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Using behavioral prompts to improve saving and investment decisions

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Abstract

The objective of this research is to enhance understanding of the behavioral biases that may adversely impact younger generations' retirement savings decisions and financial outcomes. Previous research suggests that differences in overconfidence, financial literacy, risk preferences, and present bias all impact saving and investment decisions. In an incentivized laboratory experiment, we study participants' investment and asset allocation decisions over a meaningful time horizon and test the efficacy of alternative behavioral prompts to motivate saving decisions. We find that individual risk tolerance and discount rates each have a persistent and significant impact on saving and investment decisions. Financial literacy is a third important driver of investment decisions. Higher levels of financial literacy, higher levels of risk tolerance, and lower discount rates increase the rate of saving and expected return. Controlling for these factors, we find that behavioral prompts encouraging reflection on goals and future needs have significant effects on allocation decisions and expected returns. We also find that the prompts increase expected returns for women and individuals with lower levels of financial literacy.

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Introduction

The objective of this research is to enhance understanding of the behavioral biases that may adversely affect saving and investment decisions and financial outcomes for today's younger generations. Previous research suggests that differences in overconfidence, financial literacy, risk preferences, and present bias all impact saving and investment decisions. Although the importance of motivating people to plan and save for retirement is not unique to one generation, each generation has grown up in different economic, demographic, and political environments, and these unique differences may cause them to make decisions differently or to be influenced by different behavioral biases. Thus, retirement plan design and choice architecture may need to address these differences to be most effective. Changes in the retirement landscape make it increasingly important for people to be consistent investors over their working careers. Whereas earlier generations had higher pension coverage and shorter retirement periods, today's workers can expect to live longer, healthier lives, but will have to rely mainly on Social Security, defined contribution employer plans, and Individual Retirement Accounts (IRAs) to fund their retirement.

Generational Differences. The two youngest generations currently in the workforce are millennials and Generation Z. Millennials, also sometimes called Gen Y or Echo Boomers, were born between 1981 and 1996, and represent roughly one-fourth of the U.S. population and half of all working adults. These individuals, currently in their 20s and 30s, grew up in the digital age, are more likely to have divorced parents, and were more sheltered and scheduled than previous generations of children. Millennials are generally considered more optimistic and less materialistic, but more self-absorbed compared other generations. They tend to focus more on lifestyle than on upward mobility. A Pew Research Center survey in 2014 showed that a larger percentage of millennials than other generations were upbeat about their financial future, with 85% saying that they either earn enough now to lead the kind of life they want or will in the future. In contrast, only 68% of Gen X (born 1965 to 1980) and 60% of baby boomers (born 1946 to 1964) agree with that viewpoint (Pew, 2014).

Generation Z, commonly called Gen Zs, are those individuals who were born after 1996. The oldest Gen Zs are just entering adulthood, and many are still in high school. Nevertheless, early evidence suggests that Gen Zs may have stronger motivations to work and save than millennials.[1] In a 2017 national survey of Gen Zs ages 14 to 21, 12% of the respondents reported that they were already saving for retirement.

Several recent reports have highlighted the special challenges faced by younger generations in financing an adequate retirement (See, e.g., Munnell and Hou, 2018; Bajtelsmit and Rappaport, 2018; Johnson, Smith, Cosic, and Wang, 2018). Although Gen Zs are coming of age in a time of relative prosperity, millennials entered the workforce during a time period characterized by recession, stagnant real wages, increasing health care costs, declining defined benefit plan coverage, increased Social Security normal retirement age, and greater average longevity. Young adults are marrying and buying homes later, if at all, and are burdened with much more student loan debt than previous generations. Under these economic and demographic conditions, it is more important than ever for individuals to make thoughtful, sound, and responsible decisions for their own retirement saving.

Unfortunately, early evidence suggests that millennials are in worse shape for retirement than prior generations were at the same age. Based on analysis of individuals ages 25-35 in the Current Population Survey (CPS), Munnell and Hou (2018) find that these individuals have less wealth in their 30s relative to earlier cohorts, which they hypothesize to be the result of economic conditions and student loan debt. They conclude that early millennials are well behind older cohorts at that same age, particularly given that they will live longer and receive less from Social Security relative to pre-retirement earnings. Johnson et al. (2018) use a microsimulation to forecast future wealth and retirement

[1] See Center for Generational Kinetics (2017).

income for Gen Xers and early millennials, with assumptions drawn from both the CPS and the Survey of Consumer Finances (SCF). They conclude that both these generational groups are not accumulating wealth as fast as earlier generations, also attributing this to lower rates of marriage (which allows pooling of resources), higher debt obligations, and lower home ownership rates. They show that, when account balances are adjusted to 2017 dollars, the 1980-1985 birth cohort had accumulated an average retirement account balance of $7,300 by ages 25-30 compared with $9,800 for the 1974-1979 birth cohort at that same age.

Financial Literacy. Policymakers, educators, and the financial services industry have all taken note of the adverse financial circumstances confronting younger savers. Some have attributed current trends to the well-documented low levels of financial literacy and numeracy in the United States. Primary and secondary education curricula are placing greater emphasis on financial education (Thaler, 2013).[2] However, in a metastudy of financial literacy intervention, Fernandes et al. (2014) find results that call into question the impact of financial education on financial literacy and financial outcomes. An experiment conducted by Atlas et al. (2018) raises similar concerns, with results showing financial education had a bigger influence on young adults' financial confidence than on their actual financial knowledge. Technological advancements in access to accounts, savings vehicles, and mobile payments ("fintech") are expected to facilitate budgeting and planning, as well as transactions. Unfortunately, recent evidence by Anna Maria Lusardi and the Global Financial Literacy Excellence Center suggests that instead of improving financial decisions, the technology used by millennials is actually associated with poorer financial decision making (Lusardi, Scheresberg, and Avery, 2017).

Behavioral Biases. To better address the needs of future generations, it is important to understand the internal biases and individual characteristics that stand in the way of future financial security. Financial planners, human resource departments, and the public have more information than ever regarding behavioral biases that can work against saving for the future and are gradually incorporating this knowledge into policy interventions. A stream of behavioral finance research has focused on how behavioral biases affect retirement planning at various stages: enrolling in a plan, choosing contribution amounts, allocating investments, and rebalancing allocations.[3] Incorporating the knowledge gained from this research can result in better retirement outcomes. For example, more than half of large-employer 401(k) plans have instituted auto-enrollment defaults in order to counteract employees' natural tendencies toward procrastination or "inertia" that can delay their enrollment in a savings vehicle (Rosenbaum, 2014). The improvements from greater participation levels with auto enrollment are partially offset by the tendency of individuals to continue saving at the low default level and by leakage in the form of outstanding loans and withdrawals (Beshears, Choi, Laibson, and Madrian, 2018). Another example of behaviorally based retirement plan design is the increasing popularity of target-date funds in 401(k) plans, which automatically rebalance asset allocations via an age-based 'glidepath' based on intended retirement dates (ICI, 2019).[4] Recent research has also investigated peer effects on financial decisions, such as sharing information about typical peer retirement contribution rates in an attempt to influence saving behavior (Beshears, Choi, Laibson, Madrian, and Milkman, 2015).

Although many behavioral biases have been identified in the literature, we focus our attention on decisions to delay spending to take advantage of saving and investment opportunities. Some behavioral issues, such as *procrastination bias* (tendency to delay making decisions or completing tasks), are important for all

[2] The Council for Economic Education *Survey of the States* (2019) reports that 45 states now include personal finance in their standards, although only 38 require implementation of the standards and 17 require students to take a course in that subject.

[3] See Mitchell, Olivia, and Stephen P. Utkus (2004) for a review of the earlier literature.

[4] Net assets in target-date funds totaled nearly $1.1 trillion in 2018, as compared with only $160 billion in 2008. In 2016, the asset allocation to target-date funds for participants in their 20s was 47.6% as compared with only 18.4% for participants in their 60s (ICI, 2019, Figure 8.12).

areas of financial planning, but the financial impact is greater for retirement. Goda et al. (2015) find that *present bias* (time inconsistency across subjective values of present consumption and future consumption) and *exponential growth bias* (failure to account for compounding) both have independent negative effects on saving.[5] Benartzi and Thaler (2007) summarize the expected effects of *inertia* that discourages savers from improving upon default retirement plan contribution rates and *diversification bias*, in which people apply the default heuristic of “divide by n,” allocating funds equally across investment choices when the selection is too cognitively taxing. They also cite their own and extant evidence that savers are biased by *mental accounting*, in which they treat existing contributions differently from new contributions, and that *framing effects* from retirement investment choices affect allocations and decisions over gains and losses.

Recent work has investigated interventions that can improve saving outcomes by either combating or leveraging specific behavioral biases. In a field experiment over employee contributions to a retirement plan, Beshears et al. (2017) find that, on average, saving rates improve with high default contribution levels, although there is a small increase in nonparticipation. Thorp et al. (2018) investigate the impact of framing retirement accounts as balances versus projected income during retirement, and discover that displaying income projections together with balances encourages saving. In a study with implications for mental accounting and behavior in the age of mobile-payment services, Meyer and Pagel (2018) show that retail investors respond differently to paper gains and losses versus realized gains and losses.

Our Contribution. We are interested in how younger savers make financial decisions, which preferences are most influential on their decisions, how these characteristics interact with financial literacy, and which interventions most effectively encourage saving and investing. As discussed above, on average, retirement savings falls short of predicted needs. Where previous literature on investment decisions relies on finding a correlation between individual characteristics, survey data, some risk preference controls, and reported savings or specific account accumulation, we analyze a particular investment decision to determine whether individuals are simply making errors, unable to understand the arithmetic behind their choices, or succumbing to biases leading to bad decisions that are inconsistent with their objectives. We find that preferences and actual financial literacy (as opposed to self-reported financial literacy) are significant factors for saving and investing decisions.

In this study, we conduct a fully incentivized laboratory experiment to test for the presence of behavioral biases and the efficacy of particular interventions designed to improve saving and investment decisions. We measure subject-specific risk preferences, discount rates, financial literacy, and overconfidence regarding financial knowledge. Subjects choose an asset allocation based on brief fund descriptions. In a between-subjects design, we test the impact of the following interventions on investment allocation:

- *Goals Prompt*: Participants set goals prior to making the investment allocation decision
- *Goals + Advice Prompt*: Participants set goals and receive investment advice prior to making the investment allocation decision
- *Future Self Prompt*: Participants think about future financial needs prior to making the investment allocation decision.

The participants in this study (average age = 21) exhibit similar profiles of discount rates, present bias, and risk aversion that have been found in other studies, although there is substantial within-sample variation. A major contribution of this research is to demonstrate that, after controlling for idiosyncratic time preferences, risk aversion, and financial literacy, behavioral interventions can be effective means of influencing saving and investment decision making, particularly for women. Our results show that: (1) setting goals prior to making

[5] Stango and Zinman (2009) provide empirical evidence suggesting that exponential growth bias causes consumers to systematically underestimate interest rates on short-term (but not long-term) loans and to systematically underestimate the benefits of long-term saving.

investment decisions changes average allocations and expected returns; (2) financial literacy has a positive effect on saving and expected return; (3) behavioral prompts have a larger impact on expected return for participants with lower levels of financial literacy; (4) individuals are more willing to save at lower rates of return if the allocation to saving takes place further in the future; (5) women have lower expected returns than men on average, but those who receive a behavioral prompt have higher expected returns than those who do not; and (6) on average, people make allocation decisions that are consistent with their time and risk preferences. Our study differs from many other experimental studies in that participants' decisions throughout the experiment are incentivized over similar stakes. While previous work has combined survey questions over risk and time preferences with information about particular account accumulations, our study is the first to investigate the decision of how to invest a specific sum of money in light of risk and time preferences elicited for approximately the same amount. In the next sections, we describe the methodology for measuring individual characteristics and biases, and we explain our experimental methodology. In the final sections, we summarize our analysis of the results and the implications for plan sponsors and policymakers.

Measurement of behavioral biases and financial literacy

Measurement of Time Preferences. It is well-accepted in the literature that people differ in their degree of time discounting and that these differences can impact motivations to save and invest. An individual with a high rate of time discounting will prefer current consumption over saving/investing even when it results in a substantial reduction in future consumption. (See Barsky et al. 1997). The multiple price list (MPL) technique is a common method used to elicit time preferences in the lab. Participants receive a series of choices between (A) payment of a certain amount of money sooner (e.g., $100 today) and (B) payment of a larger amount of money (e.g., $105) in the future, presented in the form of list of choices between A and B, with the B values increasing with each subsequent row. If a participant prefers the larger amount in the future, then we infer that their discount rate is at least as large as the (annualized) percent difference; if not, we infer that their discount rate is at most the percent difference. Experiment participants select one option from each row, with most selecting the earlier lower payment in the first rows where the rate of return is lower, but eventually switching to taking the larger future amount when the rate of return makes this preferable to them. The participant's time preference is thus bounded by the discount rates represented by the switching row and the previous row.

By varying the time periods between the near and future payouts, researchers can estimate discount rates over time. Some studies have found that people exhibit constant discount rates (Andersen, et al., 2008, 2014), whereas others find evidence of present bias, or hyperbolic discounting, wherein subjects have higher discount rates for nearer time periods than for equivalent-length future periods. For example, with hyperbolic discounting, the discount rate from three months in the future to the present could be much higher than the discount rate from six months to three months. (See Bradford et al., 2019, for a review of this literature and various explanations for this phenomenon.) The existence of present bias has been called into question in some recent studies that criticize previous research based on the reliance on insufficiently incentivized college students as subjects (Andersen, et al., 2014). In our study, we use this methodology with economically meaningful incentives.

Measurement of Risk Preferences. Risk preferences have been shown, both theoretically and empirically, to be related to individual risk taking and financial decisions. There are several methods for identifying risk preferences from survey data or in experimental settings. In the past, it was fairly common for researchers to infer risk preferences from individual portfolio choice or self-assessed risk attitudes (e.g., Bajtelsmit and Jianakoplos, 1998). Financial advisors routinely use risk questionnaires to better understand clients' risk profiles.[6] To economists, these types of self-assessment are not ideal for measuring risk preferences because respondents may differ in interpretation of the questions and responses. Analysis of survey responses also calls the reliability into question in light of evidence that many respondents who say they are not willing to take any financial risks actually are holding stocks in their portfolios.

A preferable alternative is to infer risk preferences from risky choices in a survey or experimental setting (e.g., Harrison, List, and Towe, 2007). The Health and Retirement Study (HRS)[7] elicits risk preferences through a series of "income gamble" questions developed by Barksy, Juster, Kimball, and Shapiro (1997). Respondents are asked to make a choice between a job with certain income and a job with risky income. The initial question asks:

> *Suppose that you are the only income earner in the family. Your doctor recommends that you move because of allergies, and you have to choose between two possible jobs. The first would guarantee your current total family income for life. The second is possibly better paying, but the income is also less certain. There is a 50-50 chance the second job would double your total lifetime income and a 50-50 chance that it would cut it by a third. Which job would you take—the first job or the second job?*

Depending on the answer to this initial question, the respondent is given follow-up questions that vary the downside risk for the risky job, decreasing the risk if they did not select the risky job the first time, or increasing the risk if they did select the risky job. The complete selection of alternatives for downside risk include -10%, -20%, -33%, -50%, -75%. By observing the point at which respondents are willing to take the income gamble, each person is assigned to a risk tolerance category. The advantage of this method of measuring risk tolerance, as compared to self-assessment, is that it is more objective and elicits risk preferences over income/wealth, which is more consistent with expected utility theory. Two disadvantages of the income gamble methodology are that (1) it presumes that respondents understand probabilities sufficiently to make their selections, and (2) it is difficult to provide laboratory incentives that correspond to the hypothetical risks in the survey.

A second method of assessing risk preferences is through a multiple price list (MPL) format in which experiment participants are presented with 10 choices in a paired series of lotteries. The probability of the higher payoff in each lottery changes from 10% to 100% across the choices, but payoffs are structured so that one lottery is riskier than the other. Participants' level of risk aversion is determined by the point at which they switch from the safe lottery to the risky lottery. Typically, one of the paired lotteries is selected and played for payment, after which participants are paid according to their choice of payoffs and the lottery outcome. In our study, we measure risk aversion using both the income gamble survey questions and the MPL lottery method.

Measurement of Financial Literacy. Recent research suggests fairly low levels of basic financial literacy. Fundamental to making appropriate long-term saving and investment decisions is that individuals need a basic understanding of inflation, compound interest, and diversification (often termed "the Big Three"), as well as some degree of numeracy. Lusardi and Mitchell (2007, 2011) designed a set of standard questions and have implemented them in various surveys in the United States and in other countries. These questions were deliberately designed to be simple and easy to compare across groups. The Big Three are as follows:

1. *[Compound Interest] Suppose you had $100 in a savings account and the interest rate was 2% per year. After five years, how much do you think you would have in the account if you left the money to grow? [**more than $102**, exactly $102, less than $102]*

[6] See Carr (2015) for an in-depth discussion of methods used for assessing client risk profiles. A commonly used tool is the Grable and Lytton 13-item risk tolerance scale. See Kuzniak, Rabbani, Heo, Ruiz-Menjivar, and Grable (2015) for discussion of reliability and validity of this measure.

[7] The Health and Retirement Study is a longitudinal biennial survey of individuals between the ages of 51 and 61 and their spouses. The income gamble questions have been asked over several waves of the survey.

2. *[Inflation] Imagine that the interest rate on your savings account was 1% per year. After one year, would you be able to buy [more than, exactly the same as,* ***less than****] today with the money in this account?*
3. *3. [Diversification] Buying a single company stock usually provides a safer return than a stock mutual fund. True or* ***False****?*[8]

When they initially fielded the questions in a special module of the Health and Retirement Survey, Lusardi and Mitchell found that only one-third of a representative group of older Americans could answer all three questions correctly. Since that time, these questions have been fielded in the National Longitudinal Survey of Youth (ages 23-28), the RAND American Life Panel (internet panel covering all ages), the National Financial Capability Study, and the Understanding America Study (internet panel covering all ages). Some of these surveys also include additional questions on more sophisticated financial concepts (e.g., mortgages, asset pricing, investment types). In all cases, the findings support the conclusion that financial literacy levels in the United States are quite low (Lusardi and Mitchell, 2014). Disaggregating the data, they also find that financial literacy levels increase with education, decrease with age, and are lower for women than men.

In this study, participants take a 15-question quiz that includes the Big Three questions above as well as numeracy and financial knowledge questions. To address some of the deficiencies in previous research, participants are given financial incentives for correct answers and are also provided with a basic calculator.

Measurement of Overconfidence. Another interesting finding from the Lusardi and Mitchell research is that, even though financial literacy levels are relatively low, individuals tend to be fairly confident of their financial knowledge. For example, Lusardi and Mitchell (2011) report that, in the Financial Capability Study, 70% of respondents rated their financial knowledge as 4 or higher (out of 7), but only 30% answered the questions correctly. Women, however, are more likely to rate their knowledge lower and to answer “Don’t Know” when given that option, rather than guessing.

In this study, we assess overconfidence by asking participants to estimate the number of questions they answered correctly (out of 15) and also to estimate the number of questions that others answered correctly (both estimates incentivized). By comparing predicted to actual scores, we can determine whether participants are overconfident in their assessment of their own ability and/or whether they overestimate their own ability compared to their estimate of others’ ability.[9]

In the following sections, we explain our experiment methodology and provide a summary of preliminary results.

The experiment

We recruited participants to take part in experiments at a university behavioral lab in summer and fall 2019. Requests for paid experiment volunteers were sent through the university email system, which includes enrolled students. A total of 234 participants[10] volunteered and participated in one of 15 experiment sessions. There were no other eligibility or exclusion criteria required for participation. In the email, subjects were informed that the study related to financial decision making, the amount of time required (1.5 to 2.5 hours), and the minimum ($20) and maximum ($270) that they could earn during the experiment. The experiment was approved by the human subjects committee at our university.

[8] Because it is expected that financial literacy may be measured with error, van Rooij, Lusardi, and Alessie asked two groups of respondents to answer the diversification question both as written here and in reverse: *Buying a stock mutual fund usually provides a safer return than a company stock. True or False?* They found that the fraction of correct answers was higher when the single stock was mentioned first.

[9] See Bajtelsmit and Coats (2019) for additional discussion of these types of biases.

[10] The maximum number per session was 20, and the smallest session was 8.

Procedures

Prior to each session, experiment participants congregated in a waiting room where they read and signed an informed consent form, and they were randomly assigned to numbered computer workstations in the lab. They were required to put away their phones and could not access the internet during the experiment.

There are four treatments, which all have common elements that are described in this section. The experiment proceeded in three phases: Instructions, Tasks, and Payment. In the Instructions stage, we provided an overview and explanation of the procedures, presented orally on a PowerPoint at the front of the room and at the participants' workstations. We explained in detail the way in which participants would be compensated at the end of the experiment: Everyone would earn at least $20 for participation, and three participants would be randomly selected for payment based on their decisions made in each of three different experiment tasks. To implement the selection for payment, each participant was given a color-coded card with their seat number on it. These were collected in large envelopes at the end of the Tasks phase for a public random drawing.

Instructions. During the Instructions phase, participants were given detailed examples of the three types of tasks that they would be undertaking during the experiment, with screenshots. After explaining each task, participants took a brief assessment to ensure that they understood the task and how they would be paid if they were selected for payment based on that task. The assessment instrument required participants to demonstrate that they understood how much they could earn from each of the tasks, and when and how payments would be made. To emphasize the importance of making each of their decisions carefully, we clearly explained that one participant in each of the three task categories would be selected to receive payment according to the task outcome. Since there were no more than 20 participants in a session, this gave each participant at least a 15% chance of earning a payment that could potentially be very large if they made careful decisions. The amount that could be earned (up to $270, including the show-up fee) ensured the salience of the incentives for careful decision making. When all participants had demonstrated their understanding, we began the computerized experiment using oTree software.[11]

Incentivized Tasks. In the Tasks phase, participants performed tasks that provided measures of their financial literacy, overconfidence, time discounting, risk aversion, and savings and investment decisions. These were labeled as the Green Task, Blue Task, and Orange Task, rather than as numbers or letters, to facilitate randomizing the order of task presentation in different sessions.[12] Each of the tasks included monetary incentives of very similar value. In the remainder of this section, we discuss the payoffs to the participants who were selected at random through the process described above. For example, the payoffs to the Green Tasks are what a participant would earn if their green card was drawn from the corresponding envelope for payment.

- **Green Tasks (Financial Literacy and Overconfidence)**
  In the Green Task, participants answered 15 questions covering topics related to financial literacy, numeracy, and personal finance knowledge. Although no strict time limit was enforced, participants were informed that most people should be able to finish the quiz in 15 minutes or less. At the end of the quiz, participants were asked to estimate the number of questions on the quiz that they answered correctly and to estimate the average number correctly answered by others. The payment for this task was explained as follows:
  "You will be paid $20 for carefully answering these questions regardless of whether you get them right or wrong. You will earn an additional $5 per correct response (maximum total $75). You will earn $12.50 more if your estimate of your score is within +/- one

[11] See Chen, Schonger, and Wickens (2016) for a description of oTree software for laboratory experiments.

[12] To minimize the impact of order effects, we randomized the order of the tasks and the order of some components within the tasks across the various sessions. Within the sessions, we randomized the order of the questions and the multiple choices on the Green Task financial literacy quiz.

question. You will earn another $12.50 if your estimate of others' average score is correct within +/- one question." In the Instructions phase, examples were given to illustrate the payment under different performance scenarios. The maximum that a participant could earn if they were chosen for payment based on the Green Task was $120 (if they answered all the questions correctly and correctly estimated their own and others' average scores within one question). The participant paid for the Green Tasks received $20 at the conclusion of the experiment, and the balance in one week. This was to align the timing of payment with the savings and investment tasks which included a minimum one-week time delay, described in more detail below.

- **Blue Tasks (Risk Preferences)**
The Blue Tasks were a standard multiple price list (MPL) format in which participants chose between a series of paired lotteries labeled Option A and Option B.[13] In the 10 decision scenarios, the high and low payoffs in the drawings remain the same, but the probability of the high payoff changes from 10% to 100%. The money payoffs were as follows:

– Option A: Low Payoff $42 and High Payoff $52

– Option B: Low Payoff $2.50 and High Payoff $100

Figure 1 shows an example screenshot for this task. The expected payoff for each lottery can thus be calculated as p_L x (Low Payoff) + p_H x (High Payoff). The expected payoffs for Option A range from $43 to $52, whereas the expected payoffs for Option B range from $12.25 to $100. The breakpoint where risk-neutral participants would be indifferent between Option A and Option B occurs between Decisions 4 and 5 since the expected value of both options is equal if the probability of the high option is 45%. For risk averse individuals, we would expect the switching point to occur in later decisions.

Figure 1. Example screenshot for Blue Task MPL risk preference elicitation

	Option A	Option B
1	$52.00 with a probability of 1/10, $42.00 otherwise	$100.00 with a probability of 1/10, $2.50 otherwise
2	$52.00 with a probability of 2/10, $42.00 otherwise	$100.00 with a probability of 2/10, $2.50 otherwise
3	$52.00 with a probability of 3/10, $42.00 otherwise	$100.00 with a probability of 3/10, $2.50 otherwise
4	$52.00 with a probability of 4/10, $42.00 otherwise	$100.00 with a probability of 4/10, $2.50 otherwise
5	$52.00 with a probability of 5/10, $42.00 otherwise	$100.00 with a probability of 5/10, $2.50 otherwise
6	$52.00 with a probability of 6/10, $42.00 otherwise	$100.00 with a probability of 6/10, $2.50 otherwise
7	$52.00 with a probability of 7/10, $42.00 otherwise	$100.00 with a probability of 7/10, $2.50 otherwise
8	$52.00 with a probability of 8/10, $42.00 otherwise	$100.00 with a probability of 8/10, $2.50 otherwise
9	$52.00 with a probability of 9/10, $42.00 otherwise	$100.00 with a probability of 9/10, $2.50 otherwise
10	$52.00 with a probability of 10/10, $42.00 otherwise	$100.00 with a probability of 10/10, $2.50 otherwise

[13] We follow the lottery choice experiment designed by Holt and Laury (2002).

The participant incentives in the Blue Task included a fixed payment of $17.50 for making the 10 choices, plus the payoffs from their lottery choice in a randomly selected decision row. The lottery payoffs were determined by using a random spinner with 10 slots to determine which of the decisions would be used for payout. Then, based on the probabilities in the chosen decision row, the High or Low outcome was determined by a draw from a bingo cage containing 10 balls labeled H or L in the corresponding proportions. For example, if Decision 3 was selected based on the spinner, the bingo cage would have 3 balls labeled H and 7 balls labeled L. The bingo ball drawing was conducted in front of the room prior to selecting the winner so that everyone would know what their payment would be if their Blue card was drawn. The possible payments from the Blue Task were $59.50 (=$17.50 + $42), $20 (=$17.50 + $2.50), $69.50 (=$17.50 + $52.00), and $117.50 (=$17.50+$100). As with the Green Tasks, the paid participant received $20 at the end of the experiment and the balance in one week.

- **Orange Tasks (Risk Preferences, Time Preferences, Risky Decision making, Behavioral Prompts)**
  The Orange Tasks began with participants earning $120 for answering survey questions (similar to the "income gamble" questions from the Health and Retirement Survey described in the previous section). These are included as an additional method of eliciting risk preferences. For comparability with earnings from the other two tasks and to mitigate the "found money effect," we framed the $120 as earnings for answering the questions carefully. Participants were told that they would receive $20 of their earnings on the day of the experiment, but could choose to save or invest the remaining $100 of earnings in a series of 46 savings and investment choices. At the end of the experiment, one of the 46 decisions was selected at random for payment to the person whose orange card was drawn from the corresponding envelope. The first 45 decisions were presented in an MPL setting similar to Bradford, Dolan, and Galizzi (2019), in which participants choose between receiving the $100 sooner (without interest) or saving it to be received later (with interest). Fifteen of the decisions require choices between payment in 1 week versus 13 weeks, 15 are decisions between 13 weeks and 26 weeks, and 15 are choices between 1 week and 26 weeks. In each case, the participants select from Option A (sooner time) and Option B (later time), with the decisions presented in order from lower to higher interest rates. The earliest payment date was chosen as one week to eliminate the potential for transactions costs or short-term cash needs to dominate time preferences. The presentation includes both the annualized interest rate and the actual dollar amount of money to be received.

  Figure 2 provides a partial screenshot example for the 1-week versus 13-week decisions. Annualized rates of interest range from the 15% shown to 85%. Since the decision period is shorter than one year, the dollar amounts are adjusted to be the interest for the appropriate period (¼ of the annual rate for the 13-week investment period, ½ of the annual rate for the 26-week investment period). It is expected that participants will choose Option A if their discount rate exceeds the rate offered in Option B. The switching point is then used to estimate their subjective discount rate. For example, if a participant chose Option A in Decision 1 and Option B in Decisions 2 and 3, we assume that their subjective discount rate (annualized) for the 1- to 13-week period is between 15% and 20%.

Figure 2. Example partial screenshot for the Orange Task MPL discount rate elicitation

	1 Week			13 Weeks	
	Amount	Option A	Option B	Annualized interest rate	Amount
1	$100.00	○	○	15%	$103.75
2	$100.00	○	○	20%	$105.00
3	$100.00	○	○	25%	$106.25

In the final (46th) decision for the Orange tasks, participants were required to allocate their $100 across four options. They could receive some or all of the money in one week, or allocate any portion into three different 26-week investments. These investments were briefly described based on average return and minimum and maximum possible outcomes, as shown in the screenshot in Figure 3. After all decisions were made, the actual returns for each of the risky investments were determined by random spinners. Each spinner had 10 possible return outcomes consistent with the investment descriptions. Each participant's payoff for the 46th decision was determined by the random returns and their individual investment allocations. The payouts from each of their investment choices were displayed privately on participants' computer screens. Therefore, after making their decisions, all participants knew exactly how much they could earn from each of the 46 Orange Task decisions. Finally, to determine which Orange Task decision would pay out, we conducted a public random draw using a bingo cage with 46 numbered balls.

Figure 3. Example screenshot of Orange Task investment choices

Investment Choice	Information About This Investment
Do Not Invest (receive in 1 week)	You will receive the money, with no additional interest, in 1 week.
Conservative 26-week Investment	This investment choice provides a moderate rate of interest and does not expose you to any risk of loss. •Average annualized return = 10% •Range of possible annualized returns: 3% to 18% gain
Moderate Growth 26-week Investment	This investment could potentially provide a high rate of return, but also exposes you to the risk of losing some of your money. •Average annualized return = 25% •Range of possible annualized returns: 5% loss to 55% gain
High Growth 26-week Investment	This investment has the highest potential rate of return, but also exposes you to the risk of losing some or all of your money. •Average annualized return = 50% •Range of possible annualized returns: 45% loss to 150% gain

Payment. After all of the tasks were completed in a session, we resolved the uncertainty about potential payments for each of the tasks. The participants were given a summary on their computer screen of their performance on the Green Task financial literacy quiz, how well they estimated their own and others' scores, and the total they would receive if their green card was selected for payment. We next resolved the Blue Task outcomes by using a computerized spinner to determine which Blue Task lottery would be used for payment. A public bingo ball drawing was conducted, with a volunteer participant turning the crank, to determine whether the payout would be the High or Low outcome for that decision. Based on that outcome, participants were shown on their computers the amount they would each earn if their blue card was drawn. Lastly, we resolved the Orange Task outcomes by displaying computerized random spinners to determine the annualized return for each of the three risky investment choices and conducting a bingo ball drawing (with balls labeled 1-46) to determine which decision would be used for payment. Participants then saw on their screen how much they would earn if their orange card was selected for payment.

The last step was to draw the three cards for payment. To maximize credibility and transparency, this drawing took place in the lab room. Each participant placed their own numbered cards in the respective envelopes, and volunteers shuffled the cards and selected the participant card for payment. All participants were paid $20 in cash, and the three participants whose cards were drawn were given a written contract that summarized how and when they would be paid the remainder of their experiment earnings. The timing of payments depended on their choices in the experiment, but were either 1 week, 13 weeks, or 26 weeks from the session date. To minimize the risk that transactions costs for different methods of receipt of payment would influence decisions, participants were told at the beginning of the experiment that they could select from three options for future payments: cash, check, or an electronic mobile payment.[14] The average time for each session, including payments, was two hours.

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Treatments. Each session was assigned to one of four treatments:

- Treatment 1 (Base Case)
- Treatment 2 (Goals Prompt)
- Treatment 3 (Goals plus Investment Advice Prompt)
- Treatment 4 (Future Self Prompt)

The base case treatment did not include any behavioral prompts and proceeded as described above. In both Treatments 2 and 3, participants were asked to set goals for their experiment earnings prior to making the Orange Task saving and investing decisions. They could select from the following options, presented in randomized order:

Which of the following <u>best</u> represents your financial goal for your experiment earnings?

- *My goal is to receive the money as soon as possible even if I will have to forego earning any interest on the money.*
- *My goal is to choose investments that may earn some interest over the next six months but have no risk of loss.*
- *My goal is to choose investments that will give me the best chance of receiving the highest amount of money possible.*
- *My goal is to choose investments that will provide me with a chance to receive a lot more than $100, but guarantee that I will end up with at least [dropdown menu: $30, $70, $90]*
- *I have no goals for how much I will receive from this experiment.*

In Treatment 3 (Goals + Investment Advice), after selecting a goal from the list, each participant received accurate advice about the saving/investment allocation that would best meet their identified goal. For example, if they said they wanted to receive the money as soon as possible, they were advised to put all $100 in Do Not Invest, whereas if their stated goal was to guarantee that they earned at least a certain amount, they were told to

[14] Most of the participants opted to pick up their payment in cash from our department, one-third chose to receive a Venmo payment and two requested payment by check

put that amount in the Conservative investment and the remainder in the High Growth Investment. In all cases, participants were told to "Feel free to use the advice or not."

In Treatment 4 (Future Self Prompt), participants were given the following prompt prior to making their saving/investing decisions:

Thinking about future financial obligations now may give you more options for adjusting your plans.

Which of the following expenses do you expect to pay for within the next six months (select all that apply):

- *Education-related expenses (tuition, books, fees, etc.)*
- *Living expenses (rent, food, utilities, phone, etc.)*
- *Entertainment and sports*
- *Big items or events (move, buy house, buy car, wedding, travel, etc.)*
- *Family expenses (childcare, help to parents and siblings, etc.)*
- *Medical expenses (insurance, prescriptions, optometrist, dentist, etc.)*
- *Other [Allow the participant to fill in]*

Descriptive statistics and results

Because we use a convenience sample of students enrolled in university courses, the sample is not necessarily representative of all individuals in that age group. The median age was 21, and the mean was 21, but there were a few outliers, with the ages ranging from 18 to 61. Because our research question relates to younger generations, we drop the data from participants over age 29. In addition, we drop participants who clearly misunderstood the lottery gamble task (those who chose Option A in the 10th decision where Option B paid $100 with 100% probability). After making this adjustment, our total sample is 223 participants. Table 1 shows the male/female breakdown by race/ethnicity and college major categories.

Table 1. Participant pool by gender, ethnicity and college major (N = 223)

Ethnicity	Female	Male	Other	Total
Asian	6.28%	4.93%	0.00%	11.21%
Black	1.35%	0.90%	0.45%	2.69%
Latino	1.79%	4.48%	0.00%	6.28%
Other	2.24%	1.35%	0.45%	4.04%
White	38.56%	37.22%	0.00%	75.78%
Total	**50.22%**	**48.88%**	**0.90%**	**100.00%**

College Major	Female	Male	Other	Total
Business or Economics	13.90%	16.59%	0.00%	30.49%
Liberal Arts	6.28%	4.93%	0.45%	11.66%
STEM (Science, Technology, Engineering, Mathematics)	13.00%	17.04%	0.00%	30.04%
Other	17.04%	10.31%	0.45%	27.80%
Total	**50.44%**	**48.68%**	**0.90%**	**100.0%**

Financial Literacy and Overconfidence. We summarize the results of the Green Task financial literacy quiz and estimation in Table 2, broken down by groupings of questions and topic areas to facilitate direct comparison to other financial literacy research. Our sample tends to be fairly financially literate, with an average quiz score of 12.5 out of 15 questions answered correctly, and 17% answering all 15 questions correctly. Only 10% of the sample answered less than 2/3 correctly. The average score on the Big Three financial literacy questions was 2.7 out of 3, with 88.7% answering all three correctly. These financial literacy results are higher on all dimensions than have been reported in other research based on various national surveys. We attribute this to several factors. First, our sample is more educated than the average person in their age group, and more than half were majoring in business, economics, or STEM disciplines. The financial literacy score is significantly higher for business and economics majors (r = 11.9%) and STEM majors (r = 17.9%). While this distribution of majors is relatively consistent with the student population at our university, it is not nationally representative of people their age. Second, we provided a calculator to each participant. Given the current environment in which everyone has a calculator on their phone, it makes sense to estimate financial literacy and numeracy this way. Many financial literacy and numeracy quizzes are given online, so it is unknown whether the test-takers are using a calculator. The third factor, and most important in our view, is that we provided substantial incentives for correct answers ($5 each). Observation during the experiment confirmed that participants took their quiz answers very seriously, taking an average of 10 minutes to answer the 15 multiple choice questions.

Table 2. Financial literacy and numeracy (N=223)

Statistic	Big 3	Big 5	Financial Knowledge	Numeracy	Exponential Growth
Avg. Number Correct	2.66	4.34	2.62	4.24	2.13
Avg. Score	88.70%	86.80%	87.33%	84.80%	71.00%
Stand. Dev.	0.61	0.89	0.65	0.88	0.87
Minimum	0	0	0	0	0
Maximum	3	5	3	5	3

On average, participants do not exhibit overconfidence in their financial literacy. The average own-score estimate is 12.15/15 (81%), and the actual average score is 12.30/15 (82%), which indicates that they are relatively well-calibrated, and the difference between participants' actual scores and their estimated scores is not significantly different from zero. However, participants' average estimate of others' average score is 10.44 (70%), which is significantly lower than the actual average. Since their accurate estimate of their own performance is higher than their inaccurate estimate of others' performance, this provides some evidence of a better-than-average bias. The average score for women in the sample is 78% as compared with 86% for men, which is significantly different at the 5% level.

Risk Preferences. We use two different elicitations for risk preferences, the paired MPL lotteries and the HRS income gamble questions explained in the previous section. In both types of elicitation, participant risk preferences are estimated based on their switching point between safe and risky choices, and a higher number represents a higher degree of risk aversion (Andersen, Harrison, Lau, and Rutstrom, 2008). Table 3 summarizes the results from the MPL lotteries in which participants chose between a series of gambles that had payoffs with increasing levels of risk. The first column is the number of safe choices (Option A) before switching to the risky choice (Option B). We use the standard method for converting the lottery choice into a coefficient of relative risk aversion (CRRA). The CRRA is given as a range because the point of indifference falls in between the two decision options. If a participant were risk neutral, the point at which they should be indifferent between Options A and B is approximately 4 safe choices, and this corresponds to a coefficient of relative risk aversion (CRRA) that is close to zero (-.005). Individuals with negative CRRA are risk loving and individuals with positive CRRA are risk averse. The distribution of CRRA corresponds fairly well with that found in other studies using student experiment participants.

Table 3. Risk preferences using MPL binary lotteries (N = 216)

Number of Safe Choices	Proportion of Total	Proportion of Females	Proportion of Males	Range of Coefficient of Relative Risk Aversion (CRRA)	Midpoint
<2	1.79%	0.89%	1.35%	<-1.74	-1.74
2	4.04%	4.46%	3.67%	-0.97 to -0.50	-0.735
3	6.28%	8.04%	4.59%	-0.50 to -0.15	-0.325
4	16.59%	10.71%	22.02%	-0.15 to 0.14	-0.005
5	11.21%	12.50%	10.09%	0.14 to 0.40	0.27
6	31.39%	33.04%	30.28%	0.41 to 0.67	0.535
7	17.49%	15.18%	20.18%	0.67 to 0.96	0.815
8	7.62%	10.71%	3.67%	0.96 to 1.36	1.16
>8	3.59%	4.46%	2.75%	>1.36	1.36
Total	100.00%	100.00%	100.00%		

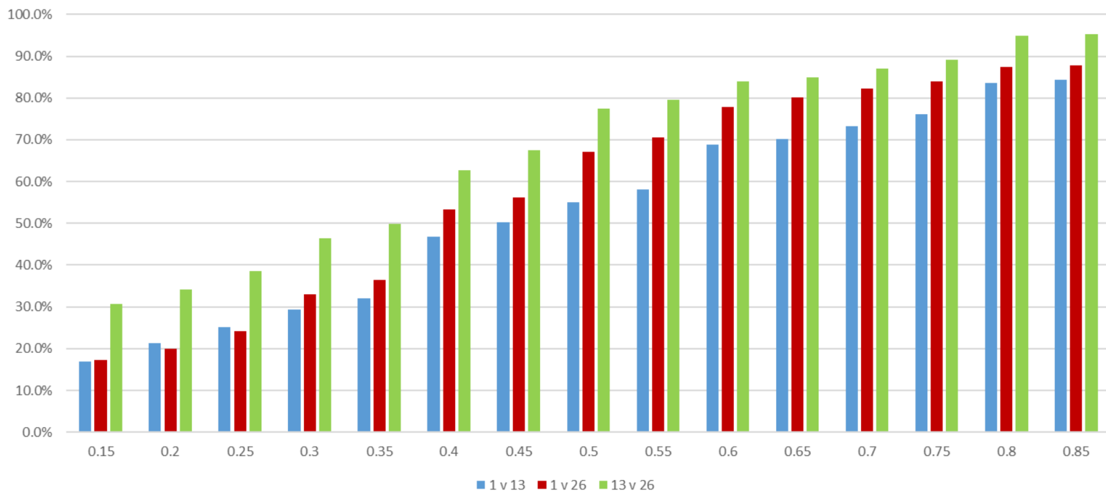
The risk preference elicitation based on income gamble choices is summarized in Table 4. The participants opted between Job A (safe) with a guaranteed income for life and Job B (risky) with a 50% chance of doubling or being cut by a stated percentage. In this methodology, we measure risk aversion based on the number of scenarios in which they selected Job A. Less than 10% of participants chose the safe job in all of the scenarios, and most were willing to take some downside risk.
As with the MPL measure of risk aversion, a higher risk aversion category shows a greater degree of risk aversion. Pearson Correlation Coefficients show that the correlation between these two measures of risk aversion is only 0.37. Because the MPL lottery choices were directly incentivized in the experiment and the income gamble questions were not, we measure risk aversion in our later empirical analysis using the CRRA midpoint estimate.

Table 4. Risk preferences using the HRS income gamble questions (N = 223)

Risk Aversion Category (Based on Number of Safe Choices)	Number of Subjects	Proportion of Subjects
0	14	6.28%
1	3	1.35%
2	6	2.69%
3	37	16.59%
4	99	44.39%
5	45	20.18%
6	19	8.52%
	223	100.00%

Saving Decisions and Time Preferences. Present bias and exponential growth bias can both adversely impact motivations to save and invest (Andreoni and Sprenger, 2012; Bradford et al., 2019; Goda et al., 2015, 2018). High discount rates favor current consumption over saving/investing even when it results in a substantial reduction in future consumption. Participants made 45 decisions between receiving $100 in one week versus receiving $100 plus interest in the future, which we will refer to as the decision to save. Figure 4 illustrates the proportion of participants choosing to save in each of the three present-future and future-future scenarios (1 week versus 13 weeks, 1 week versus 26 weeks, and 13 weeks versus 26 weeks). As interest rates rise, more participants choose to save in all three scenarios. The average discount rate for present consumption versus future savings is 52% in the 1-week versus 13-week scenarios and 47% for the 1-week versus 26-week saving period. However, in the future-future scenario (future 13-week versus future 26-week saving period), the average discount rate is only 39%. T-tests show that the 13-week discount rate is significantly higher than the 26-week discount rate ($p = 0.0002$), which is consistent with hyperbolic discounting. Further, the discount rate for the future-future scenario is significantly lower than the discount rates for either of the two present-future decisions, providing evidence of present bias in our participant pool.

Figure 4. Proportion choosing saving with interest over different time frames, by interest rate



The blue bars represent the proportion of participants who select Option B (saving with interest) for 13 weeks over current consumption in the Orange Task MPL experiment decisions. The orange bars represent the proportion who choose to save for 26 weeks over current consumption, and the green bars represent the proportion who choose to save for 26 weeks over 13 weeks (without interest).

Investing Decisions. In the final decision for the Orange Task, participants allocated their $100 earnings between four choices, two that had no risk of loss (Do Not Invest and Conservative) and two that had a chance of both gain and loss (Moderate Growth and High Growth). The Conservative, Moderate Growth, and High Growth investment choices required a 26-week delay of receipt of funds with investment earnings, whereas the Do Not Invest (DNI) choice was paid out in one week. Table 5 shows the average allocations made by participants in each of the four treatment groups. Savings and investment decisions are driven by participants' understanding of the trade-offs, as well as their time preferences and risk preferences. We expect that behavioral prompts to make informed decisions will encourage participants to make decisions that align with their heterogeneous preferences. Since we use a between-subjects design, we are comparing different participant groups across treatments. In the aggregate, we see that a larger percentage of the money is kept for current consumption by the participants who receive behavioral prompts (20.1% - 23.5%) as compared with those in the base case who do not receive prompts (18.5%). The participants also appear to be consistent across their savings and investment decisions because we find that a higher discount rate in the savings decision is significantly correlated with the Do Not Invest investment decision ($p < .0001$) and higher risk aversion is negatively correlated with investment in the High Growth option ($p < .01$).

Table 5. Average allocations to investment choices, by treatment (N = 223)					
	Average Allocation to Investment				
Treatment	N	Do Not Invest	Conservative	Moderate Growth	High Growth
T 1 Base Case	49	18.5	21.7	34.5	25.3
T 2 Goals Prompt	48	22.5	15.3	35.1	27.1
T 3 Goals + Advice Prompt	72	20.1	19.1	31.5	29.4
T 4 Future Self Prompt	54	23.5	19.9	37.6	19.0
All Treatments	223	20.7	18.8	34.2	26.3

We examine the characteristics that predict percentage allocation to each investment choice using a regression of the form:

%Allocation = *f*(personal characteristics, treatment effects) (Eq.1)

where personal characteristics include: *financial literacy*, measured as the percentage correct on the financial literacy quiz (out of 15); *risk aversion,* measured as the midpoint CRRA from the MPL experiment task (Table 3); *discount rate,* the rate at which a participant chooses to save for 26 weeks over receiving cash in 1-week (Figure 4); and *female,* a dummy variable (equal to 1 for female and 0 otherwise). Treatment dummies are included for Treatments 2 (Goals Prompt), 3 (Goals + Advice Prompt), and 4 (Future Self Prompt), with the reference category being Treatment 1 (Base Case without behavioral prompts).

As reported in Table 6, higher discount rates reduce savings by significantly increasing the percentage of money allocated to taking cash now ($p < 0.0001$). Consistently, those with higher discount rates have lower allocations to the Conservative and Moderate Growth investments. Higher risk aversion also significantly increases the allocation to cash. These results indicate that, on average, participants make allocation decisions that are consistent with their preferences as measured by discount rates and risk aversion. Financial education also makes a difference, with business/economics majors allocating significantly less to cash and those with higher financial literacy allocating less to Conservative and more to High Growth. We are particularly interested in the effects of behavioral prompts on these decisions after controlling for preferences. The interaction terms show that women in Treatment 2 (Goals Prompt) and Treatment 4 (Future Self Prompt) allocate less to Cash and more to the Moderate Growth investment than those who did not receive behavioral prompts.

Table 6. The effect of personal characteristics, preferences and behavioral prompts on saving and investment choices

	Saving and Investment Choices			
Variable	Do Not Invest	Conservative	Moderate Growth	High Growth
Intercept	-1.949	49.263***	39.694**	12.992
	(13.199)	(11.784)	(13.877)	(12.868)
Financial Literacy Score	-1.342	-1.640**	1.132	1.851**
	(0.875)	(0.781)	(.920)	(0.853)
Risk Aversion	8.272**	1.950	-3.626	-6.597**
	(3.386)	(3.023)	(3.559)	(3.301)
26 Week Discount Rate	56.093***	-26.661***	-21.698***	-7.733
	(7.058)	(6.301)	(7.419)	(6.880)
Female	21.538***	7.387	-15.059*	-13.866*
	(7.937)	(7.086)	(8.344)	(7.737)
Business or Econ Major	-8.574**	1.864	-0.436	7.146
	(4.087)	(3.648)	(4.296)	(3.984)
Treatment 2 (Goals)	19.764***	-3.713	-10.069	-5.982
	(7.488)	(6.685)	(7.873)	(7.300)
Treatment 3 (Goals + Advice)	8.6298	-3.483	-11.351	6.204
	(7.198)	(6.426)	(7.567)	(7.017)
Treatment 4 (Future Self)	18.298**	1.265	-10.856	-8.708
	(7.771)	(6.937)	(8.169)	(7.575)
Treatment 2 X Female	-33.161***	-4.445	22.398*	15.208
	(11.212)	(10.009)	(11.787)	(10.929)
Treatment 3 X Female	-14.985	-0.193	16.178	-1.000
	(10.092)	(9.010)	(10.610)	(9.839)
Treatment 4 X Female	-33.234***	-1.676	28.587**	6.323
	(10.903)	(9.734)	(11.462)	(10.629)
Adjusted R-square	0.299	0.086	0.054	0.099

***significant at the 1% level, **significant at the 5% level, *significant at the 10% level

This table reports the results of OLS regressions in which the dependent variables are the percentage allocations by experiment participants to Do Not Invest and the three risky investments (Conservative, Moderate Growth, High Growth). The amount allocated (out of $100) to DNI is received in one week without interest. The amounts allocated to the three investment choices are received in 26 weeks and the rate of return for each choice is subject to a risky distribution. The Conservative investment was described as having an average annual return of 10% and a range of 3% to 18%. The Moderate Growth investment was described as having an average annual return of 25% and a range of -5% to 55%. The High Growth investment was described as having an average annual return of 50% and a range of -45% to 150%.

Another method of measuring asset allocation is to estimate the expected return for each participant's investment portfolio. Because each participant starts with $100, we convert the dollar investments into percentages and calculate a weighted average of their dollar expected returns, allowing us to better capture the effect of diversification across investment choices. We estimate several models of the form given in Equation 2:

Expected Return = *f*(personal characteristics, treatment effects) (Eq.2)

We use the same explanatory variables and interactions as in Table 6 in various combinations. The results of these estimations are summarized in Table 7. Consistent with our expectations, individual characteristics have significant effects on expected return in all of the estimations. On average, participants with lower discount rates, lower risk aversion, and higher financial literacy earn higher expected returns. Because expected return is directly related to riskier asset portfolios, these results demonstrate that participants make allocation decisions that are generally consistent with their preferences. We also find that financial literacy has a positive effect on expected return. In addition, controlling for other factors, male participants and business or economics majors have higher expected returns. Model 1 includes the base set of controls and treatment dummies without interactions, and Model 2 collapses the three behavioral treatments into a single dummy Any Behavioral Prompt (omitted = Treatment 1). We do not find any significant effect of behavioral prompts on expected returns in either of these models. However, in Model 3, we find that although women overall still have lower expected returns than men in our sample, those women who receive a behavioral prompt (*Any Prompt X Female*) have significantly higher expected returns than those who do not. When we break this out by individual treatments, we find that the effect of prompts is driven by Treatments 2 and 4, which is consistent with the results reported in Table 6. Women who set goals and those who consider their future self have higher expected returns than those who do not receive behavioral prompts. In Model 4, we explore the interaction between financial literacy and behavioral prompts. The overall effect of financial literacy is positive, but we find that prompts have a larger impact on expected return for participants with lower levels of financial literacy. This provides some evidence that behavioral prompts may act as a substitute for financial literacy.

Table 7. The effect of behavioral prompts and personal characteristics on expected return (N = 223)

	Coefficient Estimate (Standard Error)				
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	0.189***	0.200***	0.238***	-0.079	0.220***
	(0.059)	(0.059)	(0.061)	(0.124)	(0.062)
Financial literacy	0.012***	0.012***	0.011***	0.034***	0.011***
	(0.004)	(0.004)	(0.004)	(.010)	(0.004)
Risk Aversion	-0.044***	-0.043***	-0.045***	-0.044***	-0.043***
	(0.016)	(0.016)***	(0.016)	(0.016)	(0.016)
26-week Discount rate	-0.138***	-0.145***	-0.138***	-0.144***	-0.123***
	(0.033)	(0.033)	(0.033)	(0.032)	(0.033)
Female	-0.041**	-0.042**	-0.107***	-0.035**	-0.107***
	(0.018)	(0.018)	(0.037)	(0.018)	(0.037)
Business or Econ Major	0.033*	0.034*	0.036*	0.031	0.040**
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)
Treatment 2 (Goals)	-0.001				-0.062*
	(0.026)				(0.035)
Treatment 3 (Goals + Advice)	0.015				0.002
	(0.024)				(0.034)
Treatment 4 (Future Self)	-0.023				-0.074**
	(0.026)				(0.036)
Any Behavioral Prompt		-0.001	-0.040	0.326**	
(omitted: Treatment 1)		(0.021)	(0.029)	(0.129)	
Any Prompt X Female			0.083**		
			(0.042)		
Any Prompt X Financial Literacy				-0.026**	
				(0.010)	
Treatment 2 X Female					0.135***
					(0.052)
Treatment 3 X Female					0.035
					(0.047)
Treatment 4 X Female					0.105**
					(0.051)
Adjusted R-square	0.172	0.170	0.181	0.191	0.194

***significant at the 1% level, **significant at the 5% level, *significant at the 10% level

This table reports the results of OLS regressions where the dependent variable is expected return measured as the weighted average of asset class expected returns based on participant allocations.

Consistency between goals and decisions

In this section, we consider more carefully the impact of goal setting on investment allocations. Table 8 shows the average allocations for participants based on the goals that they set in Treatments 2 and 3, and compares these to the decisions made by participants in Treatments 1 and 4 who did not set goals for their experiment earnings prior to making their investment allocation decision. Average allocations by gender are also reported.

Table 8. Investment allocations by participant goals and gender

Stated Goal for the Experiment	N	Average Allocations to Investments: Do Not Invest (Cash in 1 week)			Conservative			Moderate Growth			High Growth		
		All	Male	Female	All	Male*	Female	All	Male	Female	All	Male*	Female
No Return: Receive cash as soon as possible	13	85.8	87.5	83.0	1.9	0.0	5.0	3.1	0.0	8.0	9.2	12.5	4.0
No Risk: Earn some interest but incur no risk of loss	25	8.8	10.9	7.1	38.2	40.5	36.4	36.6	24.5	46.1	16.4	24.1	10.4
Guarantee Return: Earn at least [30,70,90] and chance to earn more than $100	32	10.9	3.6	16.7	15.2	6.4	21.9	39.3	54.0	27.8	34.7	36.0	33.6
Maximize Return: Chance to receive highest amount possible	44	12.1	14.4	9.3	14.1	9.2	20.0	34.7	29.6	40.8	39.2	46.9	30.0
No Goal: Subject has no goals for their experiment earnings	6	51.7	33.3	70.0	4.2	3.3	5.0	35.8	50.0	21.7	8.3	13.3	3.3
With Goal Setting: Weighted average allocations for Treatments 2 and 3	120	21.0	21.9	20.2	17.6	12.8	22.4	32.9	31.4	34.4	28.5	33.9	23.0
Without Goal-Setting: Weighted average allocations for Treatments 1 and 4	103	21.2	18.4	23.8	20.8	16.1	25.4	36.2	36.6	35.7	22.0	28.9	15.2

*Significantly different from Female at the 1% level based on paired two sample means test.

The upper panel of this table reports the average percentage allocated (out of $100) to be received in cash in 1 week (Do Not Invest) and three 26-week investment choices by experiment participants based on the goal that they selected in Treatments 2 and 3. A total of 120 participated in Treatments 2 and 3 in which they set goals, and 103 participated in Treatments 1 and 4. The bottom panel summarizes the average allocations with and without goal setting.

Descriptive statistics show large differences in allocations to each category by goal, and they also suggest that decisions are relatively consistent with goals. For example, the participants whose goal is to receive cash as soon as possible allocate an average of 85.8% to DNI. Those who have the goal of receiving the highest amount possible also allocate the highest percentage to the High Growth investment (39.2%). Comparing outcomes with and without goal setting in the lower panel, we see higher allocation to High Growth with goal setting (28.5%) than without (22%). Means tests confirm that there are also significant gender effects, with men investing significantly more to High Growth than women (p = .004) and less to Conservative (p = .015).

Does investment advice make a difference?

In Treatment 3, participants set investment goals and then received simple investment advice designed to help them achieve the goals that they had set. Table 9 compares the allocation decisions in Treatments 2 and 3 based on investment goals, and we observe only slight differences in average allocations. Although we are limited to consideration of averages due to the between-subjects nature of the design, we consider whether participants with the same goals make decisions that are more consistent with their goals with versus without advice.

Table 9. Investment allocations by participant goals in Treatment 2 (Goals Prompt) and Treatment 3 (Goals + Investment Advice Prompt)

			Average Allocations to Investments			
Stated Goal	Treatment	N	Do Not Invest (Cash in 1 week)	Conservative	Moderate Growth	High Growth
No Return: Receive cash as soon as possible	T2 Goals	5	100.00	0.00	0.00	0.00
	T3 Advice	8	76.88	3.13	5.00	15.00
No Risk: Earn some interest but incur no risk of loss	T2 Goals	10	10.00	35.50	41.50	13.00
	T3 Advice	15	8.00	40.00	33.33	18.67
Guarantee Return: Earn at least [30,70,90] and chance to earn more than $100	T2 Goals	13	11.92	13.85	38.54	35.69
	T3 Advice	19	10.26	16.05	39.74	33.95
Maximize Return: Chance to receive highest amount possible	T2 Goals	17	13.23	11.18	36.47	39.12
	T3 Advice	27	11.29	15.93	33.52	39.26
No Goal	T2 Goals	3	33.33	3.33	50.00	13.33
	T3 Advice	3	70.00	5.00	21.67	3.33

We further explore the effect of goal setting on both allocation decisions and expected return estimating OLS regression models with dummy controls for each type of goal (omitted = no goal setting). The results are reported in Table 10. As compared with participants who do not receive a goal-setting prompt, participants who set a goal to get cash have significantly lower expected return and those who set goals for higher returns have significantly higher expected returns. Consistent with those findings, the allocation models show that those who identify cash as their goal allocate significantly more to DNI, and those who identify guaranteed minimum or maximizing returns as their goals allocate significantly more to High Growth than those who do not set goals. Investment allocation to Conservative is also significantly higher for those whose goal was low risk. We view this is evidence that goal-setting prompts can help to align goals and outcomes.

Table 10: The effect of goals on expected returns

	Dependent Variable			
Variable	Expected Return	% DNI	% Conservative	% High Growth
Intercept	0.206***	10.006	43.150***	15.147
	(0.554)	(11.452)	(10.689)	(11.815)
Financial literacy	0.008**	-1.008	-1.350*	1.181
	(.004)	(0.807)	(0.754)	(0.833)
Risk Aversion	-0.029*	4.151	2.927	-4.697
	(0.015)	(3.090)	(2.885)	(3.188)
26-week Discount rate	-0.094***	44.194***	-21.133***	-4.999
	(0.033)	(6.752)	(6.303)	(6.966)
Female	-0.049***	3.543	5.888*	-10.326***
	(0.017)	(3.497)	(3.264)	(3.608)
BusEcon	0.027	-5.776	2.628	5.557
	(0.078)	(3.684)	(3.429)	(3.801)
Goals for Experiment Earnings:				
Cash	-0.132***	50.087***	-14.210**	-9.357
	(0.037)	(7.639)	(7.131)	(7.881)
No Risk	-0.013	-7.894	13.419**	-4.284
	(0.027)	(5.665)	(5.288)	(5.845)
Guaranteed Minimum	0.068***	-8.014	-6.708	12.716**
	(0.024)	(5.047)	(4.711)	(5.207)
Maximum Return	0.066***	-3.397	-8.009*	15.126***
	(0.022)	(4.525)	(4.224)	(4.669)
No Goal	-0.069	22.073**	-14.549	-11.882
	(0.051)	(10.535)	(9.834)	(10.869)
Adjusted R-square	0.273	0.412	0.162	0.153

***significant at the 1% level, **significant at the 5% level, *significant at the 10% level

The table reports the results of OLS regressions with different dependent variables. The dependent variables are expected return, measured as the weighted average of asset class expected returns based on participant allocations, and the allocation percentages to Case, Conservative, and High Growth investments, respectively. Dummy variables for goal options are compared with those participants who did not set goals in the experiment. (N = 223)

Conclusions and policy implications

Based on previous research, we know that individual characteristics and behavioral biases can affect saving and investing decisions, resulting in suboptimal retirement outcomes. For example, present bias and financial illiteracy may cause people to save too little or too late. High levels of risk aversion may result in overly conservative investment portfolios. For the reasons discussed previously, younger generations are more at risk for retirement income shortfalls and will need to save more to support their expected longer retirement periods.

In this study, we use an incentivized laboratory experiment to consider the role of behavioral biases and individual characteristics in investment decisions of younger individuals and to test the efficacy of alternative behavioral prompts to motivate improved outcomes. As compared with many lab experiments, our experiment incorporates salient financial incentives (up to $270) over a meaningful time horizon (26 weeks). In the base case, participants make investment decisions without receiving any behavioral prompts. In the other treatments, we consider the effects of invoking the future self, setting goals in advance of saving/investment decisions, and receipt of investment advice targeted to achieving goals. In addition to testing the effects of these behavioral prompts, our experiment design is distinguished from previous research in that we carefully measure and control for risk aversion, time discounting, and financial literacy.

Consistent with findings of other studies on time discounting, our sample exhibits generally high discount rates. We also find a significant present bias in that participants require higher discount rates between present and future consumption than they do for similar periods of future versus future consumption. For plan sponsors and policymakers interested in encouraging increased retirement saving, this suggests that plan prompts that focus on future saving decisions will be more successful. Individuals with a present bias would be more likely to agree to salary reduction agreements that apply to future income rather than current income.

We measure financial literacy in several ways to be able to compare our results to other studies using different methodologies. In contrast to many other studies of financial literacy, the participants in our experiment exhibit high levels of financial literacy and numeracy, on average. Our sample is drawn from a population of college-aged students at a large public university, as are many other studies. A unique design feature for our experiment is that we provided the participants with a calculator and incentivized correct answers. Future financial literacy research using financial calculators may shed more light on this, but our results suggest that levels of financial knowledge and ability may be higher than that measured in previous research studies.

To test the effect of behavioral prompts on saving and investment decisions, we measure outcomes by directly analyzing average asset allocations and indirectly measuring the distribution of asset allocations through expected returns. Our most important contribution is that these behavioral prompts do not have a statistically significant effect on average levels of asset allocation, and thus should not be administered in a "one size fits all" policy. Prompts that provide additional information guiding careful decisions can help to align allocations with individual goals, but outcomes will differ based on individual risk preferences and discount rates. In these circumstances, assistance with goal setting could result in significant increases in expected return and expected utility.

Higher levels of financial literacy result in significantly lower allocations to cash and conservative investments and higher allocations to the high growth investment choice. Participants with higher discount rates took more of their funds in cash instead of investing. Overall expected returns were positively related to financial literacy and negatively related to personal discount rates.

Younger generations are saving too little from society's standpoint, but their level of saving may be consistent with their risk attitudes and time preferences. Even if behavioral prompts can nudge people toward saving more, the results of our study suggest that helping young people understand how to think about and process risk and delay may be more important than telling them how much to save or which investment to choose. Risk in retirement planning architecture is often presented as the risk of losing some of the investment. Instead, perhaps the risk of having too little money in the future should be emphasized. If savers' discount rates are too high relative to what is optimal to achieve societal goals, interventions directed at savers could aim to increase understanding and conceptualization of the importance of future income. In addition, it may be important to reconsider the trade-offs of a very long period of historically low interest rates to promote current expansion. The Great Recession, which affected millennials' ability to start saving, also negatively impacts boomers' and Gen Xs' ability to annuitize accumulated savings for retirement income, none of which encourages saving for Gen Z.

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