. All rights reserved.

Keywords: Financial technology; Financial software; Positive financial behaviors

1. Introduction

Technological innovation plays an important role in the development of the financial services industry. The way households manage finances now has changed rapidly over the past decade as a variety of technologies, such as electronic banking and automated advisers, have been designed to help households achieve better financial well-being. However, today's

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financial world is much more complicated because of the wide range of financial products and services (Parrish & Servon, 2006). Most of these products and services are associated with e-banking products and services provided by banks and financial institutions, such as automated teller machine (ATM), credit cards, direct deposit, preauthorized debit, phone banking, online banking, and so forth. A recent report on consumer mobile banking finds that over three-fourths of the U.S. population now has a smartphone (Pew Research Center, 2018), and about 50% of users have used mobile banking in the past 12 months (Merry, 2018). It is said that electronic banking technologies have improved the effectiveness of distribution channels by reducing the transaction costs and service time (Lee & Lee, 2001) and expanding credit access in consumer lending (Jagtiani & Lemieux, 2018). However, there is mixed evidence regarding whether e-banking technologies are helpful in managing household finance. Some research finds that electronic banking technologies help consumers save time in managing their finances through easier access to financial services (Anguelov, Hilgert, & Hogarth, 2004). Other studies find that consumers are concerned about security issues associated with online banking (Hamlet & Strube, 2000).

Although many researchers have investigated the determinants for consumers to adopt Internet banking (Kim, Widdows, & Yilmazer, 2005; Jun & Cai, 2001; Lee, Lee, & Eastwood, 2003; Lee & Lee, 2000), the literature on the impact of electronic technology is very limited. Son and Hanna (2011) find that the Internet affects how consumers use financial services and how consumers search and evaluate financial information before making financial decisions. Evidence shows that technological training and e-banking support financial literacy (Servon & Kaestner, 2008). While the question is: *are households who adopt these transaction-based technologies improving their financial well-being status?* In this article, we use the term "financial technology" to include both electronic technology and computer software technology, and examine the impact of using financial technology on households' positive financial behaviors.

We hypothesize that different types of financial technologies affect household financial behaviors differently. Specifically, we use a life cycle and human capital theoretical framework and differentiate two types of financial technologies: transaction-based financial technologies (i.e., ATM card, credit card, phone banking, and computer banking), and planning-based financial technologies (i.e., preauthorized debit, direct deposit, and computer software use). We hypothesize that transaction-based financial technologies should be negatively related to positive financial behaviors as they greatly increase the ease of accessing financial capital and the risks of overspending as well, especially for customers with self-control issues. In contrast, planning-based financial technologies should be positively associated with financial behaviors as households with clear planning goals are more likely to save for the future efficiently.

To test the hypotheses, we construct our sample using the data from the 2013 Survey of Consumer Finances (SCF). Following previous studies in Dew and Xiao (2011), Xiao et al. (2007), Worthy et al. (2010), and Hayhoe et al. (2000), we first measure positive financial behaviors based on 13 financial behaviors. We then create three proxies for positive financial behaviors using different methodologies including principal component analysis based on these thirteen financial behaviors. To test how different types of financial technologies affect household financial behaviors, we also use principal component analysis to construct a

measure of transaction-based technology usage and a measure of planning-based technology usage, respectively. Last, we include a vector of other variables to control for the impact of other factors that are likely to affect household financial behaviors.

Our univariate analysis suggests that 81.9% of respondents use an ATM card, 72.4% of respondents use a credit card, 21.2% of respondents use phone banking, 67.5% of respondents use computer banking, 57% of respondents used preauthorized debit, 86.4% of respondents use direct deposit, and 21% of respondents use computer software to manage their household finances. These findings are consistent with previous studies demonstrating that household adoption of electronic technologies has expanded substantially (Anguelov, Hilgert, & Hogarth, 2004; Servon & Kaestner, 2008). For the multivariate analysis, the results are consistent with our hypotheses that not all currently used financial technologies contribute to positive financial behaviors and personal financial well-being. Households that use planning purposed financial technologies are significantly related to higher positive financial behaviors while households using transactional purposed financial technologies are negatively related to positive financial behaviors. These results are robust after controlling for various household-level and economic factors, as well as to different measures of financial behaviors. Our findings suggest that planning-based financial technologies appear to create a more positive environment and enhance household financial well-being.

Previous research has shown that the very act of monitoring progress promotes better goal attainment and behavioral moderation (Harkin et al., 2016). The present study demonstrates that technological innovations like computer banking that assimilate planning-based financial technology have the potential to improve households' financial well-being and promote savings behavior and progress towards long-term goals (e.g., saving for retirement). U.S. households are facing an increasingly complex world that places more responsibility on their shoulders. Our findings in this study suggest that policymakers, financial planning professionals, employers, and financial service providers should find means and methods to assist consumers with better financial tools and help households manage their financial resources and behaviors so that households can enjoy the peace of mind and security from financial well-being.

The rest of the article is organized as follows. Section 2 reviews related literature and develops our hypotheses. We show data and variable constructions in Section 3. Section 4 presents the results and discusses the findings. Finally, Section 5 provides the conclusions.

2. Literature review and hypothesis development

2.1. Positive financial behavior

Garman, Leech, and Grable (1996) define poor financial behaviors as personal and family money management practices that have consequential, detrimental, and negative impacts on one's life at home and/or work. Prior research finds that positive financial behaviors are associated with positive life outcomes (Shim et al., 2009) and negative financial behaviors tend to cede to more negative financial behaviors (Dean et al., 2013). Given the common

financial activities that households need to deal with, we consider positive financial behaviors in three categories: debt management, planning activities, and risk management.

2.1.1. Debt management

Consumer credit use plays an important role in how modern households handle their debt. Among all household debt management activities, the most obvious positive financial behavior is to pay bills on time. However, almost seven percentage of U.S. households reported having at least one payment in the past year that was at least 60 days late (Hogarth & Anguelov, 2004). Other than loans and mortgages, credit card use is another financial activity that will cause consumers into debt. In 2008, the total outstanding credit debt carried by Americans is about $976 billion (Federal Reserve, 2009). According to the Federal Reserve (2013), credit card transactions increased at a 7.6% annual rate, rising from $21 billion in 2009 to $26.2 billion in 2012. The average number of credit cards that U.S. credit users hold is more than five and the average balance for each card is at least $1,000 (Experian, 2009). Recently, a report by TransUnion (2019) shows that bank-issued (private) credit card balances increased to $5,668 ($2,022) on a personal level as of Q3 2019.[1]

Rutherford and DeVaney (2009) define two types of credit card users: convenience users and revolvers. Convenience users are those who pay the balance in full on a regular basis while revolvers are those who pay only a portion of the balance and let the remaining balance accrue interest. Other research suggests that high credit card balances are a result of behavior problems instead of liquidity problems (Gross & Souleles, 2001). Thus, carrying a balance in credit cards while having money in the checking account is not considered a positive financial behavior because one has to pay high interest on the credit card balance and the checking account provides no or little interest. Moreover, making late payments on credit cards will lead to late fees and a negative remark on the credit report. It is worth mentioning that consumers with a history of late payments are less likely to be convenience users (Rutherford & DeVaney, 2009), as they tend to pay off small debts first even when the larger debt have higher interest rates (Amar et al., 2011).

The high debt-payment-to-income ratio is another detriment to households' lives. According to the SCF, 11% of all families in the United States had debt-payment-to-income ratios greater than 40% in 2001. This number increased to 15% in 2007 and 18.5% in 2010. Bricker et al. (2017) examined changes in financial management of U.S. families and reported that over 20% of families felt constrained in credit though their access to consumer credit has been increased. Aizcorbe et al. (2003) point out that most of the debtors who had greater than 40% debt-payment-to-income ratios were from lower-income families. Severe consequences such as bankruptcy might happen to these families in the long-run if they are unable to make adjustments on their debt management. Late payments along with high debt-payment-to-income ratios will negatively affect credit scores and limit future possibilities (i.e., access to credit, housing, or employment) of exhibiting positive debt management behaviors.

2.1.2. Planning activities

According to life cycle theory, individuals are saving and borrowing to smooth out consumption over lifetime (Modigliani & Brumberg, 1954). The assumption of life cycle theory is that people are forward-looking and making plans for the future. Planning for the future is a positive financial behavior as it allows households to smooth out consumption to maximize lifetime utility. To effectively transfer financial resources from one period to another, individuals need to have an extensive planning process. Rutherford and DeVaney (2009) suggest that financial advisors and educators must encourage and assist households in preparing financial plans that extend beyond five years. They find that households who have financial planning horizons of at least five years are more likely to be convenience users of credit.

Stawski et al. (2007) find that goal clarity serves as an important psychological mechanism, which motivates individuals to plan for the future. For example, Neukam and Hershey (2003) demonstrate that financial goals have a significant impact on retirement savings contributions. Specifically, goals help individuals structure perceptions and form expectations about future resource needs so they help increase both actual savings levels and the intention to save (Stawski et al., 2007). Moreover, households who had not engaged in planning activities are significantly less likely to accumulate wealth (Ameriks et al., 2002; Lusardi, 2010).

Another class of financial planning activities involves information-seeking, especially when individuals are shopping for credit, savings, and investment products. Lee and Hogarth (1999) find that households who extensively search when shopping for credit are more likely to have lower APRs and more likely to solve their credit card debts. Consumers who take more effort to shop for credit are likely to find loans with good terms and conditions as well as being more likely to be convenience credit users (Rutherford & DeVaney, 2009). The more exploration a household does when making financial decisions on credit, savings, and investments, the more likely it is going to get a better deal.

2.1.3. Risk management

Households are vulnerable when facing a variety of unexpected events that could lead to serious financial difficulties. Insurance is a tool to protect against substantial financial losses when unplanned perils or health circumstances occur. Thus, insurance is an important aspect of personal financial management.

Lin and Grace (2007) find that financial vulnerability has a significant impact on the amount of term life or total life insurance purchased. They argue that the key determinant of the demand for life insurance is the impact of the insured's death on the future consumption of other household members. Households with dependent children are more financially vulnerable because children consume most resources but generally contribute little to the household income. Preparing for the potential loss of the breadwinner of the household is very beneficial especially for households with children under 18 present (Lewis, 1989). Evidence shows that around two-thirds of poverty among surviving women and more than one-third of poverty among surviving men result from failures to insure survivors against sudden loss of household head (Bernheim et al., 2001). Although other research finds that life insurance

is essentially uncorrelated with financial vulnerability at every stage of the life cycle (Bernheim et al., 2003), we consider protection for your dependents as a positive financial behavior because it protects the family from the financial shock of losing a breadwinner.

Households need to insure against the loss of health-related human capital of its earners to ensure viability. However, health insurance products are too complicated for most households. According to data from the 1977 National Medical Expenditure Survey, 4.3% of nonelderly families spent more than 20% of their income on health care (Feenber & Skinner, 1994). Health expenditure shocks can lead to households' bankruptcy (Livshits, Tertilt, & MacGee, 2007) yet only high-income households accumulate precautionary savings to shield themselves from catastrophic health expenditures (Jeske & Kitao, 2009).

Other than health-related human capital loss, households are facing temporary or permanent disability risks as well. In theory, disability insurance provides benefits to workers who are physically unable to find suitable work. Although programs like Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI) are designed to help workers with disabilities, these benefits are not enough to lift incomes above the poverty line (Stapleton et al., 2006). Between 1985 and 2004, the number of disabled individuals receiving disability insurance increased by over 100% (Chen & Van der Klaauw, 2008). However, SSDI only pays benefits to "insured" workers and certain members of their family. In other words, workers with a disability need to have worked and paid Social Security taxes for a long enough period to receive disability benefits from SSDI. A recent fact sheet from the Social Security website shows that about over one in four of today's 20 year-olds will become disabled before reaching age 67 (SSA, 2019) (https://www.ssa.gov/pubs/EN-05-10029.pdf). In addition, 68% of the private sector workforce has no long-term disability insurance (SSA, 2019). Because the purpose of disability insurance is to provide substitute income to workers with disabilities, individuals need to be covered with disability insurance if they are currently working and should not need coverage if they have retired.

In addition to protecting against health issues, disability, and potential loss of life—unexpected events could also place households into financial difficulties. Setting aside a bucket of money to prepare for rainy days is imperative so households do not have to sell off their cars, appliances, and other household durables (Huston & Chang, 1997). A three-month income reserve is used as an adequate holding of an emergency fund in household emergency fund research (Chang & Huston, 1995; Huston & Chang, 1997).

2.2. Financial technology

Electronic banking technologies include ATM, online banking, debit (or check) card, direct deposit, direct payment (also electronic bill payment), electronic bill presentment and payment (EBPP), electronic check conversion, electronic fund transfer (EFT), payroll card, preauthorized debit (or automatic bill payment), prepaid card, smart card, and stored-value card (Anguelov, Hilgert, & Hogarth, 2004). Because the diffusion of innovation has not been applied to financial innovations, the current understanding of electronic banking technology, such as ATM card, debit card, direct deposit, and direct payment is very limited (Lee & Lee, 2000).

Anguelov, Hilgert, and Hogarth (2004) use three specific technologies to represent different types of e-banking technologies at different stages in their development: debit cards, preauthorized debits, and electronic banking. Computer ownership and internet access are related to the adoption of electronic banking but many studies have been unable to control for those variables. Consumers' acceptance of technological innovations is influenced by socioeconomic characteristics, demographic characteristics, perceptions of specific technologies, and the characteristics of different products and services. Electronic banking technologies can be classified as either "passive" or "active" (Kolodinsky, Hogarth, & Hilgert, 2004). Passive technologies (i.e., direct deposit and preauthorized debit) do not require any behavioral changes or continuous effort by the consumer so it is easier to spread. In contrast, active technologies (i.e., electronic banking) require new behaviors or repeated effort so they are hard to spread (Kolodinsky et al., 2004; Servon & Kaestner, 2008).

Davis (1989) created the technology acceptance model (TAM) that shows that perceived usefulness and ease of use are factors associated with the adoption of a system. Interconnections between technologies exist because the diffusion of any technology is not independent of the diffusion of another technology (Stoneman & Kwon, 1994). Moreover, a consumer's prior pattern of adopting related technology will affect his or her willingness to adopt new technology (Bayus, 1987). Consumers with good knowledge of computers are generally more likely to engage in electronic banking usage. Demographic factors such as age, income, education, occupation are significant factors for Internet banking adoption as well (Kim et al., 2005).

When relating financial technology to financial behaviors, we can categorize financial technologies into two main functions—technologies that are fundamentally transactional and technologies that aid in planning. Transaction-based technologies include ATM cards, credit cards, phone, and electronic banking. Households use an ATM card to access their bank account at an electronic terminal without the limitations of finding the nearest branch of their local bank. This is especially useful for transactions when traveling. It is more common to see consumers use credit cards to complete transactions for online purchases now than 50 years ago. Credit cards make online transactions convenient and safe by allowing households to set up transaction alerts on their mobile device and monitor spending instantaneously. Households also use preauthorized debit to set up electronic auto-payments on loans. Phone banking and electronic banking provides 24/7 financial service with almost no cost. Using these e-banking technologies, households can access their account information with little or no cost and conduct financial transactions conveniently (Lee & Lee, 2001).

Another important reason for using financial technology is to plan for the future. Research finds that computer-based mediated interventions contribute to a variety of behavior changes. Behavioral modification strategies include self-monitoring, goal-setting, shaping, reinforcement, and stimulus control (Butryn, Webb, & Wadden, 2011). The very act of monitoring progress towards goals has demonstrated evidence of significant improvement towards behavioral changes and the actual outputs desired (Harkin et al., 2016). Household finance-related computer software can help households make better financial decisions by providing financial knowledge and information, enhancing numerical ability on calculations, and monitoring finance on a regular basis. Governments and organizations use direct deposit as the preferred way to make reimbursements and distributions on salaries. Households who

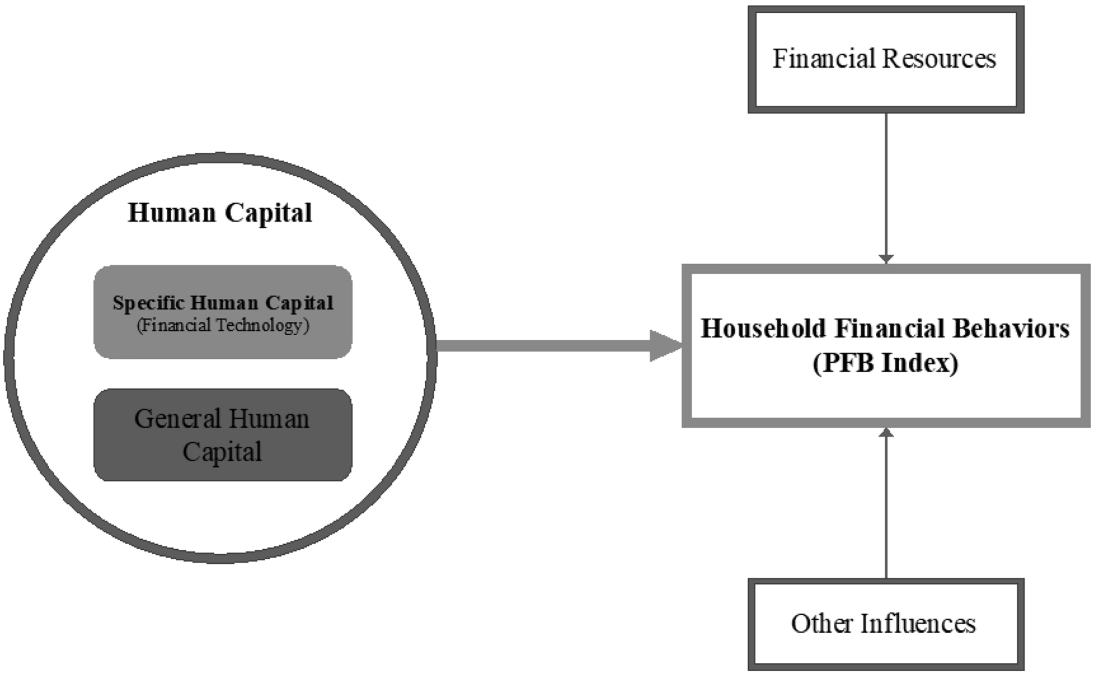

Fig. 1. Household financial behavior conceptual framework.

use preauthorized debit and direct deposit are trying to simplify their financial management, and automate their savings for the future.

The conceptual framework used for this study builds upon life cycle theory (Modigliani & Brumberg, 1954) and human capital theory (Becker & Tomes, 1994). According to the life cycle theory, an individuals' objective is to maximize lifetime utility. Individuals try to achieve higher lifetime utility through improved financial well-being. In our article, we measure household financial well-being through positive financial behaviors regarding debt management, planning activities, and risk management.

The positive financial behavior (PFB) index in Fig. 1 is a set of household financial behaviors that will lead to positive financial outcomes. Household financial behaviors are affected by household human capital, the endowed and acquired knowledge and skills a household has (Huston, 2010). Following previous studies, we consider two types of household human capital: specific human capital and general human capital (Becker & Tomes, 1994), as illustrated in Fig. 1 Specific human capital represents knowledge and skills that a household has towards specific areas such as financial technology and financial management. Specifically, financial technology indicates how well a household can understand and potentially use technology-related products and services to increase the probability of increased positive financial behaviors. Financial literacy indicates how well an individual can understand and potentially use personal finance-related information to increase expected lifetime utility from consumption (Huston, 2010). In contrast, general household capital represents the knowledge and skills that a household has and

could be used in many areas. For example, households who have more education are more likely to perform better in a wide variety of tasks. Last, household financial behaviors are also influenced by other factors such as behavioral biases, self-control, family, peer, cultural, environmental, and economic conditions (Huston, 2010). Financial resources also impact the household's financial well-being.

Households with more positive financial behaviors are more likely to have a higher level of financial well-being, after controlling for financial resources and other influences. Based on our theoretical framework in Fig. 1, positive financial behavior is a function of household capital, cultural/environmental influences, economic status:

$$\begin{aligned} &Positive\ Financial\ Behaviour(PFB) \\ &\quad = f\{Specific\ Household\ Capital,\ General\ Household\ Capital,\ Cultural/ \\ &\quad\quad Environmental\ Influences,\ Economic\ Stat \end{aligned}$$

Using this conceptual framework, we test the impact of specific household capital (financial technology) on positive financial behaviors, controlling for all other factors, using the following empirical regression model.

PFB = β_0 + β_1(*Specific Household Capital*) + β_2(*General Household Capital*) + $\beta_{3\text{-}6}$(Financial sophistication level) + β_7(Homeownership) + $\beta_{8\text{-}10}$(Age groups) + $\beta_{10\text{-}12}$(Education level) + β_{13}(Married) + $\beta_{14\text{-}17}$(Income quintiles) + $\beta_{17\text{-}20}$ (Net worth quintiles) + $\beta_{21\text{-}22}$(Household size) + β_{23}(Presence of children under 18) + β_{24}(Female) + $\beta_{25\text{-}26}$(Race groups) + β_{27}(Economic expectation) + β_{28}(Interest rate expectation) + $\beta_{29\text{-}30}$(Risk tolerance) + ϵ (2).

3. Data and variables descriptions

This study uses data from the 2013 Survey of Consumer Finances (SCF).[2] The SCF is a triennial survey of U.S. households sponsored by the Federal Reserve, in cooperation with the Internal Revenue Service, Statistics of Income Division, and collected by NORC at the University of Chicago. The survey data includes information on families' balance sheets, pensions, income, and demographic characteristics. Information is also included from related surveys of pension providers and the earlier such surveys conducted by the Federal Reserve Board.[3]

In the 2013 SCF survey, 6,015 households were available in the public dataset. While our study focuses on the use of financial technology and requires households to have at least a checking or a savings account. As a result, we censored the data to include banked households only for the purpose of this study. After applying this filter, our final sample includes a total of 5,447 households.

3.1. Positive financial behaviors proxies: The dependent variable

Based on the theoretical framework, we identify thirteen financial behaviors from the SCF to construct our positive financial behavior proxies. These behaviors cover three

Table 1 Percentage of banked households engaging in positive financial behavior

Positive financial behavior	Measurement	Banked households (%)	Standardized scoring coefficients
Debt management			
No late payments	1 if all loan and mortgage payments made on time or ahead of time, 0 otherwise.	85.9	0.219
Good credit report	1 if not been turned down for credit or if turned down but received full amount when they reapplied or never apply within the past five years because of afraid of being turned down, 0 otherwise.	76.4	0.227
Credit card balance	1 if not carrying credit card balance when having money in bank accounts, 0 otherwise.	61.5	0.101
No bankruptcy	1 if never filed for bankruptcy, 0 otherwise.	86.5	0.144
Total debt payment ratio	1 if total debt payment ratio smaller than 36%, 0 otherwise.	89.6	0.111
Planning activities			
Planning horizon	1 if planning horizon is a few years or more, 0 otherwise.	58.5	0.227
Currently saving	1 if have at least one reason to save, spending is less than income, and actually have saved for that reason, 0 otherwise.	58.6	0.276
Level of shopping for credit	1 if when making major decisions about credit or borrowing, do a moderate to a great deal of shopping, 0 otherwise.	75.1	0.099
Level of shopping for savings and investments	1 if when making major decisions about saving or investing, do a moderate to a great deal of shopping, 0 otherwise.	69.8	0.145
Risk management			
Children under 18 covered by life insurance	1 if children under 18 covered by life insurance or no children under 18 present in the household, 0 otherwise.	89.0	0.184
Health insurance	1 if everyone in the household is covered under health insurance, 0 otherwise.	81.1	0.219
Disability income insurance	1 if head of household is working and covered by disability insurance or is retired and not covered by disability insurance, 0 otherwise.	25.4	0.126
Emergency fund	1 if having $3,000 emergency fund prepared or being confident about borrow $3,000 from friends or relatives, 0 otherwise.	86.6	0.207

decision-making domains in debt management, planning activities, and risk management, respectively.

Table 1 shows the descriptions and measures of these financial behaviors and the summary statistics. For debt management activities, our results show that more than 85% of respondents have no late payments, no bankruptcy, and a total debt payment ratio that is smaller than 36%. Further, 76.4% of respondents indicate having a good credit report; 61.5% of respondents do not carry credit card balances when they have money in their bank accounts. For financial planning activities, 58.5% of respondents indicate that they are planning a few years ahead and have saved for specific goals. 75.1% of respondents report that they do a lot of shopping when making decisions on credit, savings, and investments. Additionally, households get involved in risk management; 89% of respondents who have children under 18 are covered by some sort of life insurance, as compared with 81.1% of respondents reporting that everyone in the household is covered by health insurance. In addition, 86.6% of respondents have an emergency fund (or are confident that they can borrow in an urgent situation), but only 25.4% of respondents have appropriate disability insurance coverage.

Based on these variables, we construct three positive behavior proxies. The first proxy is the number of positive financial behaviors adopted, that is, a simple summation of these 13 behavior dummies. The second proxy is a positive behavior index created through principal component analysis. Finke and Huston (2013) use the principal component analysis and construct a measure of time preference through eight financial decisions that indicate individual time preference. Letkiewicz, Robinson, and Domian (2016) apply the same approach and create a measure of financial self-efficacy and a measure of financial stress based on individuals' financial circumstances. Following their studies, we construct component factors based on the thirteen positive financial behaviors and select the first factor as our proxy for the positive financial behavior. This factor has an eigenvalue of 2.27 and is the only factor with an eigenvalue larger than 1.50. The standardized scoring coefficient to each behavior dummy variable is provided in Table 1. The majority of the behavior dummy variables carry a scoring coefficient in a narrow range of 0.10 and 0.25, suggesting that most of the positive financial behaviors included in this study contribute to the measure of a single positive behavior proxy. Last, we also create a dummy variable to indicate above-average positive behavior if a respondent's positive behavior index score is greater than the median index score of the full weighted sample. To ease our interpretation, for all proxies, the higher the score, the more the adoption of financial behaviors, and the higher lifetime utility.

Table 2 presents summary statistics of our three positive financial behavior proxies for the full weighted sample. The range of the number of positive financial behaviors is from zero to 13. All households in the sample report engaging in at least two positive financial behaviors. The mean and median number of positive financial behaviors is nine and 10, respectively. The majority of households engage in eight to 12 positive financial behaviors but only 4.28% of them have engaged in all of them. The mean and median of the index are provided in Table 2.

Table 2 Descriptive statistics of dependent variables: Positive financial behavior proxies

Number of positive financial behaviors	Banked households %
Panel A: Number of positive financial behaviors	
Zero	0
One	0
Two	0.03
Three	0.33
Four	0.91
Five	2.05
Six	5.62
Seven	9.4
Eight	13.33
Nine	16.48
Ten	17.35
Eleven	17.36
Twelve	12.88
Thirteen	4.28
Mean	9.44
Median	10
Panel B: Principle Component Index	
Mean	−0.153
Median	−0.011
Panel C: Above-average positive behavior	
Mean	0.500
Median	0.000

3.2. Independent variables on personal finance-specific human capital

Personal finance-related human capital illustrates how well an individual understands and potentially uses personal finance-related information to increase expected lifetime utility from consumption (Huston, 2010). From this perspective, financial technology is part of the personal finance-related human capital, which indicates how well an individual can use technology to help manage household resources or finances. In this study, we use the following financial behaviors available from SCF and create seven dummy variables to measure personal finance-specific human capital.

3.2.1. Transaction-based financial technologies

ATM card: "An electronic terminal provided by financial institutions and other firms that permits consumers to withdraw cash from their bank accounts, make deposits, check balances, and transfer funds" (Anguelov, Hilgert, & Hogarth, 2004).

Credit card: Using credit cards allows households to borrow up to the credit limit, build good credit, reap rewards, and make payments for online merchandise easier. However, we consider borrowing too much without an appropriate repayment schedule as bad financial behavior because of the high interest and fees on the unpaid amount and the negative impact on their credit record.

Phone banking: Phone banking provides households an immediate solution to emergency issues such as reporting a stolen or lost card, applying for new credit cards, checking account balances, etc. Mobile banking has also been developed very fast recently. Phone banking makes it very convenient for households to solve banking related financial problems so they can better manage their money.

Computer banking: "Banking services that consumers can access, by using an internet connection to a bank's computer center, to perform banking tasks, receive and pay bills, and so forth (Anguelov, Hilgert, & Hogarth, 2004). Computer banking allows the households to manage their accounts wherever they are as long as they have computers and internet access. Computer banking allows households to check account balances, make electronic transfers, transfer money into designated saving accounts, keep themselves updated on new banking services or receive important warnings from financial institutions, and so on. It provides a convenient channel for households to manage their finance with almost no costs.

3.2.2. Planning-based financial technologies

Preauthorized debit: "A form of payment that allows a consumer to authorize automatic payment of regular, recurring bills from his or her account on a specific date, and usually for a specific amount" (Anguelov, Hilgert, & Hogarth, 2004). For example, households use pre-authorized debit to set up automatic car payments, housing payments, utility bills, and so on. This method makes it easier for the households to make their payments on time.

Direct deposit: "A form of payment by which an organization pays funds via an electronic transfer" (Anguelov, Hilgert, & Hogarth, 2004). Direct deposit makes it easier for households to save because it transfers directly into designated accounts before the consumer has a chance to spend the money elsewhere.

Computer software: Households who use computer software to manage their finance are more likely to make the right decisions for savings and investments. Computer software can help households calculate how much they need to save for each goal, such as retirement savings, college fund savings, and so on. It provides more accurate spending and saving information, which can assist households with better data to make proper financial decisions. Using computer software can increase the probability of households reaching financial goals by facilitating consumers to save amounts that are more appropriate and aiding consumers in considering multiple goals simultaneously.

The descriptive statistics of financial technology variables are presented in Panel A of Table 3. Direct deposit is the most commonly used technology, as 81.9% of banked households report that they use it. With the new technologies coming out, phone banking is not as popular as before. Our results suggest only 21.2% of banked households report using phone banking while 67.5% report using computer banking. Moreover, 21.2% of banked households report using computer software to help managing their finance.

Similar to how we construct the positive financial behavior index, we also adopt principal component analysis to form two composite technology usage measures: transactional tech usage index and planning tech usage index. The transactional tech usage index is a measure of transaction-based technology usage based on ATM card use, credit card use, phone banking use, and computer banking use. The planning tech usage index measures planning-based technology usage based on the last three technology-use behaviors. Both composite measures use the first component factor from principal component analysis as the proxy. The standardized scoring coefficients are provided in Table 3.

Table 3 Descriptive statistics of financial technology variables and other control variables

Panel A: Key independent variables on specific household capital

Variables	Measurement	Banked households (%)	Standardized scoring coefficients
Transaction technologies			
ATM card	1 if use ATM card as one of the main ways you do business with bank or if you have a card that allows you to deposit or withdraw money from your bank using an ATM, 0 otherwise	81.9	0.43
Credit card	1 if have any credit card or charge card, 0 otherwise	72.4	0.389
Phone banking	1 if use automated phone system as one of the main ways to do business with bank, 0 otherwise	21.2	0.222
Computer banking	1 if use computer as one of the main ways to do business with bank, 0 otherwise	67.5	0.571
Planning technologies			
Preauthorized debit	1 if have utility bills, mortgage or rent payments, or other payments automatically paid directly from bank accounts without having to write a check, 0 otherwise	57	0.608
Direct deposit	1 if have paychecks or Social Security benefits or other money automatically paid directly into accounts, 0 otherwise	86.4	0.426
Computer software	1 if use computer software to manage money, 0 otherwise	21	0.52

Panel B: Composite technology usage measures from principal component analysis

	Mean	Median
Transactional tech usage index	−0.095	0.286
Planning tech usage index	−0.058	0.385

Panel C: Other control variables on general household capital

Variables	Measurement	Banked households (%)
Financial sophistication		
0–20 percentile	1 if household financial sophistication level is in the 0% to 20% range, 0 otherwise	20
21–40 percentile	1 if household financial sophistication level is in the 20% to 40% range, 0 otherwise	20
41–60 percentile	1 if household financial sophistication level is in the 40% to 60% range, 0 otherwise	20
61–80 percentile	1 if household financial sophistication level is in the 60% to 80% range, 0 otherwise	20

(continued on next page)

Table 3 (Continued)

Panel C: Other control variables on general household capital

Variables	Measurement	Banked households (%)
81–100 percentile	1 if household financial sophistication level is in the 80% to 100% range, 0 otherwise	20
Homeownership	1 if household owns or partially owns a home, 0 otherwise	68.1
Age		
18–34	1 if the head of household is age 18-34, 0 otherwise	21.3
35–49	1 if the head of household is age 35-49, 0 otherwise	26.4
50–64	1 if the head of household is age 50-64, 0 otherwise	29
65 and over	1 if the head of household is age 65 and over, 0 otherwise	23.3
Education level		
Less than high school	1 if household highest level of school completed is <12, 0 otherwise	6
High school/GED	1 if household highest level of school completed is =12 or high school diploma/GED, 0 otherwise	24.8
Some college	1 if household highest level of school completed is >12 but never get a college degree, 0 otherwise	26.8
Bachelors or higher	1 if household highest level of school completed is bachelors or higher, 0 otherwise	42.4
Married	1 if head of household is currently married or living with a partner, 0 otherwise	59
Financial resources		
Income		
0–20 percentile	1 if household income is between $1 and $25,000, 0 otherwise (reference)	23.9
21–40 percentile	1 if household income is between $25,001 and $48,000, 0 otherwise	25.5
41–60 percentile	1 if household income is between $48,001 and $85,000, 0 otherwise	23.2
61–80 percentile	1 if household income is between $85,001 and $192,000, 0 otherwise	20.8
81–100 percentile	1 if household income is between $192,001 or more, 0 otherwise	6.7
Net worth		
0–20 percentile	1 if household net worth is less than $0 to $10,682, 0 otherwise (reference)	23
21–40 percentile	1 if household net worth is between $10,683 to $90,119, 0 otherwise	25
41–60 percentile	1 if household net worth is between $90,120 to $352,741, 0 otherwise	26.8
61–80 percentile	1 if household net worth is between $352,742 to $1,825,468, 0 otherwise	19.8
81–100 percentile	1 if household net worth is between $1,825,469 or more, 0 otherwise	5.5
Household size		
One person	1 if number of people in household = 1, 0 otherwise	25.3
Two person	1 if number of people in household = 2, 0 otherwise	34.2
Three or more	1 if number of people in household>=3, 0 otherwise	40.5
Presence of children under age 18	1 if children under age 18 are present in the household, 0 otherwise	34.4
Other influences		
Female	1 if head of household is female, 0 is male	51.9

(continued on next page)

Table 3 (Continued)

Panel C: Other control variables on general household capital

Variables	Measurement	Banked households (%)
Race and ethnicity		
White and "other"	1 if household describes itself as White, Asian, Pacific Islander, or Native American, 0 otherwise	77.7
Black	1 if household describes itself as Black, 0 otherwise	12.7
Hispanic	1 if household describes itself as Hispanic, 0 otherwise	9.6
Economic expectations	1 if expect the U.S. economy to perform better over the next 5 years, 0 otherwise	45.4
Interest rate expectations	1 if expect interest rates will be higher 5 years from now, 0 otherwise	77
Risk tolerance		
No risk	1 if not willing to take any financial risks, 0 otherwise	44.4
Moderate risk	1 if willing to take average or above average financial risks expecting to earn average or above average return, 0 otherwise	52.7
Substantial risk	1 if willing to take substantial financial risks expecting to earn average or above average return, 0 otherwise	2.9

Based on Shefrin and Thaler's (1981) "doer versus planner" model, consumers experience a costly intrapersonal conflict between a "Planner" and a "Doer" (Gul & Pesendorfer, 2001) where the planner is concerned with lifetime utility but the doer exists for only one time period and would consume most of their resources today. The authors suggest that to shift intertemporal choice (Benabou & Pycia, 2002) and prevent the doer from consuming total lifetime income in the first period, some psychic technology capable of affecting the doer's behavior is required.[4] Based on the theoretical model of Shefrin and Thaler (1981), planning purposed financial technologies have the potential to fulfill all three ways the authors identify for shifting the myopic doer to more of a "planner" mindset: (1) Modify the doers' preferences, (2) Force doer to input to a savings program or budget, "simply keeping track seems to act as a tax on any behavior the planner views as deviant," and (3) Alter incentives. We expect that using transaction-based financial technologies may not have a positive impact on households' engagement in positive financial behaviors because transaction-based technologies basically enhance consumer discretion and ability to myopically overextend themselves by consuming too much today. In contrast, we expect that the use of planning purposed financial technologies will have a positive impact on positive financial behaviors. In Panel B of Table 3, it shows that the mean (median) of the transitional technology usage index and planning technology usage index is −0.095 (0.286) and −0.058 (0.385), respectively.

3.3. Other control variables

To control for other factors that are likely to be related to households' positive financial behaviors, we include a range of other measures as shown in Panel B of Table 3.

***Financial sophistication**:* A score from four questions in SCF that represents the financial literacy of a household (Huston et al., 2012). We expect that households with higher financial sophistication levels are more likely to engage in positive financial behaviors.

***Homeownership**:* Households with homeownership have more personal finance experiences, such as payments of mortgage loans, and refinance options. We expect that such households are more likely to engage in positive financial behaviors.

3.3.1. General human capital

Age: As age goes up, years of experience become valuable human capital.

Education level: Generally speaking, more years of schooling will increase households' general productivities. We expect that older households and those with more education are more likely to engage in positive financial behaviors.

Marital Status: From the whole household level, married households have more general human capital because one partner can access the other's resources. We expect married households are more likely to engage in positive financial behaviors.

3.3.2. Financial resources

Income: The more income a household has, the more resources that could be managed to achieve higher lifetime utility.

Net Worth: If the households have higher net worth, they are more likely to be in good shape with their finances but it does not necessarily mean that they are better financial managers compared with the others.
Household composition: Having children under 18 influences household expenditure. We expect households without children under 18 are more likely to engage in positive financial behaviors.

3.3.3. Cultural/environmental influences

Gender: Gender differences have been explored, identified, and established for different financial behaviors from savings (Strömbäck et al., 2017; Fisher, 2010) to willingness to take risks (Fisher & Yao, 2017). For example, Hayhoe et al. (2000) found that gender was more influential in predicting financial management practices than was affective credit attitude, with female students employing a greater number of financial practices. Gender differences have also been demonstrated for objective financial knowledge and numeric ability, where males typically perform better than females (Chen & Volpe, 2002; Fonseca et al., 2012; Lusardi & Mitchell, 2008; Powell & Ansic, 1997). Lind et al. (2020) attempted to explore how gender impacted broader measures of financial behavior while controlling for differences in relevant cognitive abilities and demographic statistics—their research discovered that women reported a lower level of subjective financial wellbeing even though they reported a more prudent financial behavior than men when controlling for socio-demographics and cognitive abilities.
Race and ethnicity: Cultural biases and behaviors affect households' financial behaviors. For example, Asian households are more likely to save and more encouraged to attain higher education.
Economic expectations: Different economic expectations affect households' financial decisions such as saving and consumption.
Interest rate expectations: Different interest rate expectations affect households' financial decisions such as saving and consumption, and chosen loan products.
Risk tolerance: Willingness to take risk affects households' investment related financial decisions. We expect households who are willing to take on some risk are more likely to engage in positive financial behaviors.

4. Multivariate analysis, results, and discussions

To determine the impact of using financial technology on positive financial behavior, we use ordinary least square (OLS) by regressing the independent variables on the positive financial behavior indexes as specified in Equation (2). Results of the regression analysis are shown in Table 4.

Models (1), (2), and (3) show the regression results using three different measures of positive financial behaviors as mentioned previously. Our results suggest that transactional technology usage is significantly and negatively related to positive financial behaviors. For example, in Model (2), it indicates that a one unit increase in the transactional technology index will cause the composite positive financial behavior index to decrease significantly by -0.051 units. This result is consistent across all three models regardless of how we measure positive financial behaviors. The results indicate that transaction-based financial technologies like ATM card, credit card, phone banking, and computer banking negatively affect households' engagement in positive financial behaviors. For example, the convenience of using ATM cards to withdraw money at any location might increase the probability of households consuming now instead of saving for the future. Overuse of credit cards could lead to high-interest expenses or over-purchasing behaviors

Table 4 The impact of technology adoption on positive financial behaviors, estimated through multiple regression specifications

Variables	Number of positive financial behaviors (1)	Principle Component Index (2)	Above-average positive behavior (3)
Constant	8.139***	−0.804***	−1.712***
Specific household capital			
Financial technologies			
Transactional tech usage index	−0.169***	−0.051***	−0.102***
Planning tech usage index	0.079***	0.035***	0.082***
Financial sophistication (relative to 41–60%)			
1–20 percentile	−0.65***	−0.323***	−0.704***
21–40 percentile	−0.234***	−0.122***	−0.227***
61–80 percentile	0.48***	0.243***	0.776***
81–100 percentile	0.78***	0.369***	1.081***
Homeownership	−0.32***	−0.105***	−0.127***
General household capital			
Age (relative to 35–49 years old)			
18–34	0.51***	0.232***	0.608***
50–64	−0.186***	−0.068***	−0.044
65 and over	0.017	0.107***	0.269***
Education level (relative to high school/ GED)			
Less than high school	−0.034	−0.022	−0.307***
Some college	0.048*	0.031**	0.024
Bachelors or higher	0.286***	0.156***	0.322***
Married	0.057*	0.052***	0.156***
Financial resources			
Income (relative to 0 to 20 percentile)			
21–40 percentile	0.104***	0.055***	0.141***
41–60 percentile	0.368***	0.192***	0.523***
61–80 percentile	0.838***	0.418***	1.015***
81–100 percentile	1.288***	0.605***	1.797***
Net worth (relative to 0 to 20 percentile)			
21–40 percentile	0.751***	0.384***	0.817***
41–60 percentile	1.427***	0.706***	1.433***
61–80 percentile	1.843***	0.889***	1.929***
81–100 percentile	1.757***	0.802***	2.023***

(continued on next page)

Table 4 (Continued)

Variables	Number of positive financial behaviors (1)	Principle Component Index (2)	Above-average positive behavior (3)
Household size (relative to two person)			
One person	0.484***	0.284***	0.616***
Three or more	−0.135***	−0.073***	−0.194***
Presence of children under age 18	−0.375***	−0.234***	−0.428***
Other influences			
Female	−0.123***	−0.063***	0.008
Race and ethnicity (relative to White and "other")			
Black	0.036	−0.006	−0.121**
Hispanic	−0.203***	−0.105***	−0.634***
Economic expectations	0.057***	0.013	−0.007
Interest rate expectations	0.062***	0.006	0.078**
Risk tolerance (relative to no risk)			
Moderate risk	−0.017	−0.058***	−0.246***
Substantial risk	−0.324***	−0.213***	−0.601***

Coefficients from Ordinary Least Square regressions are reported in the first two columns, coefficients from logistic regression are reported in the last column. ***,**,* indicate significance at the 0.01, 0.05, and 0.10 levels, respectively.

that households cannot afford to repay. Using phone banking and computer banking seems to have negative effects on positive financial behaviors. A recent study by TransUnion showed that both the volume and balance of personal unsecured loans have been increasing significantly in the past few years as consumers become more likely to choose FinTech than traditional lenders for borrowing.[5] Overall, our results are consistent with these findings by showing that, though the convenience provided by transaction-based e-banking technology saves time and costs for households to complete financial transactions, it also increases the ease of accessing funds and can be detrimental to household financial well-being in the long run.

In contrast, the regression results in Models (1), (2), and (3) also indicate that planning-based financial technologies, including preauthorized debit, direct deposit, and computer software use, positively affect households' engagement in financial behaviors. Our results show that the coefficients of the planning technology usage index are significantly positive across all models. For example, the positive coefficient of 0.082 in Model (3) suggests that planning technology usage is more likely to be positively related to households' positive financial behaviors. The results hence support our hypothesis that planning-based financial technologies will have a positive impact on households' financial behaviors.[6] Planning-based financial technologies appear to create a more positive environment for enhancing household financial well-being. For example, preauthorized debit is used to set up future automatic payments on loans and bills while direct deposit makes it easier to save and budget. Computer software helps households plan for the future by providing financial knowledge, calculation help, and action plans. Our results hence are consistent with previous studies showing that planning behaviors have a significant impact on personal savings practices (Lusardi, 2010). Also, our findings are consistent with Shefrin and Thaler's (1981) theory that individuals will be more likely to save or become a "planner" when preferences or incentives are altered, behaviors are tracked, or the doer's set of choices is limited with constraints. Households with clear goals are more likely to save for the future, which will lead to higher levels of financial well-being and life satisfaction.

Consistent with other research findings (Smith, Finke, & Huston, 2011, 2012a, 2012b), we also find that financial sophistication significantly affects households' financial behaviors. Specifically, low financial sophistication in households is negatively related to positive financial behaviors, while high financial sophistication is significantly and positively associated with positive financial behaviors. Households with high education, high income, and high net worth are also related to high positive financial behaviors. Households with homeownership or less risk-averse (i.e., who are willing to take a substantial risk) are engaging in low positive financial behaviors. Consistent with our expectation, households with children under 18 are associated with low positive financial behaviors. For the impact of age, households with young individuals between ages 18 and 34 show higher positive financial behaviors than those with older individuals with ages between 50 and 64.

5. Conclusions and implications

Given the rapid growth of technology innovation in the finance sector, it is natural to ask whether these technologies help households engage in positive financial behaviors. Using

the 2013 Survey of Consumer Finances commissioned by the Federal Reserve Board, this study found that not all kinds of financial technologies are helpful for households' engagement in positive financial behaviors.

In this study, we use a life cycle and human capital theoretical framework to illustrate the impact of financial technology on household financial behavior. Consistent with the theoretical framework, we find that financial technology-specific household capital has a significant impact on positive financial behaviors but not all types of financial technology will enhance positive financial behaviors. Specifically, we found transaction-based financial technologies like ATM card use, credit card use, phone banking, and computer banking have a negative impact on the number of positive financial behaviors reported. Providing easy access to bank accounts may encourage people to overspend in current periods, especially for those with self-control issues. In contrast, planning-based financial technologies like direct deposit and computer software use have positive impact on the number of positive financial behaviors. Financial sophistication, general household capital such as age and education, financial resources, and other resources such as expectation on the economy and risk tolerance are also found to have a significant impact on positive financial behavior.

Given the findings of this study, we suggest financial planners and financial educators encourage clients and individuals to use planning-based financial technologies such as computer software. Financial planners must focus on improving clients' personal finance management skills by emphasizing the importance to think from a long-term perspective when making financial decisions. Although the effectiveness of financial education programs is mixed (Willis, 2008), it is important to educate households on the effective use of tools to change their financial behaviors, rather than simply delivering financial education. To take full advantage of financial technology, consumers and professionals that assist consumers need to be aware of what types of technology will help in achieving higher financial satisfaction over the long run. Our findings in this study suggest that simply providing financial technology to complete transactions does not appear to improve household financial well-being. Only planning-based financial technologies have a positive impact on household financial well-being and hence should be given more attention in terms of technology development and marketing perspectives. For example, hyperbolic consumers are those who know that they should save for the future but it is hard for them to give up current consumption (Angeletos et al., 2001). Guiding these myopic consumers through planning-based financial technology may be an effective way to enhance their financial behaviors because it helps them create commitment devices to realize the benefit from engaging long-term financial practices that are consistent with maximizing lifetime utility.

We realize that there are limitations in our study. Because of data constraints, the positive financial behavior indexes used in this study cover only a few, not all, positive financial behaviors. Also, we do not look at the various types of computer software that are used by households to help manage their finance use in this study. Future research could explore households that switch financial technology and examine the impact of this change on their positive financial behaviors engagement.

Notes

1 See https://newsroom.transunion.com/consumers-poised-to-continue-strong-credit-activity-this-holiday-season
2 The data is available on Federal Reserve at https://www.federalreserve.gov/econres/scfindex.htm
3 The 2013 SCF collect data using computer-assisted personal interviewing (CAPI). Thus, there is no questionnaire in the usual sense. SCF uses a dual-frame sample design consisting of a standard, geographically based random sample and an oversample of affluent households. Missing values are imputed by making multiple estimates of the missing data and creating five implicate data sets. We use all five implicates to avoid inaccurate results on the significant test (Rubin, 1987).
4 Two main techniques are available for this: (1) The doer can be given discretion in which case either his preferences must be modified or his incentives must be altered, or (2) the doer's set of choices may instead be limited by imposing rules that change the constraints the doer faces" (Shefrin & Thaler, 1981).
5 Available at https://www.transunion.com/blog/consumer-credit-origination-balance-and-deliquency-trends
6 In untabulated results, we also regress three dependent variables on individual financial technology variables instead of the composite indexes. The results are consistent with these reported in the main texts.

References

Aizcorbe, A. M., Kennickell, A. B., & Moore, K. B. (2003). Recent changes in U.S. family finances: Evidence from the 1998 and 2001 Survey of Consumer Finances. *Federal Reserve Bulletin*, *89*, 1-32.

Amar, M., Ariely, D., Ayal, S., Cryder, C. E., & Rick, S. I. (2011). Winning the battle but losing the war: The psychology of debt management. *Journal of Marketing Research*, *48*, S38-S50.

Ameriks, J., Caplin, A., & Leahy, J. (2002). Wealth accumulation and the propensity to plan. *National Bureau of Economic Research*, No. *w8920*,

Angeletos, G. M., Laibson, D., Repetto, A., Tobacman, J., & Weinberg, S. (2001). The hyperbolic consumption model: Calibration, simulation, and empirical evaluation. *Journal of Economic Perspectives*, *15*, 47-68.

Anguelov, C. E., Hilgert, M. A., & Hogarth, J. M. (2004). US consumers and electronic banking, 1995-2003. *Federal Reserve Bulletin*, *90*, 1–18.

Bayus, B. (1987). Forecasting sales of new contingent products: An application to the compact disc market. *Journal of Product Innovation Management*, *4*, 243-255.

Becker, G. S., & Tomes, N. (1994). Human capital and the rise and fall of families. In *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education* (3rd ed., pp. 257–298). Chicago, IL: The University of Chicago Press.

Bénabou, R., & Pycia, M. (2002). Dynamic inconsistency and self-control: A planner–doer interpretation. *Economics Letters*, *77*, 419-424.

Bernheim, B. D., Carman, K. G., Gokhale, J., & Kotlikoff, L. J. (2001). *The Mismatch Between Life Insurance Holdings and Financial Vulnerabilites: Evidence from the Survey of Consumer Finances*. NBER working paper, No. 8544, October.

Bernheim, B. D., Carman, K. G., Gokhale, J., & Kotlikoff, L. J. (2003). Are life insurance holdings related to financial vulnerabilities? *Economic Inquiry*, *41*, 531-554.

Bricker, J., Dettling, L. J., Henriques, A., Hsu, J. W., Jacobs, L., Moore, K. B., & Windle, R. A. (2017). Changes in US family finances from 2013 to 2016: Evidence from the Survey of Consumer Finances. *Federal Reserve Bulletin*, *103*, 1-42.

Butryn, M. L., Webb, V., & Wadden, T. A. (2011). Behavioral treatment of obesity. *The Psychiatric Clinics of North America*, *34*, 841-859.

Chang, Y. R., & Huston, S. J. (1995). Patterns of adequate household emergency fund holdings: A comparison of households in 1983 and 1986. *Financial Counseling and Planning*, *6*, 119-128.

Chen, S., & Van der Klaauw, W. (2008). The work disincentive effects of the disability insurance program in the 1990s. *Journal of Econometrics*, *142*, 757-784.

Chen, H., & Volpe, R. (2002). Gender differences in personal financial literacy among college students. *Financial Services Review*, *11*, 289-307.

Davis, F. (1989). Perceived usefulness, perceived ease of use and user acceptance of information technology. *MIS Quarterly*, *13*, 319-340.

Dean, L. R., Joo, S. H., Gudmunson, C. G., Fischer, J. L., & Lambert, N. (2013). Debt begets debt: Examining negative credit card behaviors and other forms of consumer debt. *Journal of Financial Service Professionals*, *67*, 72-84.

Dew, J., & Xiao, J. J. (2011). The financial management behavior scale: Development and validation. *Journal of Financial Counseling and Planning*, *22*, 43-59.

Experian. (2009). *With Age Comes Wisdom . . . and a Higher Credit Score*. Experian. (available at http://www.experian.com/assets/business-resources/studies/snapshot-seniors-debt.pdf)

Federal Reserve. (2009). *Consumer Credit November 2008. Federal Reserve Statistical Release*. Washington, DC: Board of Governors of the Federal Reserve System.

Federal Reserve. (2013). *The 2013 Federal Reserve Payments Study: Recent and Long-Term Payment Trends in the United States: 2003–2012*. Washington, DC: Board of Governors of the Federal Reserve System.

Feenber, D., & Skinner, J. (1994). The risk and duration of catastrophic health care expenditures. *The Review of Economics and Statistics*, *76*, 633-647.

Finke, M., & Huston, S. (2013). Time preference and the important of saving for retirement. *Journal of Economic Behavior & Organization*, *89*, 23-34.

Fisher, P. J. (2010). Gender differences in personal saving behaviors. *Journal of Financial Counseling and Planning*, *21*, 14-24.

Fisher, P. J., & Yao, R. (2017). Gender differences in financial risk tolerance. *Journal of Economic Psychology*, *61*, 191-202.

Fonseca, R., Mullen, K. J., Zamarro, G., & Zissimopoulos, J. (2012). What explains the gender gap in financial literacy? The role of household decision making. *The Journal of Consumer Affairs*, *46*, 90-106.

Garman, E. T., Leech, I. E., & Grable, J. E. (1996). The negative impact of employee poor personal financial behaviors on employers. *Financial Counseling and Planning*, *7*, 157-168.

Gross, D. B., & Souleles, N. S. (2001). *Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence From Credit Card Data* (No. w8314). Cambridge, MA: National Bureau of Economic Research.

Gul, F., & Pesendorfer, W. (2001). Dynamic inconsistency and self-control. *Econometrica*, *69*, 1403-1436.

Hamlet, C., & Strube, M. (2000). Community banks go online. *ABA Banking Journal*, *92*, 61-65.

Harkin, B., Webb, T. L., Chang, B. P., Prestwich, A., Conner, M., Kellar, I., Benn, Y., & Sheeran, P. (2016). Does monitoring goal progress promote goal attainment? A meta-analysis of the experimental evidence. *Psychological Bulletin*, *142*, 198-229.

Hayhoe, C. R., Leach, L. J., Turner, P. R., Bruin, M. J., & Lawrence, F. C. (2000). Differences in spending habits and credit use of college students. *Journal of Consumer Affairs*, *34*, 113-133.

Hogarth, J. M., & Anguelov, C. E. (2004). Are families who use e-banking better financial managers? *Financial Counseling and Planning*, *15*, 61-78.

Huston, S. J., & Chang, Y. R. (1997). Adequate emergency fund holdings and household type. *Financial Counseling and Planning*, *8*, 37-46.

Huston, S. J. (2010). Measuring financial literacy. *Journal of Consumer Affairs*, *44*, 296-316.

Huston, S. J., Finke, M. S., & Smith, H. (2012). A financial sophistication proxy for the Survey of Consumer Finances. *Applied Economics Letters*, *19*, 1275-1278.

Jagtiani, J., & Lemieux, C. (2018). Do fintech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business*, *100*, 43-54.

Jeske, K., & Kitao, S. (2009). US tax policy and health insurance demand: Can a regressive policy improve welfare? *Journal of Monetary Economics*, *56*, 210-221.

Jun, M., & Cai, S. (2001). The key determinants of internet banking service quality: A content analysis. *International Journal of Bank Marketing*, *19*, 276-291.

Kim, B. M., Widdows, R., & Yilmazer, T. (2005). The determinants of consumers' adoption of internet banking. In Proceedings of the Consumer Behavior and Payment Choice 2005 Conference. (pp. 1-34). Boston, MA.

Kolodinsky, J. M., Hogarth, J. M., & Hilgert, M. A. (2004). The adoption of electronic banking technologies by U.S. consumers. *International Journal of Bank Marketing*, *22*, 238-259.

Lee, J., & Hogarth, J. M. (1999). Returns to information search: Consumer credit card shopping decisions. *Journal of Financial Counseling and Planning*, *10*, 23-35.

Lee, E., & Lee, J. (2000). Haven't adopted electronic financial services yet? The acceptance and diffusion of electronic banking technologies. *Financial Counseling and Planning*, *11*, 49-60.

Lee, E., & Lee, J. (2001). Consumer adoption of Internet banking: Need-based and/or skill based? *Marketing Management Journal*, *11*, 101-113.

Lee, E., Lee, J., & Eastwood, D. (2003). A two-step estimation of consumer adoption of technology-based service innovations. *Journal of Consumer Affairs*, *37*, 256-282.

Letkiewicz, J., Robinson, C., & Domian, D. (2016). Behavioral and wealth considerations for seeking professional financial planning help. *Financial Services Review*, *25*, 105-126.

Lewis, F. (1989). Dependents and the demand for life insurance. *The American Economic Review*, *79*, 452-467.

Lin, Y., & Grace, M. F. (2007). Household life cycle protection: Life insurance holdings, financial vulnerability, and portfolio implications. *Journal of Risk & Insurance*, *74*, 141-173.

Livshits, I., Tertilt, M., & MacGee, J. (2007). Consumer bankruptcy: A fresh start. *American Economic Review*, *97*, 402-418.

Lind, T., Ahmed, A., Skagerlund, K., Strömbäck, C., Västfjäll, D., & Tinghög, G. (2020). Competence, confidence, and gender: the role of objective and subjective financial knowledge in household finance. *Journal of Family and Economic Issues.*

Lusardi, A. (2010). Information, expectations, and savings for retirement. In H. J. Aaron (Ed.), *Behavioral Dimensions of Retirement Economics* (pp. 81-115). Washington, DC: Brookings Institution Press and Russell Sage Foundation.

Lusardi, A., & Mitchell, O. S. (2008). Planning and financial literacy: How do women fare? *American Economic Review*, *98*, 413-417.

Merry, E. A. (2018). Mobile banking: A closer look at survey measures. FEDS Notes. Washington: Board of Governors of the Federal Reserve System, March 27, 2018.

Modigliani, F., & Brumberg, R. (1954). Utility analysis and the consumption function: An interpretation of cross-section data. *Franco Modigliani*, *1*, 388-436.

Neukam, K. A., & Hershey, D. A. (2003). Financial inhibition, financial activation, and saving for retirement. *Financial Services Review*, *12*, 19-37.

Parrish, L., & Servon, L. (2006). *Policy Options to Improve Financial Education: Equipping Families for Their Financial Futures*. Washington, DC: Asset Building Program, New America Foundation.

Pew Research Center. (2018). *Mobile Fact Sheet*. (available at http://www.pewinternet.org/fact-sheet)

Powell, M., & Ansic, D. (1997). Gender differences in risk behavior in financial decision making: An experimental analysis. *Journal of Economic Psychology*, *18*, 605-628.

Rubin, D. (1987). *Multiple Imputation for Nonresponse in Surveys.* New York, NY: John Wiley & Sons.

Rutherford, L., & DeVaney, S. A. (2009). Utilizing the theory of planned behavior to understand convenience use of credit cards. *Journal of Financial Counseling and Planning*, *20*, 48-63.

Servon, L. J., & Kaestner, R. (2008). Consumer financial literacy and the impact of online banking on the financial behavior of lower-income bank customers. *Journal of Consumer Affairs*, *42*, 271-305.

Shefrin, H. M., & Thaler, R. H. (1981). An economic theory of self-control. *Journal of Political Economy*, *89*, 392-406.

Shim, S., Xiao, J. J., Barber, B., & Lyons, A. (2009). Pathways to success: A model of financial well-being of young adults. *Journal of Applied Developmental Psychology*, *30*, 708-723.

Smith, H. L., Finke, M. S., & Huston, S. J. (2011). The impact of financial sophistication on adjustable rate mortgage ownership. *Journal of Financial Counseling and Planning*, *22*, 3-15.

Smith, H. L., Finke, M. S., & Huston, S. J. (2012a). Financial sophistication and housing leverage among older households. *Journal of Family and Economic Issues*, *33*, 315-327.

Smith, H. L., Finke, M. S., & Huston, S. J. (2012b). The influence of financial sophistication and financial planners on Roth IRA ownership. *Journal of Financial Service Professionals*, *66*, 69-81.

Social Security Administration (2019). Disability Benefits. SSA Publication No. 05-10029. ICN 456000. Baltimore, MD (July).

Son, J., & Hanna, S. (2011). The relation between internet use and financial planner use for savings and investment decisions. Proceedings of the Academy of Financial Services.

Stapleton, D. C., O'Day, B. L., Livermore, G. A., & Imparato, A. J. (2006). Dismantling the poverty trap: Disability policy for the twenty-first century. *The Milbank Quarterly*, *84*, 701-732.

Stawski, R. S., Hershey, D. A., & Jacobs-Lawson, J. M. (2007). Goal clarity and financial planning activities as determinants of retirement savings contributions. *International journal of aging & human Development*, *64*, 13-32.

Stoneman, P., & Kwon, M. J. (1994). The diffusion of multiple process technologies. *The Economic Journal*, *104*, 420-431.

Strömbäck, C., Lind, T., Skagerlund, K., Västfjäll, D., & Tinghög, G. (2017). Does self-control predict financial behavior and financial well-being? *Journal of Behavioral and Experimental Finance*, *14*, 30-38.

Willis, L. E. (2008). Against financial literacy education. *Iowa Law Review*, *94*, 08-10.

Worthy, S. L., Jonkman, J., & Pike, L. B. (2010). Sensation-seeking, risk-taking, and problematic financial behaviors of college students. *Journal of Family and Economic Issues*, *31*, 161-170.

Xiao, J. J., Shim, S., Barber, B., & Lyons, A. (2007). *Academic Success and Well-Being of College Students: Financial Behaviors Matter (TCAI Report).* Tucson, AZ: University of Arizona.

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Using investor utility to determine portfolio choice with REITs

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Abstract

This article examines the decision of individual investors to allocate a portion of their existing investment portfolios to REITs. It first derives the risk preferences of investors represented by their benchmark portfolios of stocks and bonds. Such risk preferences are then used for portfolio decisions regarding REITs. The analysis shows that investors with lower risk aversion tend to have a more substantial stock component in their benchmark portfolio and will obtain higher risk-return benefits from adding REITs. In addition to the theoretical analysis, the article provides a practical solution to evaluate the benefit of investing in REITs. © 2021 Academy of Financial Services. All rights reserved.

JEL classification: G11

Keywords: REITs; Target fund; Efficient frontier; Portfolio

1. Introduction

REITs (i.e., equity REITs) offer individual investors the ease of investing in real estate using publicly traded shares. Historically, REITs have provided investors dividend-based income, competitive market performance, transparency, liquidity, inflation protection, and portfolio diversification. They have been advertised as a potential candidate for investment

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or portfolio construction that is less correlated with stocks and bonds than other asset classes (see Glascock et al., 2000) for further discussion of REITs' correlation with stocks and bonds.).

Many studies explore the benefits of including REITs in investment portfolios, such as Anderson and Springer (2003), Chen et al. (2005), and Hudson-Wilson et al. (2005). It is necessary to note that REITs are generally treated as an alternative asset by many individual investors who hold the majority of their investments in traditional assets like stocks and bonds. To study the benefits of alternative or less traditional assets like REITs, we need to examine the investor's existing holdings and risk preferences. Besides, the existing studies that examine the inclusion of REITs in investment portfolios use mean-variance analysis but ignore the fact that that investors tend to make different choices due to their diverse risk preferences. It is essential to study the role of risk preference when determining the appropriate asset allocation to REITs.

This study explores the portfolio implications of risk preference. It starts by examining investors represented by their investment in stocks and bonds. Their existing allocations serve as the benchmark portfolio to evaluate the benefit obtained from including REITs. We derive the investor's risk preference from his existing holdings. We further use such a risk-preference to construct a new portfolio by adding REITs. We compare this new portfolio with the original benchmark to gauge the benefit of REITs. This approach incorporates the role of risk preference in portfolio management. The results suggest that investors with lower risk aversion achieve more benefit from investing in REITs. This approach illustrates the role of risk preference in portfolio decisions and provides an explanation of the gap between the theoretical mean-variance framework and diverse portfolio choices in practice.

The article is organized as follows. First, it reviews the related studies on REITs and portfolio choice. It then introduces the methodology to derive the investor risk preference from a benchmark portfolio allocation. The analysis then applies the risk preference to portfolio construction and explains the additional benefit from the addition of REITs. The empirical discussion follows the methodology. The final section concludes.

2. Related studies

2.1. REITs as an alternative investment class

In this study, a "REIT" is defined as an equity REIT. The data used in the analysis does not include mortgage REITs or companies whose primary business is related to financing real estate. Equity REITs operate along with a straightforward business model. This type of company generates income by leasing space and collecting rent on its real estate and from gains from the sale of its real estate. Income is then paid out to shareholders in the form of dividends. When reporting financial results, REITs, like other public companies, must report earnings per share based on net income as defined by generally accepted accounting principles. REITs are required to distribute at least 90% of their taxable income to shareholders annually in the form of dividends to avoid taxation at the firm level. Significantly higher, on average, than other equities, the industry's dividend yields have historically produced a

steady stream of income through a variety of market conditions. REITs over time have demonstrated a historical track record of providing a high level of current income combined with long-term share price appreciation, inflation protection, and prudent diversification for investors across the age and investment style spectrums. They have been noted as a useful diversifier for portfolio construction (e.g., Hudson-Wilson et al., 2003 and Chen et al., 2005).

2.2. Strategies to invest in REITs

Many studies address the benefit of including REITs in a stock and bond portfolio. For example, Barone (2016) shows how the inclusion of REITs would improve portfolio performance when targeting minimal portfolio variance or maximum Sharpe-ratio. Such approaches, though often theoretically utilized, cannot explain the diverse portfolio choices in practice. The portfolio diversity stems from the varying risk preference among investors. Studies such as Waggle and Agrrawal (2006), Waggle and Moon (2006), and Bhuyan et al. (2014) introduce risk preferences in the decision process. They assume the utility function $U = \mu - 0.5\theta\sigma^2$, where μ is the portfolio return, σ is the portfolio return standard deviation, and θ is the risk preference. Using unconstrained optimization, they examine the benefit of including REITs in stock and bond portfolios for investors with a risk preference (θ) varying from 1 to 10. However, these authors' choice of risk preference (θ) is random, and their portfolio choice does not present an implementable solution to individual investors. Instead of randomly assuming risk preference, this current article derives the risk preference of the investor from commonly used benchmark portfolios and applies such a risk preference to include REITs. This study emphasizes that the benefit of investing in REITs is contingent upon the allocation of stocks or bonds that the investor gives up for REITs.

Due to the historically low correlation between stocks and bonds, portfolios can generally be constructed with these two asset classes to achieve better diversification and improved risk-adjusted performance than is available when using only one of these asset classes. The stock-bond combination has been a significant theme in investment practice. For example, target-date retirement funds (also known as lifecycle funds, see TIAA (2019) and Vanguard (2019) are a popular form of mutual fund that invests in a combination of stocks and bonds. The target fund gradually shifts its asset allocation from stocks to bonds as the target date approaches, and beyond. For instance, a target-date fund intended for people retiring in 30 years might have 90% of its assets in stocks and 10% in bonds, while a fund intended for 5-year retirees may have a 50-50 mix. While the exact asset mix depends on the design from a particular fund company, the underlying rationale for the target fund is that as people get older, they tend to be more risk-averse, which leads to more conservative portfolio choices (Singh, 2016; Spitzer & Singh, 2008). The practice of target-date funds suggests that investors choose different stock-bond allocations suitable to their risk preferences.

This study originates from the above observation of target-date funds. It examines how investors, varying in risk preference as reflected in their choices in stock and bond allocation, would invest in REITs. We assume investors initially are fully invested in a stock and bond portfolio and are considering adding REITs. We derive a risk preference based on the

investor's existing (or benchmark) stock-bond allocation and apply this risk preference to construct portfolio construction among stocks, bonds, and REITs. The study shows the varying benefit among investors with diverse risk preferences. Being advertised as a safe alternative asset, REITs bring more benefits to investors with lower risk aversion than those with higher risk aversion.

3. Data and analysis

The analysis uses the monthly return history from February 1990 to October 2018 of the S&P 500 Total Return index, the Barclays Long-term Government Bond index (LGBI), and the Dow Jones U.S. Select REIT Index as proxies for an investment of stock, bond, and equity REITs, respectively.

It is worth noting that the S&P 500 includes 31 REITs in that index.[1] Thus, in the analysis of this article, there is "double dipping" (i.e., an investment in the same company twice) in some REITs that are included in both the S&P 500 and the Dow Jones U.S. Select REIT Index. This fact has been considered by the authors and is a real-world detail faced by individual investors. An investor that desires to allocate a portion of his portfolio to REITs will not likely short (or otherwise reduce exposure to) REITs in the S&P 500 before adding a REIT exposure. We treat an allocation in the S&P 500 as an investment to "stocks," and an allocation in the REIT index as an investment to REITs. We feel that this approach is consistent with what an individual investor will likely do in practice and mimics what might happen when an investor faces a choice of mutual funds, ETFs, or similar diversified portfolios in which to invest.

We use the Barclays Long-term Government Bond index as a proxy for the bond component in the target-date fund. This index has been widely adopted as a benchmark for returns from U.S. Treasuries. It represents the complementary investment to the equity market. Besides the U.S. Treasuries, target-date funds also include the investment-grade fund and can allocate a small percentage in high yield corporate bond funds. Those corporate bonds feature a risk-return profile that positions between equity and treasury bonds. For the convenience of discussion, we only use the U.S. Treasuries to represent the bond component. However, the major conclusions and methodology also apply to situations with additional assets or asset classes.

As noted above, the analysis focuses on the equity REITs, because mortgage REITs represent an investment in real-estate-backed debt and not the actual real estate. The Dow Jones U.S. Select REIT Index comprises publicly traded equity REITs such as owners and/or operators of commercial and/or residential real estate. Business excluded from this index includes specialty REITs, Hybrid REITs, mortgage REITs, home builders, and companies whose primary business is related to financing real estate.

All these indices have actively been tracked with multiple index ETFs, which provide a convenient and cost-effective approach to invest in a diversified manner. Because this article examines long-term asset allocation, transaction cost incurred to reallocate a portfolio (while potentially important in trading) is a relatively minor issue. This treatment is more justified recently because many of the major brokerages have moved to $0 costs per trade, and

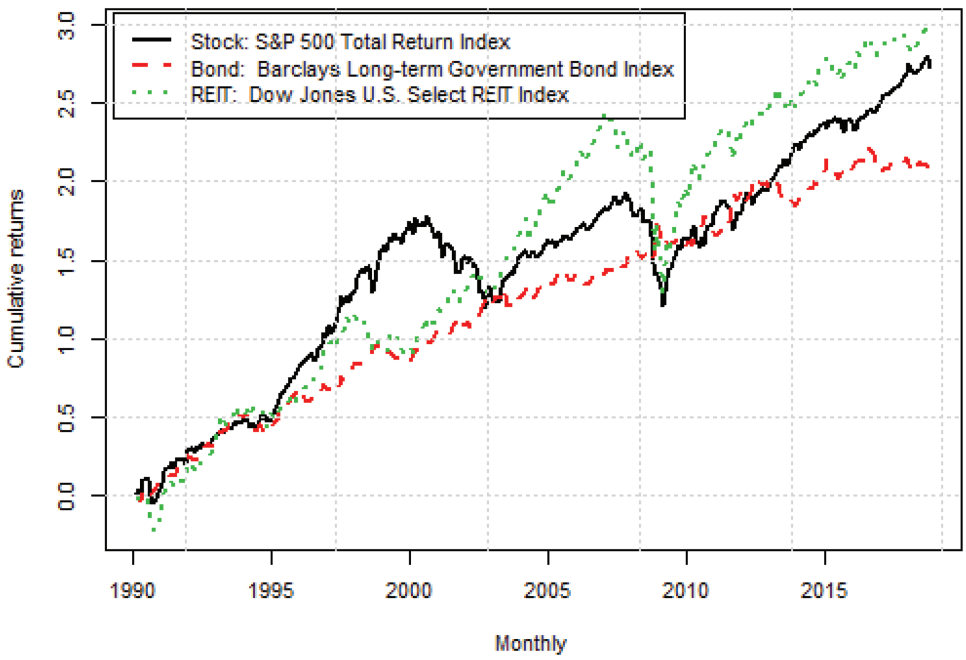

Fig. 1. Return histories from stock, bond, and REIT indices.

individual investors, especially, can reallocate many stocks, ETFs, REITs, and other funds for $0 commission.

Fig. 1 illustrates the history of the stock, bond, and REIT indices. Table 1 includes the statistical details over the return history for those proxy indices. The descriptive return statistics and correlation tables show that stocks and bonds tend to have a low correlation with each other, which provides a convenient approach for portfolio construction.

We use a stock and bond mix along the efficient frontier to represent the investor' existing or benchmark portfolios. Investors, especially individuals, generally allocate the majority of their investable assets between stocks and bonds. Even if an investor does not invest directly in the indexes used in the analysis, the results can still be applied to a diversified portfolio of stocks and bonds. From the benchmark portfolios, we introduce a utility function and derive the investor's risk preference. Such a risk preference is applied to construct a new portfolio with an allocation to stocks, bonds, and REITs. The benefit from including REITs is evaluated by comparing the original benchmark portfolio and the new portfolio.

3.1. Investor's risk preference

To explain the role of risk preference over the portfolio choice, we model an investor's utility function as:

$$\mathrm{U} = \mu - .05\theta\sigma^2 \tag{1}$$

where μ is the average portfolio return, and σ is the standard deviation of portfolio returns.

Table 1 Statistics from history returns (Feb. 1990 through Oct. 2018)

Panel A	Return statistics		
Asset	Stock	Bond	REIT
Monthly average	0.87%	0.64%	0.99%
Monthly standard	4.07%	2.80%	5.30%
Skewness	−0.61	0.14	−0.69
Kurtosis	1.35	1.54	8.23
Max drawdown	−0.51	−0.16	−0.68
Annual average	10.50%	7.64%	11.94%
Annual standard	14.11%	9.70%	18.36%
Panel B	Correlation		
	Stock	Bond	REIT
Stock	1.00	−0.11	0.55
Bond	−0.11	1.00	0.05
REIT	0.55	0.05	1.00

Note: Table 1 reports the return statistics for stock, bond, and REIT indices. Panel a provides the monthly return average, standard deviations, skewness, kurtosis, and maximum drawdowns. Annualized return and standard deviations are also included. Panel B shows the correlation between the monthly returns.

The utility function in Equation (1) illustrates the risk-return tradeoff in a straightforward manner. Other utility functions give similar results. On an iso-utility curve, the risk-return tradeoff follows:

$$\rho^{\mathrm{U}} = d\mu/d\sigma = \theta\sigma \tag{2}$$

The coefficient, θ, is a measure of risk aversion. Higher θ suggests higher risk aversion. The risk-return tradeoff along the utility curve, $\rho^{\mathrm{U}} = \theta\sigma$, increases with higher σ.

The utility function in Equation (1) would be latent for investors. However, the portfolio choices would ultimately be dictated by the investors' inherent risk-preferences. We assume that the investors' comfortable allocation reflects his best choice between stocks and bonds and achieves maximum utility. Then, we can take the existing portfolio as a benchmark and calibrate the risk preference of the investor.

3.2. Current benchmark portfolio

Fig. 2 shows the efficient frontier from stock and bond allocations. Given a benchmark portfolio with a profile of (μ^*, σ^*; e.g., the 80/20 stock-bond mix) on the efficient frontier, we can show that the investor achieves maximum utility when the iso-utility curve is a tangent to the efficient frontier at point (μ^*, σ^*). This condition requires the risk-return tradeoff along the efficient frontier, denoted as $\rho^F(\mu^*, \sigma^*)$, equal to tradeoff along the iso-utility curve, or $\rho^{\mathrm{U}} = \Delta\mu/\Delta\sigma$.

$$\rho^F(\mu^*\ ,\ \sigma^*) = \rho^{\mathrm{U}}(\mu^*\ ,\ \sigma^*) = \theta^*\sigma^* \tag{3}$$

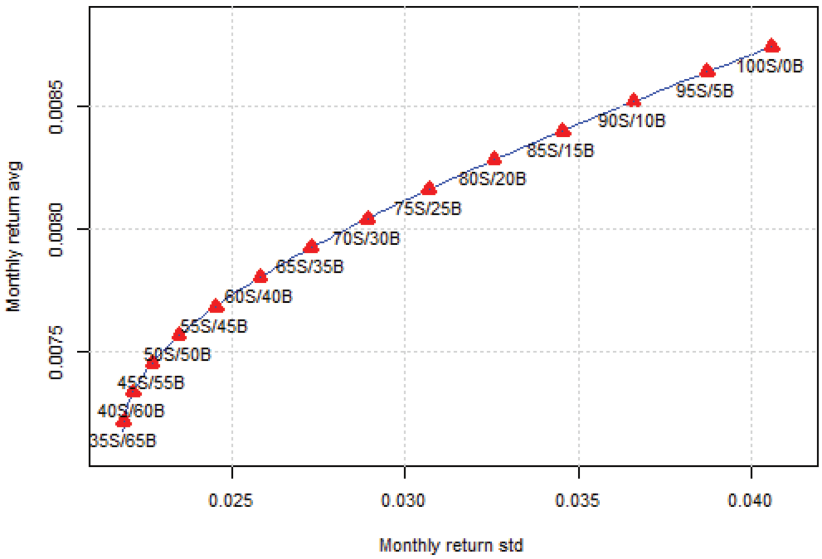

Fig. 2. The efficient frontier between stock (S) and bond (B).

Therefore, we can empirically estimate the risk preference as:

$$\theta^* = \rho^F(\mu^*, \sigma^*)/\sigma^* \tag{4}$$

Using the same reason, we then apply the derived preference (θ*) to construct a portfolio among stocks, bonds, and REITs.

3.3. Portfolio with REITs

An individual investor will not (or should not, for diversification reasons) exchange all his existing stock or bond allocation into REITs. It is more realistic to assume that he will only allocate a portion of assets into REITs. Mean-variance optimizations using expected returns on REITs and other assets during the 1980s indicate allocations to real estate of 10% to 15% (Ennis & Burik, 1991). Giliberto (1993), using a hedged REIT index, finds an optimal allocation to real estate of 19%. Therefore, we impose a 20% cap on the allocation to REITs and explore the efficient frontier from the combination among stocks, bonds, and REITs. In Fig. 3, we derive the risk preference θ* from the original benchmark portfolio and illustrate the new efficient frontier formed from the addition of REITs.

The benefit from the inclusion of REITs is evaluated as the change in the utility from the benchmark to the new portfolio.

$$\Delta \mathrm{U} = \mathrm{U}(\mu^{\mathrm{N}}, \sigma^{\mathrm{N}}) - \mathrm{U}(\mu^*, \sigma^*) \tag{5}$$

Note that the risk parameter $\theta = \theta^*$ in the utility function is estimated using Equation (4) above.

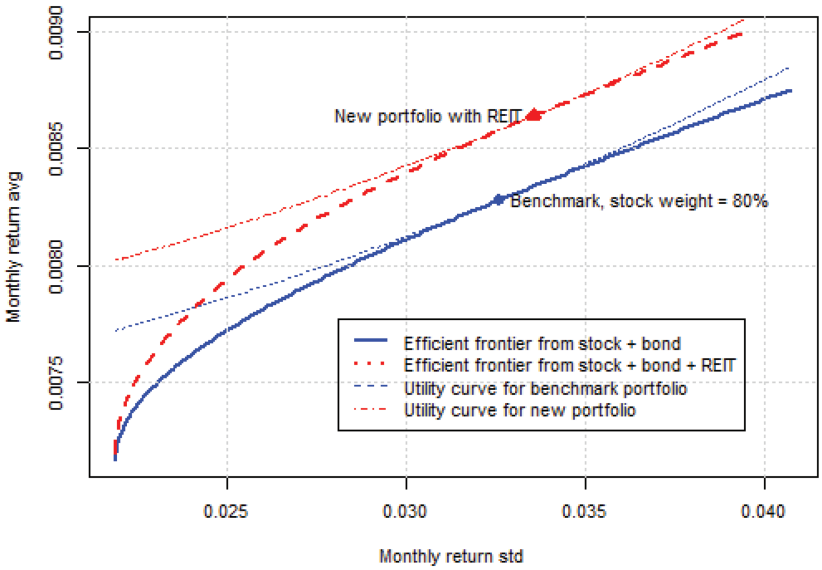

Fig. 3. Portfolio choice over efficient frontiers.

3.4. Including REITs over different benchmark portfolios

We further extend the analysis to allocations along the stock-bond efficient frontier. For each benchmark portfolio, we derive the risk preference (θ*). The new portfolio is constructed by adding REITs and maximizing the utility of the investor with preference θ*. Fig. 4 illustrates both the old benchmark allocations and new portfolios along the

Fig. 4. Including REITs over benchmark portfolios (REITs capped at 20%).

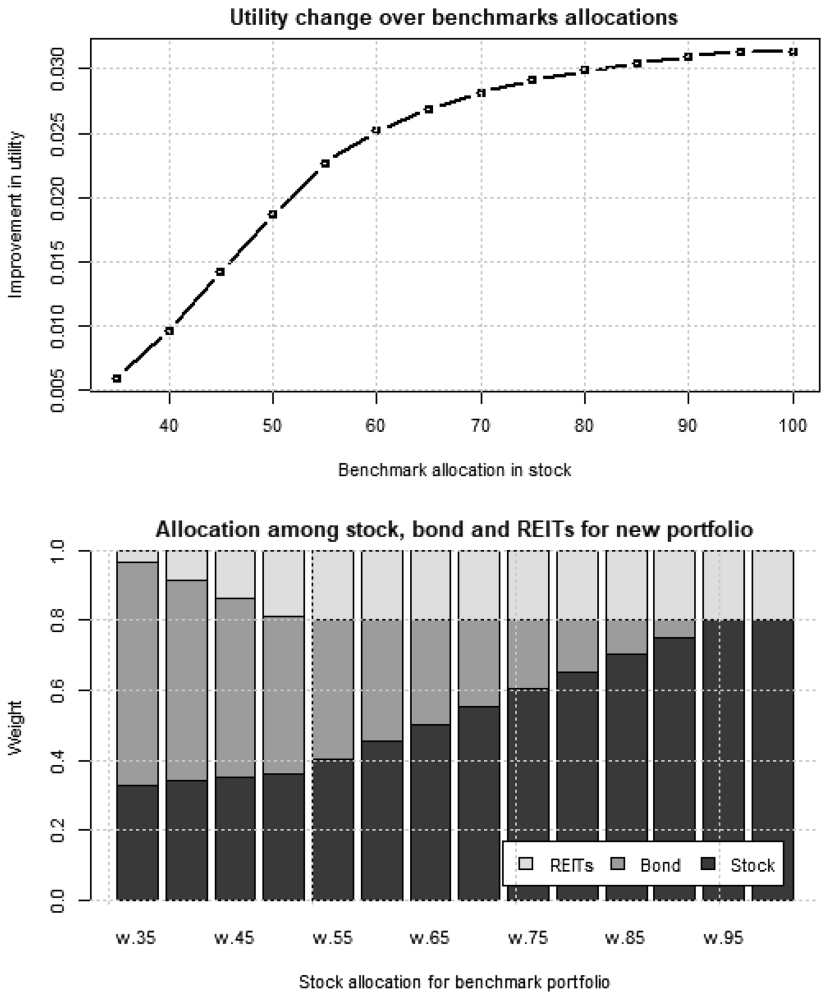

Fig. 5. Utility improvement for different risk preferences (REITs capped at 20%).

efficient frontier curves. Because we incorporate the risk preference in portfolio decision, the diversity in portfolio choices is vastly different from the result constructed using variance-minimization and Sharpe ratio maximization. The change in risk-return profiles and utility reflects the varying benefits of REITs over respective benchmark portfolios.

Fig. 5 plots the utility improvement over different benchmark allocations and the associated risk preferences (θ). Panel A shows a positive relationship between the weight allocated to stocks of the benchmark and improvement in the utility. This result suggests that investors with lower risk aversion (higher benchmark allocation in stocks or lower θ) will achieve more benefit from the inclusion of REITs. Panel B shows the allocation among stocks, bonds, and REITs in the newly formed portfolio. For the extreme case of investors with 35% benchmark stock weight, the new portfolio has a tiny (less than 5%)

allocation to REITs. On the contrary, the cases with over 55% benchmark stock weight reach the maximum cap (20%) for REITs. Thus, for any initial stock allocation of 55% or higher, a REIT allocation of 20% is beneficial. For any initial stock allocation of 40% to 50%, a REIT allocation of between 15% to 20% is helpful.

Table 2 shows the portfolio statistics from adding REITs to a spectrum of benchmark portfolios. The results suggest that while allocating to REITs, in general, improves the risk-return profile over traditional assets, investors with lower risk aversion tend to achieve more benefit. Table 2 also provides a guideline for the inclusion of REITs. An investor can look directly at Table 2, find the row with his current allocation between stock and bonds, and then read that row to the new weights with stocks, bonds, and REITs. For example, if the benchmark portfolio is a 60/40 stock-bond split, the investor would look to the 60% stock row, look right and see an appropriate new allocation given this initial allocation would be about 45% stocks, 35% bonds, and 20% REITs.

The benefit of adding REITs to a portfolio is inversely related to investor risk aversion. While the REITs have been noted as a safe alternative asset, highly risk-averse investors (higher θ or lower benchmark allocation in stocks) with less than 40% in benchmark stock allocation can only get minimum benefit from including REITs. Meanwhile, less risk-averse investors will receive more significant benefits from adding REITs. An investor with an initial stock allocation of 55% or more will experience an increase in utility with the REITs allocation quickly reaching the cap allocation of 20%. With 95% or more benchmark allocation to stocks (i.e., the least risk-averse investors), the new portfolio weights include a 20% allocation to REITs with no bonds allocation. Also, all benchmark stock allocations between 55% and 90% result in a new allocation of 20% in REITs with a reduction in benchmark stock allocation of about 15% and a decrease in the bond allocation of about 5%. Any benchmark stock allocation below 55% leads to a new portfolio weight in REITs of less than the cap of 20% and varying decreases in stock and bond allocations.

We also extend the analysis by raising the maximum REITs allocation from 20% to 50% and 80%. These tests generate similar conclusions.

4. Conclusion

This study examines how REITs could benefit a traditional investment approach that relies on allocation between stocks and bonds. We derive the investors' risk preferences from their existing allocations between stocks and bonds. The risk preferences are used in the portfolio choice of adding REITs. We compare the original portfolio with the new one to evaluate the benefit of REITs across investors with varying risk preferences. The results show that investors with lower risk aversion obtain more benefit from the inclusion of REIT into their traditional portfolio of stocks and bonds. This study highlights the role of risk preference in portfolio construction and provides an intuitive and practical approach to evaluate the value of other alternative assets.

Table 2 Portfolio statistics from including REITs (capped at 20%)

Benchmark portfolio			New portfolio		Risk parameter	New portfolio weight			Benchmark utility	New utility	Change in utility
wgt.stock	avg1	std1	avg2	std2	theta	Stock	Bond	REIT	tu1	tu2	tu.chg
35.00	0.00721	0.02190	0.00727	0.02190	50.70760	0.32839	0.63784	0.03377	−0.00495	−0.00489	0.00006
40.00	0.00733	0.02216	0.00749	0.02237	13.10380	0.33959	0.57287	0.08754	0.00411	0.00421	0.00010
45.00	0.00745	0.02272	0.00770	0.02334	7.52400	0.35034	0.51050	0.13916	0.00551	0.00565	0.00014
50.00	0.00756	0.02349	0.00790	0.02467	5.38420	0.36064	0.45074	0.18862	0.00608	0.00626	0.00019
55.00	0.00768	0.02455	0.00804	0.02584	4.12670	0.40244	0.39756	0.20000	0.00644	0.00666	0.00023
60.00	0.00780	0.02584	0.00817	0.02710	3.34540	0.45397	0.34603	0.20000	0.00669	0.00694	0.00025
65.00	0.00792	0.02731	0.00828	0.02844	2.81280	0.50183	0.29817	0.20000	0.00687	0.00714	0.00027
70.00	0.00804	0.02894	0.00840	0.03005	2.42660	0.55336	0.24664	0.20000	0.00702	0.00731	0.00028
75.00	0.00816	0.03070	0.00853	0.03181	2.13350	0.60490	0.19510	0.20000	0.00715	0.00745	0.00029
80.00	0.00828	0.03258	0.00864	0.03354	1.90370	0.65275	0.14725	0.20000	0.00727	0.00757	0.00030
85.00	0.00840	0.03455	0.00876	0.03551	1.71850	0.70429	0.09571	0.20000	0.00737	0.00768	0.00030
90.00	0.00852	0.03660	0.00888	0.03742	1.56620	0.75214	0.04786	0.20000	0.00747	0.00778	0.00031
95.00	0.00864	0.03872	0.00899	0.03939	1.43870	0.80000	0.00000	0.20000	0.00756	0.00787	0.00031
100.00	0.00874	0.04060	0.00899	0.03939	1.34380	0.80000	0.00000	0.20000	0.00763	0.00795	0.00031

Note: In Table 2, the benchmark portfolios are constructed between stock and bond at designated weight. The risk preferences of the investors are reflected by their choice of benchmark portfolios using the utility function $U = \mu - 0.5\theta\sigma^2$. The risk parameter ($\theta$) derived from the benchmark portfolios is extended to the construction of new portfolio constructed with stock, bond, and REITs. The utilities for both the existing benchmark and new portfolios are calculated for comparison.

Note

1 The S&P 500 included 31 REITs as of February 2020. See https://www.reit.com/data-research/reit-indexes/reits-sp-indexes for more information.

References

Anderson, R., & Springer, T. (2003). REIT selection and portfolio construction: Using operating efficiency as an indicator of performance. *Journal of Real Estate Portfolio Management*, *9*, 17-28.

Bhuyan, R., Kuhle, J., Ikromov, N., & Chiemeke, C. (2014). Optimal portfolio allocation among REITs, stocks, and long-term bonds: An empirical analysis of US financial markets. *Journal of Mathematical Finance*, *4*, 104-112.

Chen, H.-C., Ho, K.-Y., Lu, C., & Wu, C.-H. (2005). Real estate investment trusts. *The Journal of Portfolio Management*, *31*, 46-54.

Ennis, R. M., & Burik, P. (1991). Pension fund real estate investment under a simple equilibrium pricing model. *Financial Analysts Journal*, *47*, 20-30.

Giliberto, S. M. (1993). Measuring real estate returns: The Hedged REIT Index. *The Journal of Portfolio Management*, *19*, 94-99.

Glascock, J. L., Lu, C., & So, R. W. (2000). Further evidence on the integration of REIT, bond, and stock returns. *Journal of Real Estate Finance and Economics*, *20*, 177-194.

Hudson-Wilson, S., Gordon, J. N., Fabozzi, F. J., Anson, M. J. P., & Giliberto, S. (2005). Why real estate? *The Journal of Portfolio Management*, *31*, 12-21.

Singh, S. (2016). The evidence on target-date mutual funds. *Financial Services Review*, *25*, 235-262.

Spitzer, J. J., & Singh, S. (2008). Shortfall risk of target-date funds during retirement. *Financial Services Review*, *17*, 143-153.

TIAA. (2019). *A Lifecycle Fund Can Help Simplify Your Retirement Investing.* Available from https://www.tiaa.org/public/offer/insights/investing-101/lifecycle-funds-simplify-retirement-investing

Vanguard. (2019). *Vanguard Target Retirement Funds.* Available from https://investor.vanguard.com/mutual-funds/target-retirement/#/

Waggle, D., & Moon, G. (2006). Mean-variance analysis with REITs in mixed asset portfolios – The return interval and the time period used for the estimation of inputs. *Managerial Finance*, *32*, 955-968.

Waggle, D., & Agrrawal, P. (2006). The Stock-REIT relationship and optimal asset allocations. *Journal of Real Estate Portfolio Management*, *12*, 209-221.

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Financial, demographic, and psychological differences between chapter 13 bankruptcy filers and non-filers

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Abstract

This study finds financial, demographic, and psychological differences between Chapter 13 filers and non-filers. Financial training reduces the likelihood of filing for personal bankruptcy. Males are twice as likely as females to be filers. Blacks are twice as likely as Whites to be filers. A single person is 38% less likely to file than a married person. Homeowners are five times as likely as renters to be filers. Increases in education, religious commitment, and parents' income reduce the likelihood of filing. Increases in the psychological factors, self-efficacy, locus of control, and self-control, reduce the likelihood of filing for Chapter 13 bankruptcies. These results can be used to influence public policy to reduce personal bankruptcy. © 2021 Academy of Financial Services. All rights reserved.

JEL classification: D12; D14

Keywords: Chapter 13 bankruptcy filers; Non-filers; Demographic differences; Psychological differences; Financial literacy

I. Introduction

Personal bankruptcy occurs frequently and is a significant problem in the United States. Evans and Bauchet (2017) state that each year, hundreds of thousands of U.S. households choose to file for bankruptcy and accept the longer-term effects that bankruptcy has on their credit reputation over the challenges of dealing with collectors and/or creditors. According

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to the U.S. Courts, in 2019, there were 752,160 non-business bankruptcies (Chapters 7, 12, and 13) in the United States, with 281,702 (38%) classified as Chapter 13. During the same period, there were 13,092 non-business bankruptcies in North Carolina (state for this study), with 7,960 (61%) being classified as Chapter 13 (http://www.uscourts.gov/statistics-reports/caseload-statistics-data-tables).

Bankruptcy can occur because of mismanagement, lifestyle, consumption patterns, economic conditions, or unpredictable misfortunes such as unexpected medical expenses and layoffs. There are different ways to deal with insolvency, including reduction of spending, consolidation of loans, obtaining consumer credit counseling, surrendering of collateral, relocation to lower costs areas, and/or filing for bankruptcy. Filing for bankruptcy reduces financial stress and provides a financial lifeline.

Even though filing for bankruptcy is a lifeline, it is still a difficult and major financial decision with long-lived impact on a consumer's credit profile. The motivation for this study is to find out more about the factors that correlate with this major financial decision. Another motivation is the limited research done on the differences between Chapter 13 bankruptcy filers and non-filers. This study expands the literature in this area. We look for relationships between demographic, psychological, and financial variables and filing for bankruptcy. We have not seen psychological variables utilized in bankruptcy filings research. In addition, we include two variables not seen in the literature. They are parents' income, and parents' education, representing intergenerational relationships. This study uses data from Chapter 13 bankruptcy filers in North Carolina and compares them to people in the state who have not filed for bankruptcy. The results from this study can be used by institutions, like the U.S. Courts, to reduce the number of personal bankruptcies in the state of study or the country. For example, we find that males are twice as likely as females to be filers, so financial literacy intervention programs can be targeted more to males to reduce their likelihood of filing for bankruptcy.

2. Literature review

2.1. Theoretical foundation

Several theoretical models are used to explain personal financial behavior. Miller, Levin, Whitaker, and Xu (1998) discuss sequential and life events models that can be used to explain financial behavior. Samuelson (1937) develops the discounted utility model where future cash flows are discounted and utilized to make financial decisions. Efrat (1998) advocates for the adoption of a multiutility model that includes two distinct sources of utility that shape the individual's behavior—pleasure and morality.

The human ecological model explains financial decisions in the context of the ecological environment, which is separated into four systems (the microsystem - immediate family and friends, the mesosystem - immediate family and friends and other systems; the exosystem - groups and institutions influencing microsystem; and the macrosystem - inclusion of all systems) (Bronfrenbrenner, 1979). Deacon and Firebaugh (1988) use the human ecological

model and systems theory to provide a context for understanding the goal-directed behavior of families, using inputs, throughputs, and outputs. This sequential managerial process, outlined by Deacon and Firebaugh, is similar to the financial planning process recommended by the Certified Financial Planners Board of Standards (establish goals, gather data, analyze information, develop a plan, implement the plan, and monitor progress toward the goal; Schuchardt et al., 2007). Thaler and Shefrin (1981) develop the theory of self-control that can also explain financial behavior. This theory suggests that individuals have personality traits to be either a planner who is concerned with lifetime utility or a doer who is focused on the present. Later, Shefrin and Thaler (1988) proposed the behavioral life cycle hypothesis suggesting that individuals practice mental accounting, meaning that they have different propensities to save in different categories of accounts.

Schuchardt et al. (2007) provide the trans-theoretical model of behavior change (TTM) that can be used to explain financial behavior. The stages of change are precontemplation (no intention to change behavior), contemplation (aware of problem but not committed to changing behavior), preparation (intending to change within a month), action (changing the problem behavior by employing a variety of strategies), and maintenance (working to prevent relapse). Research has shown that successful self-changers use a variety of strategies to achieve their goal. In terms of filing for bankruptcy, the theory gives some structure of what a filer may be going through, from not wanting to file, contemplating to file, filing, receiving financial training (using strategies to change behavior), and hopefully not relapsing into a second filing.

We have reviewed the sequential model, the live event model, the discounted utility model, the human ecological model, the theory of self-control, and the trans-theoretical model of behavior change. These different models and theories can be used to explain financial behavior in general. We have not seen any theory that directly explains personal bankruptcy behavior.

2.3. Personal bankruptcy

2.3.1. Demographic and financial factors. Domowitz and Sartain (1999) find that medical and credit card debt are the strongest contributors to bankruptcy, with homeownership playing an important role with respect to both the decision to declare bankruptcy and the alternative choice of bankruptcy (e.g., debt consolidation). Chakravarty and Rhee (1999) find several factors affecting an individual's decision to file for bankruptcy. These factors include age of the head of household; past problems with money management; the gender of a single head of household; the (un)employment status of the household head; the length of employment of the household head; (bad) health; (the lack of) Medicare/Medicaid protection; household income; and the dollar benefit level of filing for bankruptcy. Clements, Johnson, Michelich, and Olinsky (1999) study 60 people who file for bankruptcy in Southern Ohio Federal District Bankruptcy Court. Their results reveal that the reason most often cited for filing is overuse of credit for clothing, household goods, paying bills, and cash advances. They find that most filers are embarrassed about their situation and have desires to learn about setting goals and about the difference between wants and needs.

Loibl, Hira, and Rupured (2006) study the difference between first-time versus repeat filers, using a sample of 489 participants from Georgia. Results indicate that repeat filers are more likely than first-time filers to start an emergency fund, to reduce spending, and to write a spending plan. Evans and Lown (2008) also study predictors of Chapter 13 completion rates. The completion of a Chapter 13 repayment plan is not associated with a debtor's monthly income or expenses. The factors, never married, having dependent children, having a previous filing, and having a higher mortgage arrears, increase the likelihood of dismissal from the program.

Caputo (2008) study marital status and other factors associated with personal bankruptcy using data from 1986 to 2004 from the National Longitudinal Survey. In 2004, those who are divorced are most likely to have declared bankruptcy (16.4%), followed by those who are separated (13.9%), married with spouse present (11.2%), and never-married (7.0%). Marital status is associated with likelihood of declaring bankruptcy in only six of the 14 survey years. Never-married persons at the time of declared bankruptcy are less likely than married persons to declare. Formerly married persons, whether divorced or separated, are more likely than married persons to declare for bankruptcy.

Beck, Hackney, Hackney, and McPherson (2014) find that religion is the driving force behind the abnormally high level of Chapter 13 filings in the southern United States. Lefgren and McIntyre (2009) look at cross-state differences in bankruptcy rates. Using zip-code level demographic research data, they find that the major differentiating factors include wage garnishment restrictions and the frequency of Chapter 13-style bankruptcy claims. Zhu (2011) studies household consumption and personal bankruptcy in Delaware using data from 2003. She finds that household expenditures on durable consumption goods, such as houses and automobiles, contribute significantly to personal bankruptcy filings. Also, medical conditions lead not only to personal bankruptcy filings, but to other adverse events, such as divorce and unemployment.

Williams, Kehiaian, and Bird (2017) find significant differences in financial actions between Chapter 13 bankruptcy filers and non-filers. Non-filers do the following significantly more often than filers: pay their bills on time; avoid living paycheck-to-paycheck; review their credit more frequently per year; pay more than the minimum on their credit card; save money to prepare for home ownership; track their expenses before budgeting; review their total financial situation; use cash for all purchases; evaluate their insurance needs; understand the true cost of credit; and have more knowledge of the components that make up their credit score.

Fisher (2019) finds that bankruptcy filers are middle income, more likely to be divorced, more likely to be Black, more likely to be veterans, less likely to be immigrants, and more likely to have only a high school degree or some college education. Filers are more likely to be employed. The bankruptcy population is aging faster than the U.S. population as a whole. Individuals are likely to get divorced in the years before bankruptcy and then remarry. He also finds that income falls before bankruptcy and rises after bankruptcy.

2.3.2. Psychological factors. Danes, Casas, and Boyce (1999) study the impact of a financial planning curriculum on self-efficacy and find a significant increase in confidence in managing money after taking the curriculum. Asaad (2015) finds that financial confidence is a critical component of financial literacy and financial behavior.

Perry and Morris (2005) find that locus of control impacts financial decisions. They find that consumers' propensity to save, budget, and control spending depends partly on their level of perceived control over financial outcomes. Miotto and Parente (2015) study the level of control in Brazilian households and find that different levels of control are linked to various levels of exercising discipline in their spending habits.

In summary, these studies have found several demographic, and financial variables related to bankruptcy. Research on psychological variables and bankruptcy are not seen in the literature.

3. Data and methodology

3.1. Data and sample selection

Primary data are collected in the Middle District of North Carolina (NC) and include the cities of Winston-Salem, Greensboro, and Durham. The sample has 559 participants, with 314 Chapter 13 filers and 245 non-filers. The sample of Chapter 13 filers is collected by one of the authors, who is an experienced trainer of Chapter 13 bankruptcy filers in North Carolina. He asks the filers to complete the financial literacy quiz and the questionnaire at the beginning of the training sessions. This is done voluntarily.

The data on filers are collected based on convenience sampling. However, we are confident that the data represent the filers adequately. We compare the sample with the population. In terms of race, our sample of filers and non-filers has 55% Whites and 40% Blacks. Winston-Salem has 56.3% Whites and 34.8% Blacks; Durham has 50.91% Whites, and 39.46% Blacks; and Greensboro has 57.03% Whites and 36.03% Blacks (https://www.census.gov/quickfacts/fact/table/). In terms of education, both filers and non-filers have high levels of education above high school (94.6%, and 97.6%, respectively) with the state having 88.2%. As important, the bankruptcy administration enrolls filers in the financial literacy workshops based on the day of their creditors' meetings. No other grouping criteria, like age, gender, or race, are used.

The data for the non-filers are also collected by the same author. He samples a wide cross section of participants from the same area. He uses an online survey created on Survey Monkey. The survey is advertised at various Cold Stone Creamery stores, and at Steals and Deals, an online advertising firm selling a wide assortment of goods and services, in the Middle District of North Carolina. This publication is distributed widely across the region studied. In addition, letters are sent to churches, and schools in the region. There are 142 non-filers who complete the survey online. The remaining non-filers include 34 from the First Pentecostal Church, 33 from the Cathedral of Faith, 20 from the Neighbor's Grove School, and 17 other individuals, all from the Middle District of NC. Those non-filers who complete the survey receive a $15 coupon for Cold Stone Creamery and a complimentary financial management class. The data for non-filers are collected across a wide base to replicate the population. For example, a wide cross-section of the population uses the Steals and Deals online advertising publication.

The data collected include two parts: a questionnaire and a financial literacy quiz. The questionnaire includes sections for demographic data, psychological data, and financial data. The variables in the questionnaire are measured using ordinal or categorical scales. A Likert scale (1 = *least* to 5 = *most*) is used for the ordinal variables. The financial literacy quiz includes 63 multiple choice questions on a wide range of personal finance topics. Some of the topics covered include financial goals, credit card usage, insurance, Rule of 72, insurance, and returns on investments. The questions are basic financial literacy questions. The score received on this quiz represents the level of personal finance knowledge. Both filers and non-filers take this quiz before the financial literacy class.

3.2. Dependent variable

The dependent variable is filer/non-filer. It is binary, with a filer coded as 1 and a non-filer coded as 0.

3.3. Independent variables

The independent variables include 17 demographic variables, 15 psychological variables, and 3 finance variables. These are listed below.

3.3.1. Demographic variables. The 17 demographic variables are: gender, age, highest level of education, race, total years of work experience, level of career, level of personal income, income potential, marital status, number of times married, number of children, number of children living at home, type of religion, level of religious commitment, primary residence (rent or own), parents' highest education level, and parents' highest income level.

3.3.2. Psychological variables. The 15 psychological variables are divided into four areas: self-efficacy (confidence in one's ability to perform), locus of control, motivation; and self-control. Self-efficacy includes three variables, general confidence level, financial confidence level, and education confidence level. Locus of control include seven variables. They are: I have had very little control over life; I have had many negative experiences with my household finances; I have very little control over my household finances; I have little control over my income level; I have no control over my savings; I have little control over my expenses; and, I believe the way I manage my money will affect my future. Motivation includes three variables. They are: I plan to take more financial education courses; I plan to substantially increase my income; and I plan to increase my net worth. Self-control includes two variables. They are: How important is immediate gratification to you? and How important is financial planning to you?

3.3.3. Financial variables. The financial variables are utilized as control variables. They are financial knowledge, financial training, and financial work experience.

3.4. Research hypotheses

We want to determine if there are significant differences between Chapter 13 filers and non-filers. To do this we analyze demographic, psychological, and financial factors.

The hypotheses are as follows:

Hypothesis 1: Demographic variables are related to filing for Chapter 13 bankruptcy.
Hypothesis 2: Psychological variables are related to filing for Chapter 13 bankruptcy.
Hypothesis 3: Financial variables are related to filing for Chapter 13 bankruptcy.

The demographic, psychological, and financial variables are stated above. This list of variables is reduced to account for correlation.

3.5. Empirical specifications

3.5.1 Correlation and endogeneity analyses. Correlation analysis is used to adjust the number of independent variables to address potential multicollinearity problems in the regression analysis. To test for endogeneity, we conduct a correlation analysis between the residuals from the binary logistic regression and the independent variables. No significant correlations imply no issues with endogeneity in the model.

3.5.2. Binary logistic regression. Binary logistic multiple regression is used to analyze the data. The dependent variable is a binary variable, representing filers and non-filers. The independent variables include the reduced number of demographic, psychological, and financial variables. The estimated regression coefficients for the independent variables are used to calculate the odds ratios, which are used to predict the likelihood of a person being a filer when there is a small change in each independent variable, holding all other variables constant. All analyses are done using the statistical software, SPSS 26.

4. Results

4.1. Descriptive results

4.1.1. Descriptive statistics for demographic variables. Descriptive statistics are presented for the demographic variables (Table 1). Filers are 43.3% males and 56.7% females, whereas non-filers are 29.3% males and 70.7% females. Eighty eight percentage of filers are 35 years or older, compared with 63.4% for non-filers. Filers are comprised of 51.9% Whites and 43.6% Blacks, whereas non-filers are comprised of 58.5% Whites and 35.8% Blacks. Whites and Blacks account for more than 90% of the sample of filers and non-filers. A high school education is the highest level of education achieved by 41.1% of filers compared with 18.7% of non-filers. Nineteen percentage of filers have financial education compared with 32.9% of non-filers. Those with 15 years or more of work experience account for 88.2% of filers compared with 67.1% for non-filers. For income, 22.6% of filers earn more than $45,000 per year compared with 35.8% of non-filers. Eighty-four percentage of filers are married compared with 65.0% of non-filers. Most filers (88.9%) have at least one child, compared with 71.5% of non-filers. Sixty percentage of filers have children living at home compared with 49.2% for non-filers. The three religious groups, Baptists, Nondenominational, and Protestants, make up more than 90% of both filers and non-filers. Eighty three percentage of filers are homeowners, compared with 59% of non-filers. Of all filers, 75% of them have parents with an education level of high school or less compared with 48.8% of non-filers. About 51.3% of filers have parents with income level of $30,000 or less per year compared with 34.5% of non-filers.

Table 1 Demographic characteristics for Chapter 13 filers and non-filers

Demographic and financial variables	Filers ($n = 314$) (percent)								Non-filers ($n = 246$) (percent)							
Codes	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
1. Gender (1 = male, 2 = female)	43.3	56.7							29.3	70.7						
2. Age (1 = 18 to 25, 2 = 26 to 35, 3 = 36 to 50, 4 = 51 to 60, and 5 = 61+)	1.3	11.1	47.5	27.1	13.1				19.1	17.1	32.1	19.9	11.4			
3. Highest level of education (1 = middle school graduate, 2 = high school graduate, 3 = some college, 4 = community college graduate, 5 = four year college graduate, 6 = masters level graduate, and 7 = doctorate level graduate)	5.4	35.7	29.3	13.7	11.5	3.5	1.0		2.4	16.3	31.3	13.4	22.4	11.8	2.4	
4. Race (1 = White, 2 = Black, 3 = Hispanic, 4 = Asian, and 5 = Other)	51.9	43.6	2.5	0.3	1.3				58.5	35.8	0.8	1.2	3.7			
5. Total years of work experience (1 = 0–3, 2 = 4–6, 3 = 7–10, 4 = 11–15, 5 =16–25, and 6 = 26+)	3.2	2.5	6.1	20.4	23.2	44.6			11.4	8.9	11.4	14.6	17.1	35.4		
6. Level of career (1 = entry level, 2 = experienced worker, 3 = supervisor level, 4 = manager level, and 5 = executive level)	10.8	51.6	20.1	15.0	2.5				16.7	50.0	13.0	14.2	6.1			
7. Level of personal income (1 = <$20k, 2 = $21–$30k, 3 = $31–$45k, 4 = $46–$75k, 5 = $76–$150k, 6 = >$150k)	19.7	24.8	32.8	18.5	3.5	0.6			26.0	19.1	28.0	15.4	10.2	1.2		
8. Income potential (1 = high, 2 = medium, 3 = low, 4 = none, and 5 = retired)	7.3	35.7	36.0	13.7	7.3				13.8	38.6	32.1	8.1	7.3			
9. Marital status (1 = married, 2 = partner, 3 = single, 4 = divorced, 5 = widowed, 6 = separated)	65.6	18.2	11.8	1.0	2.5	1.0			52.8	12.2	30.9	2.0	1.2	0.8		
10. How many times have you been married (1 = once, 2 = twice, 3 = three times, 4 = never)	57.6	25.5	5.4	11.5					47.2	18.3	4.1	28.9				
11. Number of children (1 = none, 2 = 1, 3 = 2, 4 = 3, 5 = 4, and 6 = 5+)	11.1	22.3	36.3	14.3	9.6	6.4			28.5	19.1	24.8	15.0	7.3	5.3		

Table 1 (Continued)

Demographic and financial variables	Filers ($n = 314$) (percent)								Non-filers ($n = 246$) (percent)							
Codes	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
Demographic variables:																
12. Number of children living at home (1 = none, 2 = 1, 3 = 2, 4 = 3, 5 = 4, and 6 = 5+)	40.4	30.6	19.1	6.1	3.8				50.8	24.0	16.3	6.5	1.2	1.2		
13. Type of religion (1 = Protestant, 2 = Catholic, 3 = Mormon, 4 = Friends, 5 = Baptist, 6 = non-denomination, 7 = Methodist, 8 = Muslim, Jewish, Lutheran, Buddhist, and don't believe	9.2	2.5	0.3	0.3	54.5	27.4	1.6	4.0	16.7	4.9	0.4	3.3	23.2	47.6	1.2	3.7
14. Level of religious commitment (1 = none, 2 = low, 3 = somewhat, and 4 = high)	7.0	20.4	29.9	42.7					5.3	13.8	25.2	55.7				
15. Primary residence (1 = own, and 2 = rent)	83.4	16.5							58.5	41.5						
16. Parents' highest education level (1 = none, 2 = middle school grad, 3 = high school grad, 4 = some college no degree, 5 = community college graduate, 6 = four year college graduate, 7 = masters level graduate, and 8 = doctorate level graduate)	5.7	19.4	49.7	10.8	5.1	6.4	2.5		0.4	12.6	35.8	19.9	8.5	13.0	8.5	1.2
17. Parents' highest income level (1 = <$20k, 2 = $21–$30k, 3= $31–$45k, 4 = $46 – $75k, 5 = $76–$100k, 6 = $100–$150, and 7 = >$150k)	19.1	32.2	22.0	14.3	8.3	2.9	1.3		13.4	21.1	21.5	18.3	13.8	6.5	4.9	0.4
Financial variables:																
1. Financial training (yes = 1, no = 2)	18.8	81.2							32.9	66.7						
2. Financial work experience (yes = 1, no = 2)	11.1	88.9							22.8	77.2						
3. Financial knowledge (total = 63)	40.49								42.37							

Note: This table provides the frequency distribution in percentage of demographic characteristics for Chapter 13 filers and non-filers. All data are measured using a Likert scale.

4.1.2. Descriptive statistics for finance variables. For financial training, 18.8% of filers have financial training compared with 32.9% of non-filers. For financial work experience, 11.1% of filers have financial work experience compared with 22.8% of non-filers. For financial knowledge, of the 63 questions, the mean financial literacy quiz scores for the Chapter 13 filers and non-filers are 40.49 and 42.37, respectively.

4.1.3. Descriptive statistics for psychological characteristics. The descriptive statistics for the psychological characteristics are presented below. The percentage representing "High" or "Agree" is the percentages of responses that are coded as 4 s and 5 s from the data for each variable. For self-efficacy, filers generally have lower levels of confidence than non-filers (Table 2). Of all filers, 53.5% of them have a high level of general confidence level compared with 63.9% of non-filers. (Table 2). Corresponding statistics for financial confidence and education confidence are (20% of filers, and 29.1% of non-filers), and (46% of filers and 60.1% of non-filers), respectively. Fo*r* locus of control, non-filers seem to have higher levels of control than do filers (Table 2). For "I have had very little control over life," 28.4% of filers agree compared with 23.2% of non-filers. For "I have had many negative experiences with my household finances," 35.1% of filers agree compared with 25.6% of non-filers. For motivation, the variable, "I plan on substantially increasing my income," 46.8% of filers agree compared with 50.4% of non-filers. For "I plan to increase my net worth," 60.2% of filers agree compared with 72.4% of non-filers. For self-control, the variable, "How important is immediate gratification to you?"; 35.7% of filers strongly agree versus 26.4% of non-filers. For commitment, about 43% of filers have high levels of commitment compared with 55.7 for non-filers.

4.3. Logistic regression results

4.3.1. Correlation results. Because of high correlations ($\rho > 0.300$), a reduced set of demographic, psychological, and financial variables are included in the regression analysis. The nine demographic variables included are gender, education, years of work, religious commitment, religious faith, home ownership, parents' income, race, and marital status. The five psychological variables included are: financial confidence for self-efficacy; control over life, negative experience with finances, and money management affecting my future for locus of control; taking financial education in the future for motivation; and importance of immediate gratification for self-control. The three financial variables included are finance knowledge, finance training, and importance of financial planning.

4.3.2. Endogeneity testing results. A correlation analysis is done between the residuals from the logistic regression estimation and each of the independent variables and no significant correlation is found. This implies that endogeneity is not an issue with the logistic regression model.

4.3.3. Binary logistic regression results for demographic variables. For gender, the odds of a male filing for bankruptcy is 2.075 times the odds for a female filing (Odds Ratio [OR] = 2.075, p-value = 0.004; Table 3). For race, the odds ratio for a Black person to file for bankruptcy is 2.264 times the odds of other races (primarily Whites) filing (OR = 2.264, p-value = 0.003). For marital status, a single person filing for bankruptcy is 0.377 times the odds of a married person filing for bankruptcy (OR = 0.377, p-value = 0.002). For education,

Table 2 Psychological characteristics for Chapter 13 filers and non-filers

Psychological characteristics	Filers (n = 314) (percent)					Non-filers (n = 246) (percent)				
Codes	1 = Least	2	3	4	5 = Most	1 = Least	2	3	4	5 = Most
1. Self-efficacy:										
a. General confidence level	5.4	8.6	32.5	32.5	21.0	4.5	4.9	26.8	40.7	23.2
b. Financial confidence level	13.7	22.3	45.5	14.0	4.5	14.2	18.3	38.2	21.1	8.1
c. Education confidence level	3.8	8.9	41.1	31.5	14.6	1.6	7.3	30.9	39.8	20.3
2. Locus of control:										
a. I have had very little control over life	17.5	18.5	35.7	16.9	11.5	29.7	23.6	23.6	17.1	6.1
b. I have had many negative experiences with my household finances	8.0	20.4	36.6	16.9	18.2	20.7	26.8	26.8	14.2	11.4
c. I have very little control over my household finances	15.9	26.8	36.9	13.4	7.0	33.7	24.4	23.2	10.2	8.5
d. I have very little control over my income level	13.1	24.2	37.9	14.3	10.5	27.2	27.2	28.5	11.0	6.1
e. I have no control over my savings	20.7	25.5	35.0	8.9	9.9	43.5	24.0	17.9	9.3	5.3
f. I have little control over my expenses	18.5	22.0	39.5	12.4	7.6	40.7	24.4	18.3	9.8	6.9
g. I believe the way I manage my money will affect my future	6.1	6.4	19.1	20.4	48.1	5.7	6.5	15.4	24.4	48.0
3. Motivation:										
a. I plan to take more financial education courses	16.6	14.6	31.2	17.2	20.4	16.7	20.3	26.4	19.9	16.7
b. I plan on substantially increasing my income	11.1	14.6	27.4	23.2	23.6	7.3	13.4	28.9	20.7	29.7
c. I plan to increase my net worth	7.6	9.2	22.9	30.3	29.9	4.9	9.8	24.0	26.0	35.4
4. Self-control:										
a. How important is immediate gratification to you?	12.1	52.2	28.7	7.0		21.1	52.4	18.7	7.7	
b. How important is financial planning to you?	2.2	28.0	53.8	15.9		2.0	33.3	41.5	23.2	

Note: This table provides the frequency distribution in percentage of psychological characteristics for Chapter 13 filers and non-filers. All data are measured using a Likert scale.

Table 3 Binary logistic regression results for demographic differences between filers and non-filers

	Demographic characteristics	*B*	SE	Sig.	Exp(B)
Demographic variables:					
1.	Gender (female = 0, male = 1)	0.730	0.253	0.004	2.075**
2.	Education	−0.247	0.090	0.006	0.781**
3.	Years of work	0.280	0.080	0.000	1.323***
4.	Level of religious commitment (1 = none, 2 = low, 3 = somewhat, and 4 = high)	−0.306	0.132	0.021	0.737**
5.	Primary residence (0 = own, and 1 = rent)	1.602	0.270	0.000	4.963***
6.	Parents' highest income level (1 = <$20k, 2 = $21–$30k, 3 = $31–$45k, 4 = $46–$75k, 5 = $76–$100k, 6 = $100–$150, and 7 = >$150k)	−0.140	0.078	0.072	0.869*
7.	Race (White = 0, (benchmark))			0.013**	
	Race (Black = 1, Whites and other races = 0)	0.817	0.278	0.003	2.264**
	Race (other races = 1, Whites and Blacks = 0)	0.592	0.538	0.270	1.808
8.	Marital status (married = 0, benchmark))			0.017**	
	Marital status (1 = partners, 0 = all other categories)	0.069	0.312	0.826	1.071
	Marital status (1 = single, 0 = all other categories)	−0.976	0.323	0.002	0.377**
	Marital status (1 = other, 0 = all other categories)	−0.151	0.535	0.778	0.860
9.	Religion (Baptist = 0, (benchmark))			0.000***	
	Religion (non-denominational faiths = 1, all other categories = 0)	−1.389	0.266	0.000	0.249***
	Religion (Protestants = 1, all other categories = 0)	−1.826	0.378	0.000	0.161***
	Religion (Catholic = 1, all other categories = 0)	−0.753	0.581	0.195	0.471
	Religion (other = 1, all other categories = 0)	−1.303	0.466	0.005	0.272**

Table 3 (Continued)

Psychological and financial characteristics:	*B*	SE	Sig.	Exp(B)
Psychological variables:				
1. Self-efficacy				
a. Financial confidence level	−0.239	0.113	0.033	0.787**
2. Locus of control:				
a. I have had very little control over life	0.030	0.095	0.752	1.031
b. I have had many negative experiences with my household finances	0.333	0.099	0.001	1.395**
c. I believe the way I manage my money will affect my future	−0.027	0.100	0.784	0.973
3. Motivation:				
a. I plan to take more financial education courses	0.124	0.092	0.179	1.132
4. Immediate gratification:				
a. Importance of immediate gratification	0.384	0.153	0.012	1.468**
Control variables (financial variables):				
a. Finance training (no = 0, yes = 1)	−0.668	0.267	0.013	0.513**
b. Importance of financial planning	0.033	0.166	0.840	1.034
c. Financial literacy quiz	−0.002	0.018	0.896	0.998

Note: This table provides the results for the differences between Chapter 13 filers and non-filers for sub-categories of psychological characteristics. Each sub-category for the psychological variables has several variables. All data are measures using a Likert scale. Binary logistic regression testing (filers = 1, non-filers = 0 for the dependent variable) is used to test the difference between the two groups. All psychological, demographic and financial variables are the independent variables. For sub-category, self-efficacy, financial confidence is significant. For locus of control, having many negative experiences with finances is significant. For the sub-category, motivation, there are no significant differences. Immediate gratification is significant. The control variable, finance training, is significant. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

the odds of a person whose education goes up by one level to file for bankruptcy is 0.781 times the odds for a person whose education has not changed (OR = 0.781, *p*-value = 0.006). For years of work, a one-year increase in years of work increases the odds of being a filer by 1.323 times (OR = 1.323, *p*-value = 0.000). For homeownership, the odds of a homeowner to file for bankruptcy are 4.963 times higher than the odds of a nonhomeowner to file (OR = 4.963, *p*-value = 0.000). This is a highly significant result. For parents' income, an increase by one level, the odds for the son or daughter to file for bankruptcy is 0.869 times the odds if the parents' income does not increase (OR = 0.869, *p*-value = 0.072). This intergenerational relationship that is not seen in the literature. For religious commitment, if a person's religious commitment increases by one level, the odds of that person filing for bankruptcy is 0.737 times the odds of filing for bankruptcy with no increase (OR = 0.737, *p*-value = 0.021). The odds of a person from a Protestant faith to file for bankruptcy is 0.161 times the odds of filing by the other faiths studied (OR = 0.161, *p*-value = 0.000). The odds of a person from a nondenominational faith filing is 0.249 times the odds of a person from another faith filing (OR = 0.249, *p*-value = 0.000). These results for different faiths impacting bankruptcy filing are not seen in the literature.

4.3.4. Logistic regression results for psychological variables. For self-efficacy, the odds that a person with an increase in financial confidence filing is 0.787 times the odds before the increase (OR = 0.787, *p*-value = 0.033; Table 5). For locus of control, the odds of a person who has an increase in negative experiences with his household finances filing is 1.395 times the odds of that person filing before the increase in negative experiences (OR = 1.395, *p*-value = 0.001). For self-control, the odds of a person with an increase in the importance of immediate gratification filing is 1.5 times the odds for that person before the increase (OR =1.468, *p*-value = 0.012). Motivation is not significant.

4.3.5. Logistic regression results for financial variables. The odds of a person who receives financial training to be a filer is 0.513 times the odds of someone who does not receive financial training (OR = 0.513, *p*-value = 0.013).

5. Discussion

This study compares Chapter 13 bankruptcy filers and non-filers using demographic, psychological, and financial variables. The significant demographic variables are gender, education, religious faiths, religious commitment, racial group, homeownership, parent's income, and marital status. The significant psychological variables are self-efficacy, locus of control, and self-interest. The significant financial variable is financial training.

5.1. Demographics

For gender, we find that males are twice as likely as females to file for bankruptcy. Chakravarty and Rhee (1999) find that the gender of a single head of household appears to be an important predictor of bankruptcy filing. For education, we find that increasing education is likely to reduce the odds of filing for bankruptcy. Fisher (2019) finds that people with lower education are more likely to file for bankruptcy. For years of work, we find that an

increase in years of work is likely to increase the odds of filing for bankruptcy. We have not seen this result in the literature for personal bankruptcy. By having more years of work, a person's income usually increases. This can trigger the accumulation of more debt, which can lead to filing for bankruptcy.

We find that homeowners are five times more likely to be filers than renters. This is a highly significant result. Home ownership puts a heavy financial strain on a homeowner and, if he or she were to have a loss of employment or a major medical occurrence, the likelihood of filing for bankruptcy increases sharply. Also, the Chapter 13 Bankruptcy Law is structured such that, a person can keep the home while implementing a restructured debt repayment plan. This benefit from home ownership increases the likelihood to file for Chapter 13 bankruptcy. Domowitz and Sartain (1999) and Zhu (2011) find that homeownership impacts the decision to file for bankruptcy.

For racial groups, Blacks are twice as likely to file for bankruptcy than Whites. This is a highly significant result. Fisher (2019) finds that Blacks and other minority groups are more likely to file for bankruptcy. For parents' income, an increase in the parents' income reduces the likelihood of the son or daughter to file for bankruptcy. We have not seen this result in the literature. There is a high correlation between a parent's income and education. These two factors show an intergenerational positive financial effect of reducing the odds of filing for Chapter 13 bankruptcy by a son or daughter. For marital status, singles are significantly less likely to be filers than married people. This is a reasonable result as married people generally have more debt (including a mortgage), more children, and more children living at home. Caputo (2008) finds that single people, at the time of declared bankruptcy, are less likely than married persons to declare bankruptcy.

We find than an increase in religious commitment reduces the likelihood of filing for bankruptcy. Increased religious commitment can instill principles of discipline, moderation and caring, which can lead to better money management and less filing for bankruptcy. Nondenominational and Protestant faiths are less likely to file for bankruptcy than other faiths. According to The Economist (02/2018), Protestants embrace the notion that diligence and self-improvement are pleasing to God. They tend to be more disciplined with their money management, which leads to less filing for bankruptcy. This supports our finding that Protestants are less likely to file for bankruptcy than other faiths. Khan (2010) studies faith and finance and finds that religion has a strong impact on economic behavior. Beck et al. (2014) find that religion is a driving force behind the abnormally higher Chapter 13 filings compared with Chapter 7 filings in the southern United States. There is a high concentration of Evangelicals and Fundamentalists in the southern United States. People of these faiths prefer to file for Chapter 13 bankruptcy because they feel that it is their moral obligation to honor their debt commitments with a new repayment plan rather than to pass them on to creditors and society at large.

5.2. Psychological factors

For self-efficacy (belief that one can accomplish a goal), we find that those with more financial confidence are less likely to be filers. Danes, Casas and Boyce (1999) and Asaad

(2015) find that financial confidence is a critical component of financial behavior. An increase in financial confidence is likely from more financial literacy education. This will likely lead to fewer personal bankruptcies. For locus of control, an increase in negative experiences with household finances increases the odds of filing for bankruptcy. Perry and Morris (2005) and Miotto and Parente (2015) also find that locus of control impacts financial decisions. Our study takes it further by showing the relationship between locus of control and the financial decision of filing for bankruptcy. For self-control, we find that an increase in the importance of immediate gratification (implying less self-control) increases the odds of filing for bankruptcy. This result is not seen in the literature. Miotto and Parente (2015) find that more self-control does lead to more savings and less financial defaults. This is a reasonable result as a person with high immediate gratification needs will spend more on satisfying these needs and pay less attention to good budgeting practices and future needs.

5.3. Financial factors

We find that financial training reduces the likelihood of filing for bankruptcy by about 50%. This result shows the importance of financial training to reduce Chapter 13 bankruptcy filing. Again, we have not seen this result in the bankruptcy filings literature. Collins (2010) study financial literacy of lower income families and find that financial education increases long-term savings and long-term credit scores. Our results show the importance of financial literacy to address the bankruptcy problem in the United States.

6. Conclusion

Filing for bankruptcy is not an easy decision, yet thousands file each year to reduce the debt pressure in their lives. We find several demographic, psychological and financial differences between filers versus non-filers of Chapter 13 bankruptcy. The significant demographic variables are gender, education, religious faiths, religious commitment, Blacks, homeownership, parent's income, and marital status. The significant psychological variables are self-efficacy, locus of control, and self-control. The significant financial variable is financial training. The variables not seen in the literature are the demographic variable, parents' income, the psychological variables, self-efficacy, locus of control and self-control, and the financial variable, financial training.

There are several implications from this study. We find a negative relationship between financial literacy and filing for bankruptcy. This implies that an increase in financial literacy is likely to reduce personal bankruptcy. We recommend that government (local, state, and federal), educational institutions, and lending institutions, especially for home purchases, provide more financial literacy education to address the personal bankruptcy situation in the society. Ongoing financial literacy education, particularly for adults, may be more effective. We find that males are twice as likely as females to be filers. We recommend targeting more males with financial literacy training to reduce bankruptcy. We find that Blacks are more likely to be filers than Whites. We recommend that more financial literacy education be offered to

Blacks to reduce bankruptcy filings. We find that an increase in education reduces the odds of filing for bankruptcy. Reduced bankruptcy is another benefit from more education. We also find that an increase in religious commitment reduces the odds of filing for bankruptcy. Hence, the encouragement to increase one's religious commitment is recommended. Religious leaders may be able to promote this finding. We also find that increases in parents' income (and education) reduce the likelihood of a son or daughter filing for bankruptcy. Information on the parents' education or income may help in the risk assessment for bankruptcy for a son or daughter applying for a mortgage or other big financial commitment. That is, lending institution can ask the question, "What do your parents do for a living?" We find that a homeowner is five times more likely to file for bankruptcy than a nonhome owner. We recommend that homeowners create a bigger financial cushion for emergencies than non-homeowners. We also recommend that homeowners take more financial literacy training, especially budgeting. These actions will reduce the likelihood of filing for bankruptcy. These actions are also relevant for married people as they are more likely to file for bankruptcy than single people.

There are also implications from the psychological results. We find that an increase in a person's financial confidence reduces the odds of filing for bankruptcy. We also find that an increase in negative experiences with household finances increases the odds of filing for bankruptcy. One recommendation to address these two findings is to increase financial literacy education. With more financial knowledge, one should become more financially confident and should have fewer negative financial experiences. This should reduce personal bankruptcies. We find that filers have higher levels of immediate gratification (less self-control) compared with non-filers. We recommend financial discipline training, especially budgeting, to alleviate the situation.

A limitation of this study is that the data are taken from the Middle District of North Carolina and hence the results may not be applicable elsewhere The results may be acceptable for places with high percentage of Whites and Blacks. Caution is required to apply the results to other states like Florida, New York, and California, where the population has a different mix of racial groups, including higher percentages of Latinos, Italians, Caribbean Blacks, African Blacks, and/or Asians. Also, we do not have the data of a few other variables that could expand to the model. These could include debt, wealth, principal balance on mortgage, and health status. Further studies can be done by looking at these demographic, psychological, and financial variables in other communities across the country or abroad. This will add more robustness to the results found in the few studies done on bankruptcy filing. In the present economic environment with unprecedented unemployment and loss of income resulting from the coronavirus pandemic, more research on personal bankruptcy is recommended.

References

Asaad, C. T. (2015). Financial literacy and financial behavior: Assessing knowledge and confidence. *Financial Services Review*, *24*, 101.

Beck, J. H., Hackney, D. D., Hackney, J., & McPherson, M. Q. (2014). Regional differences in Chapter 13 filings: Southern legal culture or religion? *Review of Social Economy*, *72*, 186-208.

Bronfrenbrenner, U. (1979). Purpose and Perspectives and Basic Concepts. *The Ecology of Human Development* (pp. 3-28). Cambridge, MA: Harvard University Press.

Caputo, R. K. (2008). Marital status and other correlates of personal bankruptcy, 1986–2004. *Marriage & Family Review*, *44*, 5-32.

Chakravarty, S., & Rhee, E. Y. (1999). *Factors Affecting An Individual's Bankruptcy Filing Decision.* Available at SSRN 164351. https://dx.doi.org/10.2139/ssrn.164351

Clements, J., Johnson, D., Michelich, K., & Olinsky, C. F. (1999). Characteristics of bankruptcy filers: Implications for educators. *Journal of Family and Consumer Sciences*, *91*, 71.

Collins, J. M. (2010). Effects of mandatory financial education on low-income clients. *Focus*, *27*, 13-18.

Danes, S. M., Huddleston-Casas, C., & Boyce, L. (1999). Financial planning curriculum for teens: Impact evaluation. *Journal of Financial Counseling and Planning*, *10*, 26.

Deacon, R. E., & Firebaugh, F. M. (1988). *Family Resource Management: Principles and Applications* (2nd ed.). Boston, MA: Allyn and Bacon

Domowitz, I., & Sartain, R. L. (1999). Determinants of the consumer bankruptcy decision. *The Journal of Finance*, *54*, 403-420.

Efrat, R. (1998). The moral appeal of personal bankruptcy. *Whittier Law Review*, *20*, 141-170.

Evans, D., & Bauchet, J. (2017). Bankruptcy determinants among US households during the peak of the great recession. *Consumer Interests Annual*, *63*, 1-7.

Evans, D. A., & Lown, J. M. (2008). Predictors of Chapter 13 completion rates: The role of socioeconomic variables and consumer debt type. *Journal of Family and Economic Issues*, *29*, 202-218.

Fisher, J. D. (2019). Who files for personal bankruptcy in the United States? *Journal of Consumer Affairs*, *53*, 2003-2026. Available at https://www.census.gov/quickfacts/fact/table/; https://www.economist.com/finance-and-economics/2018/02/22/protestantism-might-be-good-for-the-wallet-after-all; http://www.uscourts.gov/statistics-reports/caseload-statistics-data-tables

Khan, A. K. (2010). Essays on faith and finance (unpublished doctoral dissertation). Harvard Business School, Boston, MA.

Lefgren, L., & McIntyre, F. (2009). Explaining the puzzle of cross-state differences in bankruptcy rates. *The Journal of Law and Economics*, *52*, 367-393.

Loibl, C., Hira, T. K., & Rupured, M. (2006). First time versus repeat filers: The likelihood of completing a Chapter 13 bankruptcy repayment plan. *Journal of Financial Counseling and Planning*, *17*, 23-33.

Miller, K. S., Levin, M. L., Whitaker, D. J., & Xu, X. (1998). Patterns of condom use among adolescents: The impact of mother-adolescent communication. *American Journal of Public Health*, *88*, 1542-1544.

Miotto, A., Paula, S. C., & Parente, J. (2015). Antecedents and consequences of household financial management in Brazilian lower-middle-class. *Revista de Administração de Empresas*, *55*, 50-64.

Perry, V. G., & Morris, M. D. (2005). Who is in control? The role of self-perception, knowledge, and income in explaining consumer financial behavior. *Journal of Consumer Affairs*, *39*, 299-313.

Samuelson, P. A. (1937). A note on measurement of utility. *The Review of Economic Studies*, *4*, 155-161.

Schuchardt, J., Durband, D., Bailey, W. C., DeVaney, S. A., Grable, J. E., Leech, I. E., . . . Xiao, J. J. (2007). Personal finance: An interdisciplinary profession. *Journal of Financial Counseling and Planning*, *18*, 1-9.

Shefrin, H. M., & Thaler, R. H. (1988). The behavioral life-cycle hypothesis. *Economic Inquiry*, *26*, 609-643.

Thaler, R. H., & Shefrin, H. M. (1981). An economic theory of self-control. *Journal of Political Economy*, *89*, 392-406.

Williams, A. A., Kehiaian, S. E., & Bird, C. L. (2017). Differences in financial actions between Chapter 13 bankruptcy filers and non-filers. *The Journal of Applied Business and Economics*, *19*, 136-155.

Zhu, N. (2011). Household consumption and personal bankruptcy. *The Journal of Legal Studies*, *40*, 1-37.

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    a. obtain higher risk-return benefits from adding REITs
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    c. obtain no risk-return benefits from adding REITs
    d. obtain equal risk-return benefits from adding REITs, compared to fixed income

2. In Feng, Jones, & Allen, what benefit do REITs provide individual investors?
    a. ability to purchase mortgage insurance in the public market
    b. ease of investing in real estate using publicly traded shares
    c. ease of locking in real estate prices using publicly traded shares
    d. ability to competitively purchase specific real estate in the public market

3. Feng, Jones, & Allen use ____ to examine portfolio decisions regarding REITs.
    a. risk measures, such as VIX
    b. risk of the S&P 500
    c. risk-neutral probabilities
    d. risk preferences

4. In "Financial, Demographic and Psychological Differences between Chapter 13 Bankruptcy Fil and Non-Filers," by Kehiaian, Williams, and Bi the following psychological variables are found be significantly different for filers and non-filers <u>except</u>:
    a. Self-efficacy
    b. Self-control
    c. Motivation
    d. Locus of control

5. Kehiaian, Williams, and Bird, found that for Chapter 13 bankruptcy filers,
    a. males and females file equally.
    b. Blacks are less likely to file than White
    c. Homeowners are less likely to file than renters.
    d. single people are less likely to file than married people

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