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Predicting Retirement Savings Using Survey Measures of Exponential-Growth Bias and Present Bias

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Abstract

In a nationally-representative sample, we predict retirement savings using survey-based elicitations of exponential-growth bias (EGB) and present bias (PB). We find that EGB, the tendency to neglect compounding, and PB, the tendency to value the present over the future, are highly significant and economically meaningful predictors of retirement savings. These relationships hold controlling for cognitive ability, financial literacy, and a rich set of demographic controls. We address measurement error as a potential confound and explore mechanisms through which these biases may operate. Back of the envelope calculations suggest that eliminating EGB and PB would increase retirement savings by approximately 12 percent.¹

Keywords: household finance; retirement savings; exponential-growth bias; quasi-hyperbolic discounting; present bias; financial literacy; survey-based elicitations.

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1 Introduction

Americans have an estimated \$16.6 trillion invested in employer-sponsored defined contribution plans and individual retirement accounts ([Investment Company Institute, 2017](#)). The decline of traditional pension plans means that balances in these individual accounts will be the major determinant of retirement income for millions of Americans, and these balances vary considerably across individuals even after conditioning on observables such as income, age, and education. Because retirement asset accumulation results from actions taken by the individual — such as contribution decisions, asset allocation, distribution decisions, etc. — variation in individual abilities and attitudes toward saving will become an increasingly important driver of Americans’ ability to smooth consumption over the lifecycle.

This paper examines the extent to which survey measures of two known biases predict differences in retirement savings after controlling for a rich set of controls in a nationally representative sample. While standard intertemporal-choice models predict that heterogeneity in time preferences, as measured by the discount rate, and features of the budget constraint, such as liquidity constraints, influence retirement savings, the complexity of the problem increases the likelihood that behavioral factors may influence saving choices. We focus on two biases that may distort the constrained optimization problem — maximize discounted lifetime utility subject to the lifetime budget constraint — in conceptually different ways. We find empirical evidence that these biases significantly predict economically important variation in retirement savings, which suggests that such biases are important to consider when evaluating retirement policies.

The first bias we consider, exponential-growth bias (EGB), is a perceptual bias whereby people underestimate exponential growth processes due to neglect of compound interest. This bias distorts individuals’ perceptions of their lifetime budget constraint: a person with EGB will underestimate the returns to saving and the costs of holding debt. A large body of evidence suggests that this bias is widespread and correlated with predicted behaviors in the lab ([Wagenaar and Sagaria, 1975](#); [Wagenaar and Timmers, 1979](#); [Keren, 1983](#); [Benzion, Granot and Yagil, 1992](#); [Eisenstein and Hoch, 2007](#); [McKenzie and Liersch, 2011](#); [Almenberg and Gerdes, 2012](#)). Most relevant, [Stango and Zinman \(2009\)](#) lay out a theoretical analysis of how EGB would lead individuals to overborrow and to undersave, and they present the first empirical evidence that measures of individual’s EGB predicts real-world behavior. [Levy and Tasoff \(2016\)](#) show how EGB can theoretically lead to undersaving for retirement in a lifecycle-consumption model and find real-world evidence of this relationship in a survey.

The second bias we consider, present bias (PB), is the tendency to overweight present consumption relative to future consumption in a dynamically-inconsistent way ([Strotz, 1956](#);

Laibson, 1997; O’Donoghue and Rabin, 1999a). This bias is qualitatively different from EGB in that it modifies the objective function rather than the perceived budget constraint, increasing the importance of immediate consumption at each point in time. A theoretical literature shows that in lifecycle-consumption models, PB can lead to lower savings relative to an unbiased person who shares the same long-run discount factor (Laibson, 1997, 1998; Laibson et al., 1998; Angeletos et al., 2001; Diamond and Kőszegi, 2003; Zhang, 2013). Furthermore, present-biased agents may procrastinate on completing the often tedious process of enrolling in a tax-deferred savings plan, also resulting in lower savings (O’Donoghue and Rabin, 1999a,b, 2001).

While there are indeed an infinite number of possible departures from the neoclassical model of exponential discounting with accurate perceptions, there are good reasons to focus on these two. First, these two biases are readily imported into standard economic frameworks, enabling sharp predictions and welfare statements. Second, they are theoretically predicted to be particularly important for long-run choices such as retirement savings. Third, further empirical evidence for the importance of these biases in retirement savings decisions is needed. There is some evidence that EGB is negatively correlated with total savings (Stango and Zinman, 2009; Levy and Tasoff, 2016), and field experiments show that interventions designed to address EGB increase retirement savings (Goda, Manchester and Sojourner, 2014; Song, 2012). As for PB, there is an extensive theoretical and experimental literature, but an empirical link between direct measures of PB and real-world retirement assets is extremely limited.²

In addition, it is especially important to distinguish between the relative importance of these two biases for retirement savings given the very different policy prescriptions they would warrant. For example, sophisticated present-biased agents can achieve first-best outcomes with pre-commitment policies, such as SaveMoreTomorrowTM. Naive present-biased agents may be prone to procrastination on retirement savings, and may explain much of the success of opt-out schemes (Beshears et al., 2009). In contrast, pre-commitment locks in exponential-growth biased agents’ most distorted choices. Their perceptions become more accurate as the horizon approaches, and thus they would benefit from flexibility to adjust their consumption or savings in order to catch up.

We follow a survey-based approach to elicit measures of EGB and PB in the spirit of a

²Bernheim, Skinner and Weinberg (2001) estimate a long-run discount factor from consumption data. Ameriks, Caplin and Leahy (2003) use a time preference elicitation measure that potentially identifies the long-run discount factor but does not identify PB, while Eisenhauer and Ventura (2006) and Heutel, Courtemanche, McAlvanah and Ruhm (2014) correlate measures of PB with a dichotomous variable for presences of a pension or any retirement assets, respectively. Brown and Previtro (2014) use procrastination behaviors as a proxy for present bias and correlate this with retirement contributions.

growing body of literature that uses “strategic surveys” to identify behavioral and preference parameters and predict choices in a variety of different settings including, for instance, long-term care insurance (Ameriks, Caplin, Laufer and van Nieuwerburgh, 2011; Ameriks, Caplin, Lee, Shapiro and Tonetti, 2015; Ameriks, Briggs, Caplin, Shapiro and Tonetti, 2017; Brown, Goda and McGarry, 2011) and retirement outcomes (Barsky, Juster, Kimball and Shapiro, 1997; Ameriks, Caplin and Leahy, 2003; Lusardi and Mitchell, 2007; Hung, Parker and Yoong, 2009; van Rooij, Lusardi and Alessie, 2012; Ameriks, Caplin, Leahy and Tyler, 2007; Banks, O’Dea and Oldfield, 2010). The literature using this approach has largely focused on how these outcomes relate to a single behavioral characteristic at a time, for instance aversion to public assistance, state-dependent utility, risk preferences, the propensity to plan, financial literacy, self-control, or numeracy. Only one other paper relates real-world outcomes to measures of multiple behavioral biases in a nationally-representative sample (Stango et al., 2016). Our paper differs from this recent work in that we target retirement savings and the biases that have a strong conceptual grounding for this outcome, while Stango et al. (2016) aim to provide an empirical foundation for behavioral economics and thereby consider a wide-range of biases that may be predictive of an individual’s overall financial condition.

The main contribution of this paper is our finding that our survey-based measures of EGB and PB are both economically and statistically significant predictors of retirement savings in a representative sample of U.S. households. We use our measures as explanatory variables in a regression model of retirement assets, controlling for income, education, measures of risk preferences, general financial literacy, and general cognitive ability, as well as a host of other demographic characteristics. We find that a one standard deviation increase in our measure of PB is associated with approximately \$19,000 (10%) less retirement savings at age 65. Similarly, a one standard deviation increase in our measure of EGB is associated with \$20,000 (11%) less retirement savings. Given the ongoing debate among experimental and behavioral economists about how to elicit these biases, it is perhaps all the more surprising that we find that our measures remain significant after controlling for a wide range of potential confounds (risk preferences, cognitive ability, etc.).

In addition, we provide some empirical evidence for the relationship between these biases and other financial outcomes, which may serve as possible mechanisms through which the biases may affect retirement savings. More PB is associated with lower regular contributions to one’s retirement fund and a greater total share of assets invested in housing. This evidence is consistent with Laibson (1997) who proposes that present-biased individuals will invest in less liquid assets. Turning to EGB, we do not find evidence that it is associated with lower regular contributions. However, EGB is associated with greater payday loan use, in line with the theoretical prediction that those with EGB underestimate the interest rate on

short-term loans (Stango and Zinman, 2009).

The next section lays out the conceptual framework and presents related literature. In Section 3 we present the research design. Section 4 contains the main results. Section 5 investigates the robustness of the findings, including the role of measurement error. Section 6 concludes.

2 Conceptual Framework

This section presents how the two biases can be modeled in an intertemporal consumption problem. While the empirical approach used in this paper is reduced form, we present the model to illustrate how these biases are relevant for retirement savings decisions. We consider the intertemporal consumption problem of an agent who potentially exhibits both PB and EGB.

2.1 Biases

We assume that PB takes the form of quasi-hyperbolic discounting functions (Phelps and Pollak, 1968; Laibson, 1997) over a vector of consumption $x \in \mathbb{R}^{T-t+1}$ of the form:

$$U_{i,t}(x) \equiv u_i(x_t) + \beta_i \sum_{\tau=t+1}^T \delta_i^{\tau-t} u_i(x_\tau) \quad (1)$$

where T is the final period, t is the current period, i is the individual, $1 - \beta_i$ is the degree of present bias, and δ_i is the (exponential) long-run discount factor. The individual may overestimate the β_i used by future selves, as in O'Donoghue and Rabin (1999a, 2001). Current utility is given by (1) but she incorrectly believes her future utility in period $s > t$ is determined with $\hat{\beta}_i \geq \beta_i$ yielding:

$$\tilde{U}_{i,s}(x) \equiv u_i(x_s) + \hat{\beta}_i \sum_{\tau=s+1}^T \delta_i^{\tau-t} u_i(x_\tau) \quad (2)$$

The individual uses backwards-induction given her beliefs to solve for her perception-perfect strategy (O'Donoghue and Rabin, 1999a).

In addition to the possibility of having biased time preferences, people may also be biased in their perceptions of exponential growth, which affects the perceived budget constraint. While PB and EGB are both referred to as biases here and in the literature, there is an important conceptual distinction: PB may be considered a preference while EGB is purely a perceptual error. In most contexts, the welfare implications of EGB are, therefore, more

clear than those from PB.

Using the parametric model of [Levy and Tasoff \(2016\)](#), let α_i represent individual i 's accuracy in her exponential perceptions. Given an interest rate \vec{r} and time horizon T , the person's perception function $p(\vec{r}, t; \alpha_i)$ is the perception of the period- T value of one dollar invested at time $t < T$:

$$p(\vec{r}, t; \alpha_i) = \prod_{s=t}^{T-1} (1 + \alpha_i r_s) + \sum_{s=t}^{T-1} (1 - \alpha_i) r_s \quad (3)$$

When $\alpha_i = 0$, the individual does not compound interest and incorrectly perceives growth to be linear. When $\alpha_i = 1$, the person correctly perceives growth to be exponential. Values of $\alpha_i \in (0, 1)$ generate perceptions that are between linear and exponential growth. Values > 1 reflect over-estimation of the returns to compounding.

When maximizing utility over the lifecycle given a vector of income \hat{y} , the person must choose a vector of consumption \hat{c} that maximizes (2) subject to expected future behavior and the true budget constraint written in terms of the period- T value of money,

$$\sum_{s=0}^T \hat{c}_s \cdot p(\vec{r}, s; 1) \leq \sum_{s=0}^T y_s \cdot p(\vec{r}, s; 1) \quad (4)$$

Since the person misperceives exponential growth, she perceives the budget constraint as:

$$\sum_{s=0}^T \hat{c}_s \cdot p(\vec{r}, s; \alpha_i) \leq \sum_{s=0}^T y_s \cdot p(\vec{r}, s; \alpha_i) \quad (5)$$

The individual is subject to the true budget constraint in (4), and thus she will revise her consumption plans in subsequent periods.³ Equation (5) reveals two errors. On the left-hand side of the inequality, the person misperceives the intertemporal prices of consumption. This is the price effect of EGB, and it can be further decomposed into a perceived income effect and a perceived substitution effect. On the right-hand side, the person misperceives the value of her asset. This is the wealth effect of EGB.⁴

The theory takes α_i as an exogenous primitive. A broader interpretation considers α_i as the output of a production process that inputs numeracy, the ability to use tools, available tools, effort, attention, and intrinsic ability. This broader interpretation allows α_i to vary for the same person based on education, the availability of tools, and incentives, and is a

³It is plausible to assume that creditors are also aware of the true budget constraint, and will not lend an amount the agent can never repay. This implies an additional constraint that (4) must hold just for c_0 : $c_0 \cdot p(\vec{r}, 0; 1) \leq \sum_{s=0}^T y_s \cdot p(\vec{r}, s; 1)$. The predictions are not qualitatively affected by including this credit constraint.

⁴Endogenizing labor supply decisions would add a further substitution effect to lifetime earnings.

helpful way to think about the distributional results in Section 3.1.3 which presents the joint distribution of α_i with other observables.

Compound-interest perceptions is one component of overall financial literacy. We model EGB formally as affecting decisions in a specific way, enabling precise point estimates and comparative-static predictions on behavior.⁵ The EGB model can be easily incorporated into many dynamic environments or married with other models of preferences and perceptions. One can estimate a person's parameter α_i and predict their behavior out of sample in completely different contexts. Thus, even though compound-interest perception may be considered a component of broader financial literacy, EGB leads to specific theoretical predictions that informal or alternative formal conceptualizations of financial literacy do not. Further, the standard measure of financial literacy, the share of a battery of common questions answered correctly, ignores information about the direction and magnitude of how responses deviate from accurate response. In contrast, our EGB and PB measures embody information about the direction and magnitude of how an individual's responses depart from neo-classical predictions. Interpreted through theory, the direction and magnitude of the deviations yield specific, testable predictions about outcomes.

2.2 Lifecycle Consumption Example

To illustrate the effects of the two biases, we consider the simplest possible lifecycle model which allows them to affect behavior. We consider a finite model with separable consumption utility, and because EGB requires compounding in order to have any effect, we set the number of periods to 3. This is also the smallest number of periods in which hyperbolic discounting may be distinguished from exponential discounting. The agent receives income in periods 1 and 2 equal to y_1 and y_2 and faces strictly positive interest rates r_1 and r_2 , respectively. Denote the agent's beliefs about the period-3 value of a dollar received in period t by $p(t; \alpha)$, as defined in equation (3). We suppress the interest rate in p for simplicity, as it does not vary in this example.

For the purposes of this exercise, we also assume log utility in each period. This is of course not without loss, although the qualitative results extend to general utility functions (Laibson, 1997; Levy and Tasoff, 2016). This assumption greatly reduces the complexity of the problem, however, as both present bias and EGB produce both income and substitution effects, and setting the intertemporal rate of substitution to one (as log utility does) results in many of these terms exactly balancing each other.

With these simplifying assumptions in place, we can solve the model by applying perception-

⁵Lusardi et al. (2011) model financial literacy differently, as increasing investment returns.

perfection (O'Donoghue and Rabin, 2001) as a solution concept. In this setting, this means that the agent in period 1 simply forms beliefs about what action will be taken by his period-2 self in all histories, and then best responds to these beliefs. Allowing for the agent to be partially naive with beliefs $\hat{\beta}$ over his future short-run discounting, the agent believes that his period-2 self will choose consumption according to the Euler equation:

$$\tilde{c}_3 = p(2; \alpha) \hat{\beta} \delta \tilde{c}_2 \quad (6)$$

We note that $p(2; \alpha) = (1+r_2)$ is correct for all values of α only because of our three-period assumption. Thus the only reason that the agent is incorrect about his period-2 consumption is due to naivete about his present bias. In a more general setting, exponential-growth bias will lead to an additional prediction error. In either case, the agent's perceived problem in period 1 then becomes:

$$\begin{aligned} \max_{c_1, \tilde{c}_2, \tilde{c}_3} & u(c_1) + \beta \delta u(\tilde{c}_2) + \beta \delta^2 u(\tilde{c}_3) \\ \text{s.t.} & p(1, \alpha) c_1 + p(2, \alpha) c_2 + c_3 \leq p(1, \alpha) y_1 + p(2, \alpha) y_2 \\ & \tilde{c}_3 = p(2; \alpha) \hat{\beta} \delta \tilde{c}_2 \end{aligned} \quad (7)$$

Note that the first constraint reflects the agent's exponential-growth bias and the second the agent's present bias. The agent will attempt solve problem (7) subject to the perceived constraints. In addition, consumption is also subject to the actual constraints, which are $p(1, 1) c_1 + p(2, 1) c_2 + c_3 \leq p(1, 1) y_1 + p(2, 1) y_2$ and $\tilde{c}_3 = p(2; 1) \hat{\beta} \delta \tilde{c}_2$. For the purpose of this example, we will assume that the actual constraints are not binding.⁶ Under log utility, solving equation (7) yields an optimal initial level of consumption c_1^* equal to:

$$c_1^* = \frac{y_1 + y_2 [p(2; \alpha) / p(1; \alpha)]}{1 + \beta \delta + \beta \delta^2} \quad (8)$$

Three things are worth pointing out about equation (8). First, both present bias and exponential-growth bias lead the agent to overconsume and thus undersave relative to an unbiased agent. The effect of present bias is clear in the denominator, given that $\beta \leq 1$. The effect of exponential-growth bias is also clear, given that the under-estimation of compounding means that $p(1; \alpha)$ is strictly increasing in α (i.e. decreasing in the degree of bias). Second, although the agent's beliefs depend on his degree of naivete regarding

⁶An additional assumption is needed if actual constraints are binding. For example, one such simple assumption would be that the agent consumes according to equation (7) until they run out of funds at which point all subsequent consumption equals zero.

present bias, in this example his behavior depends only on his actual discounting. Third, the two biases operate through distinct channels. Exponential-growth bias means that the agent mis-perceives the price of consumption in period 1 or, equivalently, over-estimates his lifetime wealth (in terms of consumption possibilities). The effect of present bias is on the allocation of consumption for a given level of lifetime wealth. Thus while the two biases both push the agent in the same direction, we would not expect strong complementarities between the two biases in this environment.

We can also solve for the agent’s level of retirement savings at retirement, i.e. c_3 . Although it is not as nice an expression as (8), it still clearly shows the effect of the two biases:

$$c_3 = (1 + r_2) \left(\frac{\beta\delta}{1 + \beta\delta} \right) ((1 + r_1) [y_1 - c_1^*] + y_2) \quad (9)$$

Because there is no further compounding once period 2 is reached, the effect of EGB in equation (9) comes only through the suboptimally-high choice of c_1 . In a more general setting with a larger number of periods, the additional contribution of EGB would instead gradually diminish as the amount of unresolved compounding gradually decreased. Present bias, in contrast, leads to over-consumption in period 1 and then again in period 2, even conditional on the lower level of accumulated assets.

3 Study Design and Data

Data collection took place online and comprised two surveys that were administered several weeks apart. The two-wave design allowed us to separate measurement of the two biases.⁷ A complete list of content covered in each survey is provided in Online Appendix Table A.1.

We administered our survey to two distinct samples, individuals in 1) the RAND American Life Panel (ALP), and 2) the University of Southern California’s Understanding America Study (UAS).⁸ To achieve national representativeness, the ALP and UAS each use population-sampling techniques to invite subjects to join the panel and provide a laptop or tablet as well as Internet services to individuals invited to join who do not have such access.⁹

We collected our data in multiple cohorts between August 2014 and June 2015.¹⁰ Overall,

⁷This mitigates concerns that the survey instrument induces a relationship between the EGB and PB, which is known as single-source bias.

⁸We extended the sample beyond the ALP because we were able to secure additional funding that was conditional on use of the UAS sample.

⁹In both samples, subjects are regularly invited to take online surveys and are typically paid a fixed amount based on the length of the survey (approximately \$20 per 30-minute survey).

¹⁰This was done for budgeting purposes due to uncertainty on response rates and performance of subjects

we invited 4,700 individuals to participate; 2,601 completed Survey 1, and 2,393 completed Survey 2 (response rate of 51% based on Survey 2). Among the respondents, we restrict our main analysis sample to the 2,315 individuals with usable responses for our variables of interest. Appendix Table B.1 shows key demographic and economic variables obtained for non-respondents and our estimation sample. Respondents were on average older than non-respondents, but not richer after controlling for age. In all analysis, we use the survey weights provided by ALP and UAS to make the analysis sample nationally-representative on demographics.¹¹

3.1 Survey Measures of Biases

3.1.1 Exponential-growth bias

We use five real-stakes questions about the value of different assets that involve compound interest calculations to construct a simple measure of α , the EGB parameter defined in Section 2. The full text of the questions can be found in Appendix A. Our participants earned payments based on the accuracy of their responses to these five questions. Most respondents could earn up to \$3 per question, for a maximum of \$15.¹²

We use the method in Levy and Tasoff (2016) to construct our measure of EGB from the five questions. Let subject i 's responses on question $j \in \{1, \dots, 5\}$ be denoted by y_{ij} . Let $\vec{a}(\alpha) : \mathbb{R} \rightarrow \mathbb{R}_+^{|\mathcal{J}|}$ be a function that generates the answers consistent with a given level of α on the five questions. Thus $\vec{a}(1)$ is a vector containing the five correct answers. Our measure of subject- i 's degree of EGB is the value of α_i which minimizes the mean squared error of the

on real-stakes questions. See Table A.2 for information on the timing and response rate of each cohort.

¹¹To pool information across two independent samples with different sets of weights from the same population, we follow Westat (2006).

¹²Participants earned \$3 if their response was within 10% of the correct answer, \$2 within 25%, and \$1 within 50%. In our sample, 67 subjects were randomly assigned to a high-stakes group where the earnings were multiplied by 5 and provided up to \$15 for each question answered, for a maximum total of \$75. However, random assignment to the high-stakes condition did not significantly affect mean Alpha (p -value=0.16), suggesting that exponential perceptions do not respond to incentive changes of this magnitude. Providing financial stakes aims to induce individuals to rely on the resources they would typically use to make economic decisions. Had we designed the experiment restricting people's naturalistic tendency to use available resources, we may have distorted our measure of EGB.

Subjects were neither encouraged nor prohibited from getting help or using tools. The instructions stated, "You may use whatever approaches you would like to answer these questions." This way we identify subjects' perceptions of exponential growth in the same unrestricted environment in which most people make important financial decisions. Allowing for subjects to use tools or assistance is important for the measure to reflect behavior in other financial contexts more accurately. Indeed, among our sample, 56% report using pencil and paper, 38% a calculator, 6% a spreadsheet, and 31% got other help.

model against their actual answers, with each question normalized by the correct answer:

$$\text{Alpha} = \arg \min_{\alpha} \frac{1}{5} \sum_{j=1}^5 \left(\frac{y_{ij} - a_j(\alpha)}{a_j(1)} \right)^2 \quad (10)$$

While not the focus of this paper, we also construct a simple measure of an individual’s self-awareness of EGB, which measures the degree of overconfidence in one’s perceptions of exponential growth. The variable’s definition can be found in [Appendix A](#).

3.1.2 Present bias

We adapt the “time-staircase” procedure from [Falk, Becker, Dohmen, Huffman and Sunde \(2014\)](#) to construct a simple measure of PB as well as the long-run discount factor as defined in [Section 2](#). The staircases have the form:

Present-Future Staircase: Would you rather receive \$100 today or \$[X] in 12 months?

Future-Future Staircase: Would you rather receive \$120 in 12 months or \$[Y] in 24 months?

Subjects begin with a common value of [X] or [Y]. If a subject indicates they prefer the money sooner (later), then the second dollar amount increases (decreases) on the next question.¹³ For each staircase, subjects answer five questions, gradually narrowing the interval that contains the indifference point. Since the questions are binary and have parallel structure, they are easily understood and can be answered quickly. We randomize the order of the Staircases and utilize different base values for the different sets of questions (i.e., the Present-Future Staircase always begins with \$100 today and the Future-Future Staircase with \$120 in 12 months) to minimize the influence of mechanical (i.e., repeating) responses. While this staircase method did not involve real stakes, [Falk et al. \(2014\)](#) show that behavior between a no-stakes and real-stakes version is highly correlated.¹⁴

From these staircases we construct measures, Beta and Delta, because each staircase identifies an indifference point within a fairly small interval.¹⁵ From the Future-Future

¹³In our survey instrument, the future value X was always greater than 100 and Y was always greater than 120.

¹⁴The authors find a correlation between the staircase measures and incentivized experimental measures of 0.524. This correlation is close to the test-retest correlation of 0.664 for the incentivized experiment.

¹⁵We cannot identify the indifference point for those who select the upper bound of the time staircase. In this case, we use the upper bound value plus the difference between that value and the second-to-last value to determine the indifference point. We include a dummy variable for those with these imputed values in the analysis. Beta is imputed for 15.9% of our sample, while Delta is imputed for 10.7% of our sample.

Staircase, $\Delta = 120/Y_{\text{cutoff}}$. We impute the cutoff as the midpoint of the interval.¹⁶ From the Present-Future Staircase $\text{Beta}_i = 100/(\Delta_i X_{\text{cutoff}})$.

We consider this survey-based monetary elicitation without stakes to be a simple approach for measuring PB. Recently real-effort tasks have been used to measure time preference (Augenblick, Niederle and Sprenger, 2015); however, these elicitations are costly and difficult to implement and there is no existing evidence that these measures correlate with other economic behaviors. In contrast, there is evidence suggesting that the monetary elicitation do.¹⁷ We conducted a real-effort time-preference elicitation as well but use the monetary elicitation in our main analysis given some likely confounds to our effort elicitation. See Appendix A for a brief description.

As with EGB, we also construct a measure of self-awareness of PB, which we refer to as sophistication. See Appendix A for a description.

3.1.3 Summary statistics for bias measures

Table 1 displays summary statistics for the two biases and other key measures of interest. A value of Alpha = 1 indicates accurate perception of exponential growth, while Alpha = 0 indicates a misperception that growth is linear. The mean of Alpha in our sample is 0.55, with a standard deviation of 0.49.¹⁸

Table 1: Survey Measures

	mean	sd	min	max
Alpha	0.547	0.493	0.000	3.000
Beta	1.022	0.214	0.468	2.135
Delta	0.695	0.170	0.461	0.985
Financial Literacy	2.273	0.795	0.000	3.000
IQ Measure	2.206	1.515	0.000	5.000
Observations	2315			

The average value of Beta is 1.02, which corresponds to approximately time-consistent preferences on average; however, there is substantial variation (standard deviation of 0.21). The average value of our annual Delta is 0.70; again, there is substantial variation (standard deviation of 0.17).¹⁹

¹⁶Inputting the midpoint bounds the magnitude of the error to be quite small. The magnitude of the error on δ , for example, is bounded to be below about 0.015.

¹⁷Augenblick, Niederle and Sprenger (2015) find that real-effort and monetary elicitation do not correlate with each other.

¹⁸The distribution of Alpha is quite similar to the only other representative sample measure found in Levy and Tasoff (2016) who find a mean of 0.53 and a median of 0.60 (Levy and Tasoff, 2017).

¹⁹By way of comparison, Heutel et al. (2014) calculate an average monthly value of Delta as 0.846 and an

Figure 1: Joint Distribution of Present Bias and EG Bias

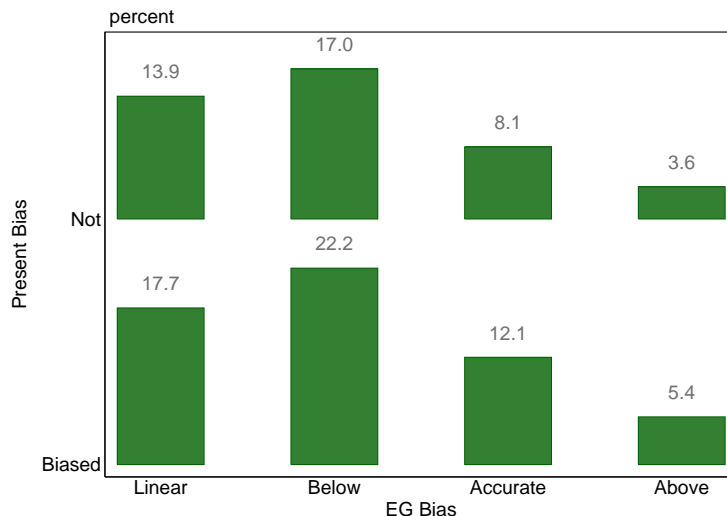


Figure 1 displays the joint distribution of EBG and PB, the first such estimates in the literature. To facilitate description, we categorize individuals into four EGB types: *Linear*, *Below Exponential*, *Accurate*, and *Above Exponential*. The types partition the range of Alpha, based on the incentive ranges used in our elicitation task. *Accurate* types, who account for 20% of the sample, are those who earned full incentive payments on the α -elicitation questions, and have values of Alpha in $[0.9523, 1.045)$. *Linear* types severely underestimate exponential growth. They have values of Alpha in $[0, 0.01)$, which would earn them \$0 in the α -elicitation. Thirty-two percent of the sample falls in this category. *Below Exponential* types have values of Alpha between *Linear* and *Accurate*, and earn intermediate payments. They underestimate exponential growth to an intermediate degree and make up 39% of the sample. *Above Exponential* types overestimate exponential growth with values of Alpha ≥ 1.045 and comprise 9% of the sample. Theory suggests that people in this group might also make sub-optimal savings decisions but in the opposite direction from those who underestimate exponential growth. We also divide individuals into either present biased (Beta < 1) or not present biased (Beta ≥ 1). Fifty-seven percent of our sample falls into the present-biased category.

The correlation between Alpha and Beta is -0.04 (p -value = 0.07), suggesting that these biases are independent (Appendix Table B.2).

average value of Beta as 0.936 using a slightly different elicitation procedure. While the point values may be implausible, the relative values within the distribution may be good predictors.

3.2 Other drivers of retirement assets

3.2.1 Financial literacy and cognitive ability measures

Recent research has devoted much attention to measuring and describing the relationship between financial literacy, numeracy, and financial decisions (e.g. [van Rooij et al., 2012](#); [Banks et al., 2010](#); [Lusardi and Mitchell, 2014](#)). There has also been research that has linked IQ to stock market participation ([Grinblatt et al., 2011](#)). It is important to determine the extent to which PB and EGB differ from cognitive skill, financial literacy, education, and other standard demographic determinants of retirement assets. If, for instance, EGB is perfectly correlated with cognitive skill, we risk simply relabeling the relationship between cognitive skill and retirement savings.

For financial literacy, we use the 3-item battery of financial literacy questions developed by [Lusardi and Mitchell \(2011\)](#) and widely used since then ([Lusardi and Mitchell, 2014](#)). Because this 3-item financial literacy assessment does not include a question that isolates understanding of compound interest, it is useful to determine to what extent Alpha is related to this highly-used metric as well as whether EGB uniquely predicts financial decisions over and above this measure of general financial literacy. We include the 3-item battery on our survey. However, because participants appear to learn the correct answers with repeated exposures to these same questions, we use each participant’s first response to this set of questions when available (i.e., fielded earlier by other researchers) to maximize the measure’s explanatory power. The average number correct on the 3-item financial literacy battery is 2.27 out of 3 (s.d. of 0.80; [Table 1](#)); 47% answered all 3 questions correctly, a rate higher than the 34% found by [Lusardi and Mitchell \(2014\)](#). We standardize the measure to a z-score in the analysis.

Similarly, we evaluate whether our bias measures of interest are different from general cognitive ability using a measure based on a subset of items from the public-domain assessment tool, the International Cognitive Ability Resource (ICAR) ([Condon and Revelle, 2014](#)).²⁰ The original ICAR test includes a total of 60 items grouped into 4 dimensions: verbal reasoning, letter and number series, matrix reasoning, and three-dimensional rotation. From the validated 16-item subset of ICAR, we selected 5 questions to measure cognitive reasoning that represent the four dimensions and that also vary in the percent of respondents who answered correctly in past research (ranging from 17% to 73% correct). The average number correct on the cognitive-ability test was 2.21 out of 5 (s.d. of 1.52; [Table 1](#)); only 7% answered all 5 questions correctly. Like financial literacy, we standardize the measure to

²⁰This tool is designed to increase the measurement of cognitive ability by being a free and flexible tool for researchers. Privately owned tools, such as the Raven’s Standard Progression Matrix (RSPM) test, are cost-prohibitive and cumbersome to incorporate into large-scale data collection.

a z-score in the analysis.

3.2.2 Household financial and background information

Our main asset accumulation measure of interest is retirement savings.²¹ We also collect data on several other financial outcomes for the household, including non-retirement savings, housing (equity and mortgages), asset allocation (retirement and non-retirement assets), debts (secured and unsecured), net worth, payday loan utilization, bankruptcy filings, and current access to employer-provided retirement plans (offering, enrollment and contributions).

Table 2 reports the summary statistics for these financial outcomes.²² Average retirement savings is \$97,185 with a standard deviation of \$228,563; 65% of the sample has positive retirement savings. The mean and median retirement savings in our sample conditional on having any retirement savings are \$148,626 and \$40,000, respectively. These moments vary some from recent data from the Survey of Consumer Finances, which reports 49% of Americans having any retirement savings in 2013, with a conditional mean and median of \$201,300 and \$59,000 (Bricker et al., 2014). Average non-retirement savings is much lower with a mean of \$39,849 and standard deviation of \$133,118. For measures of debt, the largest debt holding is mortgage debt, followed by secured and unsecured debt.

Because variation in these financial outcomes may be due to variation in household attributes other than time preferences, EGB, financial literacy, and cognitive ability, we use a rich set of controls in the analysis. Table 3 reports the summary statistics for many of these measures. The ALP and UAS panels include a rich set of background information on each respondent, including gender, age, marital status, number of household members, state of residence, ethnicity, work status, highest education, and occupation category. The average age is 46.8 years, 62% of the sample is married, and 52% of the sample is female. Among the control variables we collect on our survey is a measure of risk aversion.²³ We conduct a real-stakes elicitation of risk preferences using individuals' choice over lotteries.²⁴

²¹Individuals were asked to think about savings in personal retirement accounts from all sources, including Individual Retirement Accounts (IRAs), Keogh accounts, and 401(k)s, 403(b)s, etc.

²²We Winsorize retirement savings, non-retirement savings, and outstanding mortgage for the top 1%, and net worth for the bottom and top 0.5%.

²³We also collect information through our survey on expected age for claiming retirement benefits and whether the respondent is the financial decision maker in the household, which we use in Tables C.3 and C.6.

²⁴Individuals could earn payments based on whether a coin flip ends in heads or tails. They choose from 6 options, from equal payments for heads or tails (Category 1) up to \$15 for heads and \$0 for tails (Category 6). The proportion of the sample in each risk category is included in Table 3.

Table 2: Summary Statistics for Household Balance Sheet and Financial Behaviors

	mean	sd	min	max
<i>Balance Sheet</i>				
Retirement Savings	97,185	228,563	0.000	1,700,000
Has Any Retirement Savings	0.654	0.476	0.000	1.000
Non-Retirement Savings	39,849	133,118	0	1,100,000
Outstanding Mortgage	53,528	92,815	0	460,000
Other Secured Debt	16,392	36,083	500	250,000
Unsecured Debt	12,459	27,064	500	250,000
Net Worth	252,566	863,318	-245500	9639000
Declared Bankruptcy (last 5 years)	0.053	0.225	0.000	1.000
<i>Planning</i>				
Thought about Planning	3.071	0.515	1.000	4.000
Confident about Planning	2.985	0.670	1.000	5.000
<i>Employer Retirement Plan</i>				
Enrolled in Employer Plan	0.741	0.303	0.000	1.000
Annual Contribution	3,582	4,433	0	100,000
<i>Asset Composition</i>				
Inv Ret Savings in Equity	0.779	0.336	0.000	1.000
Housing % of Assets	0.698	0.214	0.000	1.000
Short-Term Loan (last 5 years)	0.080	0.271	0.000	1.000

Notes: Retirement Savings, Non-Retirement Savings, Outstanding Mortgages winsorized for top 1%. Net Worth Winsorized for top 0.5%. Other Secured Debt and Unsecured Debt represent midpoints from categorical responses. Thought about Planning scored on 4-point Likert scale (1 = Not at all, 4 = A great deal); Confident about Planning on 5-point scale (1 = Strongly disagree, 5 = Strongly Agree).

Table 3: Demographic Controls

	mean	sd	min	max
Age	46.8	16.8	18.0	96.0
Female	0.526	0.500	0.000	1.000
Family Income	60,569	54,760	0	200,000
<i>Education</i>				
HS or Less	0.420	0.494	0.000	1.000
Some College	0.199	0.399	0.000	1.000
Assoc Degree	0.089	0.285	0.000	1.000
BA/BS Degree	0.177	0.382	0.000	1.000
Post BA/BS	0.115	0.320	0.000	1.000
<i>Marital Status</i>				
Married/Partnered	0.624	0.485	0.000	1.000
Separated	0.019	0.137	0.000	1.000
Divorced	0.107	0.309	0.000	1.000
Widowed	0.040	0.196	0.000	1.000
Never Married	0.211	0.408	0.000	1.000
Missing	0.000	0.000	0.000	0.000
Add'l HH Members	1.284	1.156	0.000	3.000
Num of Children	0.908	1.245	0.000	9.000
Hispanic/Latino	0.173	0.378	0.000	1.000
<i>Race</i>				
White/Caucasian	0.774	0.418	0.000	1.000
Black/African American	0.121	0.326	0.000	1.000
American Indian	0.013	0.112	0.000	1.000
Asian	0.027	0.163	0.000	1.000
Other	0.065	0.246	0.000	1.000
Missing	0.000	0.010	0.000	1.000
<i>Risk Aversion</i>				
Category 1	0.320	0.466	0.000	1.000
Category 2	0.164	0.370	0.000	1.000
Category 3	0.181	0.385	0.000	1.000
Category 4	0.081	0.272	0.000	1.000
Category 5	0.045	0.207	0.000	1.000
Category 6	0.208	0.406	0.000	1.000
Missing	0.003	0.059	0.000	1.000
Observations	2315			

Notes: Family Income shown Winsorized for top 5%. Higher risk aversion categories represent decreasing risk aversion.

3.2.3 Predictors of EGB and PB measures

Before proceeding, it is worth understanding how measures of EGB and PB are associated with other individual characteristics. To explore this, we regress Alpha and Beta on conventional demographic characteristics captured by our control variables as well as the financial literacy and IQ measures. Results are reported in [Appendix B](#) in [Table B.3](#). We find a positive relationship between the IQ measure and Alpha, while Alpha and financial literacy are not related. We also find that Alpha is positively related to educational attainment and is lower for females relative to males. As for PB, there is some evidence of differences in Beta by racial and ethnic group. Adjusted- R^2 of 0.081 and 0.127 for Alpha and Beta, respectively, provide evidence that standard factors explain only a small share of their variation.²⁵

3.3 Identification

We aim to test for the existence of and measure the magnitude of a relationship between retirement assets (Y) and both EGB and PB (α, β). Because retirement savings, a stock variable, accumulates over the lifecycle and is subject to exponential growth, it is unlikely to be linear in α and β . A retirement-savings regression, to be properly specified, needs to have an interaction term between years of accumulation and α and β (e.g., at 0 years of accumulation the effect of α and β is 0 but at 30 years it could be quite large). To flexibly allow for these heterogeneous effects across the lifecycle, we interact each bias measure with age. This yields the model:

$$Y = \pi_1 T + \pi_2 T * (age - 65) + \pi_3 X + \epsilon \quad (11)$$

where T includes α and β as well as potentially-confounding factors that may be correlated with both Y and (α, β) : discount rate (δ), financial literacy, and cognitive skill. To guard further against omitted-variable bias, we condition on the rich set of demographic and economic variables discussed in [Section 3.2.2](#) along with an intercept, all denoted X . The coefficients on the factors in T are, therefore, interpreted as the effect on the relationship with retirement assets at age 65, near retirement. Our main specification models the level of retirement savings Y . Results from an alternative specification, using a natural log outcome, are also presented.

Under the assumption that unobserved influences are mean independent of predictors ($E[\epsilon|T, T*(age-65), X] = E[\epsilon]$), the model is identified and can be estimated by OLS. [Stango et al. \(2017\)](#) ([Table 8](#)) show that in a regression of financial condition on behavioral factors,

²⁵For comparison, we also present the correlation of other predictors with Delta, BetaxDelta, our measures of overconfidence and sophistication, and financial literacy in this sample.

the coefficients on EGB and PB are invariant to the omission of numerous controls. This evidence supports the identifying assumption. To make the estimates nationally-representative, we use weighted least squares (WLS).

4 Results

4.1 Retirement assets

In Table 4, Column (1), we include a set of controls that are plausibly exogenous to the bias measures: indicator variables for age in 10-year bins, a linear term in age, gender, marital status, size of household, number of children, racial group, Hispanic ethnicity, risk-aversion categories, state of residence, and indicators of imputed and missing values. The dependent variable is individual level of retirement assets. The coefficient on Alpha, \$77,224, can be interpreted as an estimate of how much more retirement savings at age 65 those with accurate perceptions of exponential growth (Alpha=1) have over those who misperceive exponential growth as linear (Alpha=0). The results imply that a one standard deviation difference in Alpha (0.493) is associated with a \$38,100 difference in retirement savings at age 65. To facilitate interpretation, we report mean retirement savings overall (\$97,185) as well as only for individuals aged 60 to 69 (\$187,202) in the table below the coefficients. The \$148,301 estimated coefficient on Beta implies that a one standard deviation difference in Beta (0.214) is associated with a \$29,600 difference in retirement savings at age 65. For comparison, the long-run discount measure, Delta, has a coefficient of \$322,092 and implies that a one standard deviation increase (0.170) is associated with a \$54,800 difference in retirement savings at age 65. All coefficients are statistically significant at levels $p < 0.01$. Moreover, the interaction terms for the two bias measures as well as the long-run discount measure with age are significantly positive, which indicates that the effects increase with age.²⁶

These estimated relationships are all in the directions that straightforward theories of EGB and time preferences predict. On average, the income and wealth effects of EGB (low Alpha) appear to dominate any substitution effect in determining retirement saving decisions, so that more biased people save less. The finding that PB (low Beta) is associated with lower savings is inconsistent with the branch of theory predicting that PB leads to higher savings. A higher discount rate (Delta) sensibly is associated with more savings. All of these associations manifest more strongly with age, proxying for the length of time people

²⁶We report results without age interactions which give the average effect across the age distribution in Appendix Table C.1.

have to earn, save, and have retirement savings compound.

Column (2) reports the results after adding additional control variables that strongly determine the level of retirement savings and which we expect, in part, are driven by the biases or the long-run discount factor: education level, retirement status, indicators for household income in 17 bins and all age-income interactions. Unsurprisingly, the adjusted- R^2 rises considerably when we add these controls, from 0.180 to 0.382. The coefficients on Alpha and Beta decrease but remain both statistically and economically significant. The estimated \$47,568 coefficient on Alpha implies that the difference between those with accurate perceptions of exponential growth and those with linear perceptions is about 26% of retirement assets for individuals at age 65. One standard deviation differences in Alpha and Beta are associated with differences of 13% (\$23,000) and 10% (\$19,000) of retirement savings at age 65, respectively. For comparison, a one standard deviation difference in Delta is associated with a difference of 13% (\$24,000) at age 65.

In Column (3), we include our financial literacy and IQ measures (standardized), and exclude Alpha and Beta. This specification includes only factors standard in the prior literature.²⁷ The estimated coefficient on financial literacy is \$18,176 and represents the average difference in retirement assets at age 65 for those with a one standard deviation difference in financial literacy. Similarly, the coefficient on our standardized IQ measure, \$15,571, is statistically significant and indicates that a one standard deviation increase in this IQ measure is associated with 9% higher retirement savings at age 65.

Specification (4) produces the paper's main result by including Alpha and Beta along with Delta, the standardized financial literacy and IQ measures, and linear age interactions for these five main regressors as well as the full set of controls. The estimated coefficients on Alpha and Beta change little from the specification in Columns (2) which exclude financial literacy and IQ. The coefficients imply that a one standard deviation difference in Alpha and Beta are associated with \$20,000 (11%) and \$19,000 (10%) differences in retirement savings at age 65, respectively. These coefficients are statistically significant at the 1% level for Beta and 5% level for Alpha.

To get a sense of the plausability of these magnitudes, consider how large assets-at-retirement effects are in terms of implicit effects on saving behavior. An additional \$1 invested each month starting at age 25 and continuing for forty years, assuming a 5% rate of return and no withdrawals, yields about \$1,500 in assets at age 65. Therefore, accumulating an extra \$20,000, similar to the coefficients on Alpha and Beta, implies about an extra \$13 per month in retirement savings.

²⁷Although our Beta*Delta, without dividing out Beta to obtain Delta separately, would be more comparable to the prior literature's measure of the discount rate.

Table 4: Relationship between Bias Measures and Retirement Assets

	DV: Winsorized retirement assets					DV: log(retirement assets + \$10,000)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Alpha	77,224*** (17,351)	47,568*** (15,985)		40,448** (16,283)	51,513*** (17,961)	.353*** (.0991)	.163** (.083)		.112 (.0843)	.172** (.0754)
Beta	148,301*** (38,934)	86,886*** (33,399)		89,523*** (33,049)	103,999*** (36,200)	1.17*** (.242)	.675*** (.222)		.692*** (.215)	.697*** (.186)
Delta	322,092*** (58,753)	139,808*** (53,079)	99,971* (51,153)	133,060** (53,450)	174,517*** (57,298)	2.04*** (.36)	.913*** (.302)	.588** (.282)	.87*** (.305)	.913*** (.253)
IQ Measure (Std.)			15,571** (7,629)	11,256 (8,076)	12,728 (8,076)			.0857* (.0448)	.0787* (.045)	.08* (.0422)
Fin Lit (Std.)			18,176** (8,280)	17,663** (8,220)	17,571** (8,155)			.153*** (.0508)	.151*** (.0503)	.14*** (.043)
Alpha x (Age - 65)	1,995*** (554)	1,505*** (509)		1,233** (512)	1,829*** (643)	.00735** (.00355)	.00412 (.00294)		.0024 (.00295)	.00636** (.00295)
Beta x (Age - 65)	3,554*** (1,099)	2,543** (1,111)		2,534** (1,107)	3,499** (1,426)	.0279*** (.00781)	.0217*** (.00762)		.0219*** (.00748)	.0219*** (.00741)
Delta x (Age - 65)	7,774*** (1,779)	4,069*** (1,493)	2,735** (1,332)	3,778** (1,473)	4,445** (1,918)	.03** (.013)	.0136 (.00967)	.00127 (.00836)	.012 (.00956)	.013 (.00906)
IQ x (Age - 65)			483* (247)	329 (252)	317 (289)			.0022 (.00162)	.00192 (.00164)	.00148 (.00163)
Finlit x (Age - 65)			701*** (257)	690*** (256)	795*** (275)			.00492*** (.00164)	.00488*** (.00164)	.0052*** (.00158)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Mean of DV	97,185	97,185	97,185	97,185	132,821	10.4	10.4	10.4	10.4	10.6
Mean of DV for Ages 60-69	187,202	187,202	187,202	187,202	220,405	11	11	11	11	11.1
Adj R ²	0.180	0.382	0.380	0.384	0.375	0.314	0.544	0.544	0.548	0.530
N	2,315	2,315	2,315	2,315	2,315	2,315	2,315	2,315	2,315	2,315

Notes: All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted measure represent the relationship between the measure and retirement assets at age 65. Demographic controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, age, and 10-year age groups. Additional controls include indicator variables for highest level of education, 17 income categories, and 10-year age groups x income category interactions. Models reported in Columns (1)-(4) and (6)-(9) are estimated using Weighted Least Squares. Columns (5) and (10) report unweighted results using OLS. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

In comparison, the coefficient on Delta, which is significant at the 5% level, implies that a one standard deviation difference is associated with a \$22,000 (12%) difference in retirement assets at age 65. The coefficient on the financial literacy measure remains essentially unchanged from Column (3) and is statistically significant at the 5% level, evidence that EGB and financial literacy have distinct relationships with retirement-asset accumulation. The IQ measure is not statistically significant in this specification. In Column (5) of Table 4 we report the results using OLS instead of WLS for comparison. Without using weights, the estimates on Alpha and Beta are slightly larger and both statistically significant at the 1% level.

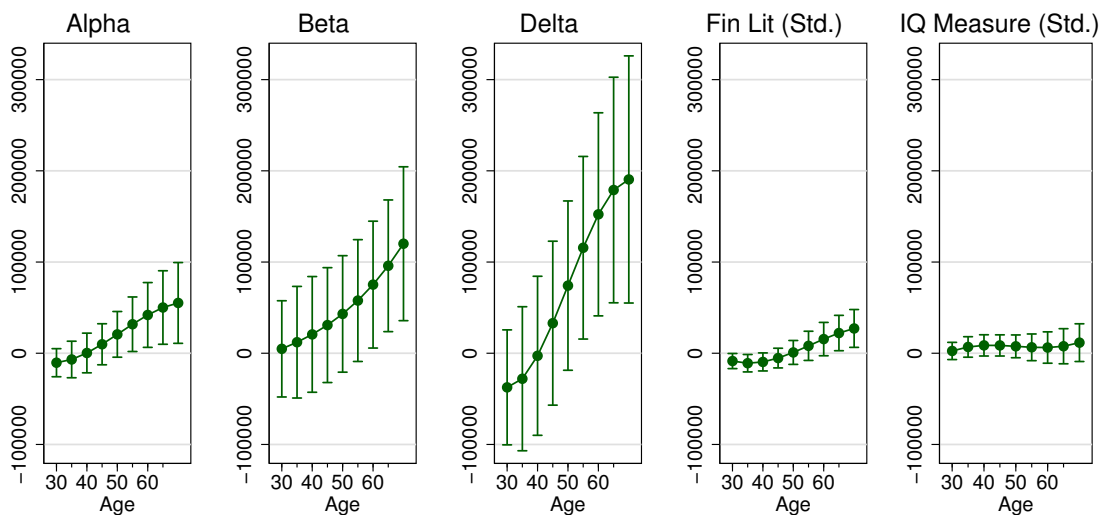
Columns (6) - (10) report estimates only changing the dependent variable from retirement asset levels to a log function of retirement asset levels. The results are generally consistent with the findings in Table 4. All the coefficients remain positive and highly significant across Columns (6)-(10), with the exception that the coefficient on Alpha loses significance in Column (9) but regains significance in Column (10) (the unweighted sample). The coefficients generally imply slightly smaller effects than the levels regression. Because a log specification estimates the average proportional effect whereas a levels specification estimates the average effect, the pattern of results can be explained by an effect that is heterogeneous in savings. In particular, it is larger in a proportional sense among those with a higher level of savings.

Figure 2 displays estimates with retirement-asset levels as the dependent variable interacting each of the five key predictors with a cubic function of age centered at 65. For Alpha, Beta, and Delta, effects are not significant at young ages, before retirement assets have had time to accumulate, but become significant by age 65. All five factors display an upward-sloping trajectory. None of the factors are significant for 30–40 year-olds, but we estimate very large and highly significant effects for people over 50. In sum, direct measures of PB and EGB have independent power to empirically explain accumulation of retirement assets by age after accounting for the asset accumulation by age associated with measures of long-run discount factor, general cognitive skill, and financial literacy as well as a rich set of controls. These results are robust to allowing for more flexible relationships between age and effects.²⁸

We also consider the relationship between self-awareness about one’s biases and retirement savings. As reported in Table C.2 in Appendix C, we regress retirement savings on the bias measures, overconfidence in exponential estimation and an indicator variable for

²⁸Moreover, there is substantial variation in the optimal level of savings early in the lifecycle. For example, Skinner (2007) calculates that some households with higher savings rates should in fact have a debt-to-income ratio of 0.5 at age 40 given their subsequent behavior. This may help explain the surprisingly negative, albeit small, estimates for Financial Literacy early in the lifecycle. Given the limited power we have among younger households, however, we leave this for future work.

Figure 2: Heterogeneous Effects of Alpha, Beta, Delta, Financial Literacy and IQ Measures on Retirement Assets by Age



Notes: Average marginal effects on Winsorized retirement assets, based on Specification (4) from Table 4 with cubic age interactions. Demographic controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, age, and 10-year age groups. Additional controls include indicator variables for highest level of education, 17 income categories, and 10-year age groups \times income category interactions. 95% confidence intervals shown.

sophistication regarding PB. We find no evidence of a statistically significant relationship between the measures of self-awareness and retirement savings.

4.2 Additional sources of heterogeneity in the relationship between bias measures and retirement savings

Our main specification assumes that the effects of Alpha and Beta on retirement assets vary by age, but are homogenous with respect to other factors after controlling for demographics and economic covariates. The effects of these bias measures may vary as a function of observable characteristics other than age. We report in Appendix Table C.3 the baseline regression among split samples of the population. We examine heterogeneity by income, whether the respondent is the financial head, marital status, age (over or under 65), gender, education, among those offered employer retirement plans, and among those enrolled in employer retirement plans by splitting the sample along these dimensions. We also report the p -values of tests for equality across subsamples of the coefficients for Alpha and Beta, as well as the joint significance of Alpha, Beta, Delta, financial literacy, and IQ.

We find evidence that the relationship between Alpha and retirement assets differs by income and by educational attainment. The relationship is stronger among those with higher income and for those with higher educational attainment. For Beta, there is evidence that the relationship with retirement assets differs by marital status and gender such that the relationship is stronger for married individuals relative to unmarried ones and for males relative to females. When we consider the five measures jointly, results indicate statistically significant differences in the relationship with retirement assets by educational attainment and accumulation vs. decumulation stage.²⁹

4.3 Other financial outcomes and behaviors

In this section, we report the results of estimating our main specification on other financial outcomes, including other items on the household balance sheet and behaviors that could shed light on the potential channels through which EGB and PB may influence retirement-asset accumulation.

We first look beyond retirement savings to study the relationship between the bias measures and other household assets and liabilities. We regress non-retirement savings, outstanding mortgage, measures of secured and unsecured debt, and net worth as well as bankruptcy experience on Alpha, Beta, Delta, financial literacy and IQ along with linear age interactions

²⁹We use over or under age 65 as a proxy for the accumulation and decumulation stage.

and our other baseline controls (i.e. the baseline specification in Column (4) in Table 4) and report the results in Table 5.

For non-retirement assets, we find a significant relationship for measures of PB and the long-run discount factor in predicting non-retirement savings, but we do not find evidence that our measure of EGB is a significant predictor. This is consistent with theory, as EGB is less important for shorter savings horizons and assets held in non-retirement accounts tends to be for more immediate needs. The IQ measure has a marginally significant relationship with non-retirement assets, while the financial literacy measure does not have a statistically significant relationship.

Columns (2) to (4) report results for liabilities. We find that those who have a higher Beta (i.e., are less present-biased) have less mortgage debt at age 65 ($p < 0.10$). We do not find evidence of a significant relationship between mortgage levels and the long-run discount factor, EGB, financial literacy or IQ measures. Those with a one standard deviation higher measure of financial literacy report more secured debt at age 65 ($p < 0.05$) and those with higher IQ report less unsecured debt ($p < 0.01$), but we do not find significant relationships between these outcomes and the the bias measures.³⁰

Net worth is the sum of retirement savings, non-retirement saving and housing equity, less secured and unsecured debt. The results for this outcome are reported in Column (5). The PB and long-run discount factor measures each have a strong and statistically significant relationship with net worth at age 65, but Alpha does not, as it only significantly predicts one component of net worth (retirement assets). A standard deviation increase in Beta is associated with an increase in net worth by \$93,000 and a standard deviation increase in Delta is associated with an increase in net worth by \$146,000. The estimated coefficients on the IQ and financial literacy measures are each small and statistically insignificant.

Second, we turn to behaviors that may serve as possible channels through which EGB and PB may influence retirement-asset accumulation. For instance, differences in retirement savings for present-biased versus time-consistent individuals could be the result of lack of adequate retirement planning, which has been shown to influence retirement assets (Ameriks, Caplin and Leahy, 2003), or delayed enrollment in retirement-savings plans. Differences in retirement savings between those with accurate and biased perceptions of exponential growth could be due to lower levels of contributions or differences in asset allocation decisions. For example, Gaudecker (2015) finds that those with below-median financial literacy lose an expected 50 basis points on average.

³⁰Because our measures of secured and unsecured debt represent the midpoints of categorical responses, we have considerably less power to detect associations. However, the relationships we report are robust to representing these measures with categorical variables using ordered probit/logit regressions or using the intervals to perform interval regressions.

Table 5: Relationship between Bias Measures and Household Balance Sheet

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Ret Savings	Mortgage	Sec Debt	Unsec Debt	Net Worth	Bankruptcy
Alpha	-1,235 (10,657)	3,437 (5,725)	1,019 (2,600)	1,249 (1,423)	3,584 (75,830)	-0.00547 (.0144)
Beta	64,412*** (24,218)	-24,761* (13,099)	-1,892 (5,156)	3,465 (4,501)	436,745*** (150,142)	-0.0174 (.0453)
Delta	79,371** (37,113)	-12,191 (19,135)	-2,649 (7,807)	7,830 (5,448)	857,042** (393,205)	-0.0529 (.054)
IQ Measure (Std.)	10,569* (5,984)	-1,686 (3,322)	-1,641 (1,546)	-4,229*** (1,392)	-7,044 (64,357)	-0.0143 (.0101)
Fin Lit (Std.)	4,083 (5,834)	3,861 (3,482)	3,227** (1,566)	271 (1,112)	9,918 (43,201)	.00222 (.0123)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of DV	39,849	53,528	16,392	12,459	252,565	.0533
Mean of DV for Ages 60-69	80,453	52,419	17,013	8,134	523,403	.0794
Adj R ²	0.235	0.280	0.078	0.137	0.245	0.058
N	2,315	2,315	2,315	2,315	2,315	2,315

Notes: Dependent variable is as indicated in table. All asset outcomes are Winsorized. Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Secured and unsecured debt represent midpoint of categorical response. Payday loan and bankruptcy outcomes equal one if respondent used payday loan or declared bankruptcy in last five years. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, age, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table 6 reports results using indicators of different behaviors as the outcome variable, including indicators of retirement planning, participation in and contributions to employer-sponsored retirement accounts, asset allocation and payday loan use, using our baseline specification that includes the bias measures as well as measures of the long-run discount factor, IQ, and financial literacy.

Across these behaviors, we find that Beta is associated with higher regular contributions to one’s retirement fund as well as associated with a lower total share of assets invested in housing. Given that housing is an illiquid asset, this is consistent with the prediction of Laibson (1997) that present-biased individuals will have lower liquidity.³¹ This failure to invest in relatively liquid asset classes, such as stocks instead of housing, could lead to lower returns and lower total retirement savings.

We find that Alpha does not predict the retirement planning outcomes or asset allocation, but is a significant predictor of payday loan usage. Compared to the unbiased type, the fully-biased type has a 2.5 percentage point higher probability of using a payday loan within the past five years, or an increase of 32% on the base rate of 8% ($p < 0.10$). This supports existing theoretical arguments and empirical evidence that agents with EGB may underestimate interest rates on short-term loans (Stango and Zinman, 2009). However, we find that less present-biased individuals are somewhat more likely to use payday loans, which is counter to theory and surprising.

As for the other main regressors, Delta is associated with higher regular contribution amounts and a higher probability of having some investment in equity.³² The measures of financial literacy is associated with retirement planning, regular contribution amount, and investment in equities. We find no evidence that the measure of IQ is a significant predictor of the behaviors examined in Table 6.

5 Robustness of Findings

In this section, we assess the robustness of our findings in several ways. First, we evaluate alternative specifications, including alternatives for the dependent, independent, and control variables. Second, we address bias in our estimates stemming from measurement error in our measures of PB and EGB using more extensive elicitations of cognitive ability and financial literacy. We also address the possibility that retirement-asset levels were measured with error in our survey.

³¹This occurs because sophisticated present-biased individuals will use low liquidity as a commitment device and naive ones will exhaust any liquid assets through lack of self-control.

³²This association with equity replicates the main result of van Rooij et al. (2011).

Table 6: Relationship between Bias Measures and Financial Behaviors

	(1)	(2)	(3)	(4)	(5)	(6)
	Ret Plan	Enrolled	Cont Amt	Inv in Equity	Housing Share	Payday Loan
Alpha	.136 (.128)	-.0307 (.0507)	-37.7 (649)	.0407 (.0303)	-.0316 (.0201)	-.0253* (.0131)
Beta	.266 (.416)	.0382 (.106)	4,122** (1,883)	-.00511 (.0922)	-.15*** (.0498)	.0941* (.0524)
Delta	-.35 (.424)	.12 (.156)	11,225*** (3,040)	.249** (.103)	-.0817 (.0676)	-.0335 (.0491)
IQ Measure (Std.)	.0726 (.071)	-.0176 (.0257)	200 (387)	.0106 (.0173)	-.00123 (.0106)	-.00259 (.0089)
Fin Lit (Std.)	.205** (.0859)	.018 (.033)	960* (548)	.0507** (.0224)	-.019 (.0136)	-.00405 (.0121)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean of DV	3.07	.741	3,582	.779	.698	.0797
Mean of DV for Ages 60-69	3.33	.744	4,843	.833	.628	.0542
Adj R ²	0.370	0.174	0.211	0.306	0.372	0.143
N	693	1,144	1,142	1,608	1,542	2,315

Notes: Dependent variable is as indicated in column heading. See text for more details. Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

5.1 Alternative specifications

We examine the robustness of our main specification in the following ways. First, we use alternative definitions of the dependent variable to address concerns that the findings are driven by irregularities in the data, such as the limited number of individuals with substantial retirement assets paired with the sizable fraction of individuals with no retirement savings. We report the results in [Appendix C](#). Our main findings are robust to different levels of Winsorizing and taking into account the censored nature of the dependent variable ([Table C.4](#)).

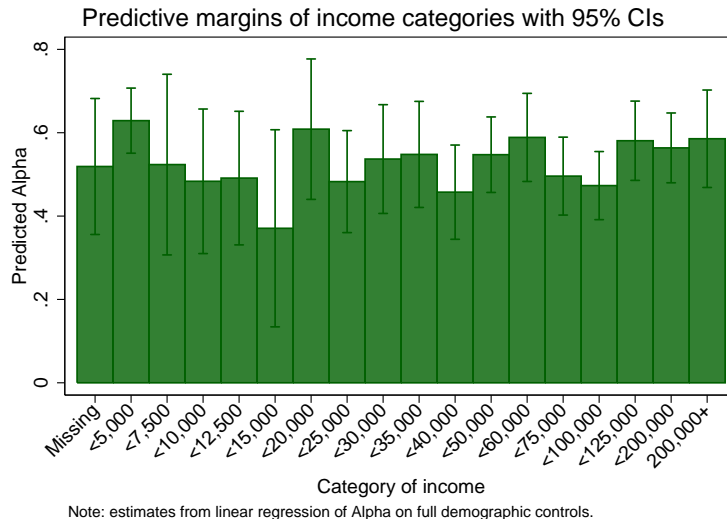
Second, we consider alternative specifications of our behavioral parameters, including interactions between the parameters, higher order terms, and alternative coding of future-biased individuals (i.e., $\text{Beta} > 1$); results are reported in [Appendix Table C.5](#). Overall, these results point to a robust relationship between the parameters of interest and retirement assets at age 65.

Third, we consider more extensive control variables to help mitigate the possibility that the estimated relationships are driven by omitted variables. We use other survey items we collected as well as draw upon prior surveys administered to the panel by other researchers to explore the robustness of our results to additional control variables in [Appendix Table C.6](#). In [Columns \(1\)–\(4\)](#), we add additional controls for occupation, employer-provided retirement plan characteristics (match, non-matching contributions), and expected retirement age. The coefficients on our main parameters are not meaningfully affected by the inclusion of these additional variables and remain strongly significant. A particular concern is that our simple measure of Beta as well as Delta are constructed from a time-preference elicitation that uses preferences over the timing of receipt of money, and so may be confounded by liquidity constraints. In [Column \(5\)](#) we add several controls for liquidity constraints (secured and unsecured debt, home ownership, and housing equity) that were collected in our survey and find no significant effect on the coefficients of our main parameters. We were additionally able to match roughly half of our subjects to FICO scores and subjective health measures asked previously in the online panel, and include these along with the other variables in [Columns \(6\) and \(7\)](#). Once again the coefficients are largely unaffected, but the standard errors increase given the sharply reduced sample. It thus appears unlikely that liquidity constraints, variation in health, or job characteristics drive our results.

5.2 Reverse Causality

We explore the possibility that reverse causality drives the observed associations of EGB and time preferences with retirement wealth. This is of particular concern for EGB in that

Figure 3: Relationship Between Income and Alpha



individuals with greater access to savings opportunities face a greater incentive to improve their understanding of exponential growth. This idea is embedded in the financial literacy literature more broadly (van Rooij et al., 2012; Lusardi et al., 2013). While we cannot rule out the possibility that reverse causality explains part of the relationship, we provide suggestive evidence against a theory that the relationship is fully driven by reverse causality.

If opportunities for savings lead to better understanding of exponential growth, then we would expect to observe a strong association between Alpha and income; high-income individuals tend to have more opportunities to save relative to low-income individuals. However, we do not find such evidence. Figure 3 shows the predicted effects of each of 17 income categories on Alpha in a regression that includes our other baseline controls and shows a flat relationship between Alpha and these income categories. Moreover, replacing the income categories with a continuous income measure results in a small and statistically insignificant association between income and Alpha ($p = 0.12$). Finally, when we stratify our sample by income in Table C.3 to focus only on those with higher-incomes and control for income and other variables, Alpha continues to have a significant association with retirement wealth.

Most economic research takes preferences such as β and δ as exogenous primitives. However, if retirement wealth influences long- or short-run discount factors, we would expect to see a positive relationship between Beta and Delta with income based on the same logic as discussed above. However, Appendix Figures B.1 and B.2 show a flat relationship between income and Beta and Delta. Moreover, the measured correlations between Beta and Delta and income are close to zero: 0.016 ($p = 0.44$) for Beta and 0.023 ($p = 0.27$) for Delta. Overall, evidence against a relationship between income and our parameters of interest sug-

gests that the relationships we estimate between our measures of EGB, time preferences, and retirement savings are unlikely to be meaningfully driven by reverse causality.

5.3 Correcting for measurement error

Our analysis thus far has assumed that all variables are measured without error. This has been the conventional approach in economics when analyzing the effects of individuals' characteristics on financial outcomes.³³ Below we consider measurement error in our bias measures as well as in our measure of retirement assets, our main dependent variable.

5.3.1 Bias measures

Our study uses simple measures of the PB and EGB parameters defined in Section 2. Existing studies that measure parameter stability find less than perfect test-retest correlations, which could be explained by measurement error.³⁴

Violations of the perfect-measurement assumption may lead to bias in our WLS estimates. Classical measurement error in a single predictor produces attenuation of that variable's coefficient and bias for other correlated predictors – even those not measured with error. If both the noisy and perfectly-measured variables have positive effects, coefficients on positively-correlated factors could inflate. A positive correlation between EGB and cognitive skill is a particular concern, given possible measurement error. If only Alpha is noisy, then the WLS estimate underestimates the true association of EGB with retirement assets, making our estimate conservative. A different and more serious concern would arise if cognitive skill were measured with more noise than EGB. When multiple predictors are measured with error, biases are more complex but well-understood (Carroll et al., 1995). The magnitude of the coefficient on Alpha could be biased upward while the coefficient on IQ could be biased toward zero.

³³See for example Ameriks, Caplin and Leahy (2003) for the propensity to plan, Stango and Zinman (2009) and Levy and Tasoff (2016) for EGB, Meier and Sprenger (2010) for time preferences, and Banks, O'Dea and Oldfield (2010) for numeracy and cognitive ability. A notable exception is Heutel et al. (2014) who explicitly attempt to deal with measurement error using multiple proxies for time preference. Also Lusardi and Mitchell (2007) and van Rooij, Lusardi and Alessie (2012) use economic education to instrument for financial literacy. While the IV strategy was not explicitly used in the papers to address measurement error in financial literacy, in principle, it could.

³⁴Test-retest correlations of time preferences exhibit considerable variation, ranging from 0.004 to 0.75 depending on methodology, sample, and duration between test and retest (see Chuang and Schechter, 2015, for a review). The only prior paper that we are aware of that has computed test-retest correlations specifically for Beta and Delta is Meier and Sprenger (2015) and they find a test-retest correlation in a sample of low-income Americans of 0.36 and 0.246 for Beta and Delta respectively. We find comparable test-retest correlations of 0.40 for Delta and 0.45 for Beta \times Delta in our sample. We are the first to measure test-retest correlations for Alpha with a correlation of 0.21.

For a subsample of subjects ($N=1,287$), we can make use of a less noisy IQ measure. While our own IQ test consists of 5 items (the same number of items used to measure α), this subsample of the ALP previously took a 45-item IQ test, consisting of 15 items in each of 3 domains (Numeric, Picture Vocabulary, and Verbal Analogy), as part of a prior study.³⁵ We reproduce our original specification in Column (1) of Table 7 for the overlapping sample and the results substituting in the alternative, less-noisy IQ measure in Column (2). If the coefficient on IQ were to rise and the EGB coefficient were to fall, this would suggest that measurement error is a significant concern for our main results. Instead, we find substantially similar results, providing no evidence that a more extensive measure of cognitive skill lowers the estimated effect of EGB.

We repeat this approach using an alternative measure of financial literacy: a standardized score on a broader 5-item financial literacy measure from other surveys in the online panel.³⁶ Column (3) of Table 7 shows the estimates from our main specification, which uses the 3-item measure, on the subsample for which we have the 5-item financial literacy measure ($n = 706$). The coefficient estimates are similar to our main findings, but the reduction in sample size renders them imprecise. More importantly, when we replace the 3-item measure with the 5-item measure (go from Column (3) to Column (4)), the estimated coefficients on Alpha, Beta, and Delta are essentially unchanged.³⁷

5.3.2 Retirement assets

It is also possible that there is non-classical measurement error which could affect our identification. In particular, if our measures of bias are correlated with measurement error in retirement assets, then we would have a biased estimate of the relationship. For example, it is conceivable that subjects reporting higher asset levels would then be “primed” to perform better on our elicitation tasks. However, there are several reasons why non-classical measurement error is unlikely to be explaining our results. First, our study design segregates EGB and time preference elicitation into different surveys, reducing the possibility that one set of questions contaminates responses to another. Second, we repeat the analysis using alternative measures of retirement assets in surveys collected previously by other researchers. In particular, we use a separate retirement-asset measure collected for a subsample of our subjects in the ALP Financial Crisis Surveys between 2014–2015. We report this alternative

³⁵We standardize scores on each domain within the sample, average each individual’s 3 domain z-scores, and standardize this average. This alternative IQ measure has a higher Cronbach’s α reliability measure than our measure, consistent with it containing less noise.

³⁶This broader measure includes questions on mortgages and the relationship between interest rates and bond prices.

³⁷Summary statistics of the variables used in this section are reported in Appendix Table B.4.

Table 7: Robustness to Alternative Definitions of Financial Literacy and IQ

	(1)	(2)	(3)	(4)
Alpha	56,779** (23,227)	59,690*** (22,500)	49,503 (32,777)	45,699 (32,027)
Beta	108,338** (42,835)	106,109** (42,174)	120,832* (68,945)	116,109 (71,344)
Delta	133,804* (75,758)	132,044* (75,702)	48,776 (105,068)	33,688 (105,838)
IQ Measure (Std.)	9,315 (11,728)		19,753 (16,522)	16,797 (17,388)
Fin Lit (Std.)	28,479** (11,251)	28,646*** (10,832)	17,975 (13,755)	
Alt. IQ Measure (Std.)		8,277 (12,313)		
5Q Fin Lit (Std.)				32,942* (19,727)
Controls	Yes	Yes	Yes	Yes
Mean of DV	107,915	107,915	105,883	105,883
Mean of DV for Ages 60-69	203,370	203,370	151,890	151,890
Adj R ²	0.419	0.419	0.437	0.440
N	1,287	1,287	706	706

Notes: Dependent variable is Winsorized retirement assets. Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Sample in Columns (1) and (2) is restricted to those with alternative IQ measure available. Sample in Columns (3) and (4) is restricted to those with 5 question financial literacy score available. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, age, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

regression in Appendix Table C.7. While our estimation sample is halved and our statistical power reduces considerably, the coefficients on Alpha and Beta remain similar in magnitude.

Taken together, the main findings and robustness results provide needed evidence on how these biases relate to retirement savings. EGB and PB both become economically and statistically significant predictors of retirement assets as individuals approach retirement. Further, both predict the amount of retirement assets but not whether an individual has any retirement savings. Differences also emerge across these biases in that PB has both a level and proportional effect on retirement savings, while EGB has only a level effect. EGB is most important among individuals with higher savings amounts. Analysis into heterogeneous effects further supports this interpretation in that EGB is only a significant predictor of retirement assets among those with above median income, while PB is a predictor for those with both below and above median income.

6 Conclusion

The analysis in this paper reveals a robust association between retirement savings and survey-based measures of two biases thought to be particularly relevant for this financial outcome. We find that measures of PB and EGB have independent, significant and economically meaningful relationships with retirement savings after controlling for a rich set of observable characteristics, including measures of cognitive ability and financial literacy. Both EGB and PB are important predictors of retirement assets with their importance increasing over the lifecycle such that they explain economically meaningful differences in retirement assets at age 65. They seem to operate on the intensive margin, as neither is a significant predictor of the likelihood of having any savings at retirement.

To the extent that they differ, EGB is most predictive of retirement savings among those substantial savings and those with higher income relative to lower income, while PB has a proportional effect on retirement savings across savings levels and its predictive power does not vary based on an individual's income. Because potential solutions for mitigating these biases are distinct, these findings suggest that efforts to address EGB are likely to have the greatest impact among individuals with greater capacity to save, in terms of higher income or more generous employer-provided plans. Alternatively, efforts to reduce the influence of PB are likely to be effective at increasing savings across individuals regardless of saving capacity.

Evidence from other aspects of the household balance sheet and financial behavior point to possible mechanisms through which these biases may relate to retirement savings. In particular, our findings indicate less PB is associated with higher regular contribution amounts

to retirement plans, greater net worth, and a lower fraction of assets in illiquid vehicles, while greater understanding of exponential growth is associated with lower use of payday loans. To give a sense of the economic magnitude of the estimated relationships and to assess the overall implications for retirement savings, we make a back-of-the-envelope prediction that retirement savings would increase by 12 percent if EGB and PB were entirely counteracted and under the assumption that both are causally related to retirement savings.

Our study estimates the association of EGB and PB measures with retirement savings, yet we use several approaches to assess the robustness of this finding. We consider alternative specifications and extensive sets of control variables as well as measures of retirement assets acquired from different surveys. We also address concerns that our findings are driven by measurement error in the elicitation of time preferences and EGB as well as the possibility that measurement error in cognitive ability and financial literacy inflate the estimated relationships on our parameters of interest. Namely, we use less noisy measures of cognitive ability and financial literacy as well as an instrumental-variables approach. While each approach has its limitations, the evidence taken as a whole suggests that our main finding is robust to classical measurement error.

This paper has several implications. First, it provides evidence for the importance of financial literacy in determining high-stakes economic outcomes. We show that EGB, a well-defined component of financial literacy, is predictive of decisions most sensitive to compound interest calculations: those with a long time horizon (i.e., retirement savings) and those with frequent compounding (i.e., payday loan use). Alternatively, broader financial literacy, as captured by standard survey measures, is positively related to retirement savings as well as to the amount of secured debt, retirement planning and investment in equities.

Second, we clarify theoretical predictions surrounding EGB and PB. Namely, our empirical findings suggest that, on average, the income and wealth effects of EGB dominate the substitution effect in determining retirement saving decisions. We also find that PB is associated with lower savings. We find empirical support for impatient individuals investing a greater fraction of their assets in illiquid vehicles, specifically housing equity, as a vehicle for saving.

Our study provides evidence that EGB and PB are distinct – their levels are not correlated within individual – and unlikely to stem from the same underlying factor. While this has important implications for theory, it also is potentially important for policy and suggests that a single policy tool is unlikely to address all misallocations these biases may cause. Defaults and other alternatives have successfully increased average contributions in many contexts, and retirement-income projections may move people toward better decisions when implemented well. However, there is no evidence that these fully counteract the effects

of EGB and PB on retirement-saving decisions and broader consideration of the current retirement system may be warranted. More evidence regarding the ability of interventions to target biases related to retirement-saving decisions is needed and remains an important direction for future research.

References

- Almenberg, Johan and Christer Gerdes**, “Exponential Growth Bias and Financial Literacy,” *Applied Economics Letters*, 2012, *19*, 1693–1696.
- Ameriks, John, Andrew Caplin, and John Leahy**, “Wealth Accumulation and the Propensity to Plan,” *Quarterly Journal of Economics*, August 2003, *118* (3), 1007–1047.
- , —, —, and **Tom Tyler**, “Measuring Self-Control Problems,” *American Economic Review*, June 2007, *97* (3), 966–972.
- , —, **Minjoon Lee, Matthew D. Shapiro, and Christopher Tonetti**, “The Wealth of Wealthholders,” February 2015. NBER Working Paper 20972.
- , —, **Steven Laufer, and Stijn van Nieuwerburgh**, “The Joy of Giving or Assisted Living? Using Strategic Surveys to Separate Public Care Aversion from Bequest Motives,” *Journal of Finance*, 2011, *66* (2), 519–561.
- , **Joseph S. Briggs, Andrew Caplin, Matthew D. Shapiro, and Christopher Tonetti**, “Long-Term Care Utility and Late-in-Life Saving,” May 2017. NBER Working Paper 20973.
- Angeletos, George-Marios, David Laibson, Andrea Repetto, Jeremy Tobacman, and Stephen Weinberg**, “The Hyperbolic Consumption Model: Calibration, Simulation, and Empirical Evaluation,” *Journal of Economic Perspectives*, 2001, *15* (3), 47–68.
- Augenblick, Ned, Muriel Niederle, and Charles Sprenger**, “Working Over Time: Dynamic Inconsistency in Real Effort Tasks,” *Quarterly Journal of Economics*, 2015, *130* (3).
- Banks, James, Cormac O’Dea, and Zoë Oldfield**, “Cognitive Function, Numeracy, and Retirement Saving Trajectories,” *Economic Journal*, November 2010, *120*, F381–F410.
- Barsky, Robert B., F. Thomas Juster, Miles S. Kimball, and Matthew D. Shapiro**, “Preference Parameters and Behavioral Heterogeneity: An Experimental Approach in the Health and Retirement Study,” *Quarterly Journal of Economics*, 1997, *112* (2), 537–579.
- Benzion, Uri, Alon Granot, and Joseph Yagil**, “The Valuation of the Exponential Function and Implications for Derived Interest Rates,” *Economic Letters*, 1992, *38*, 299–303.
- Bernheim, B. Douglas, Jonathan Skinner, and Steven Weinberg**, “What Accounts for the Variation in Retirement Wealth among U.S. Households?,” *American Economic Review*, 2001, *91* (4).
- Beshears, John, James J. Choi, David Laibson, and Brigitte C. Madrian**, “The Importance of Default Options for Retirement Savings Outcomes: Evidence from the United States,” in “Social Security Policy in a Changing Environment,” Chicago, IL: University of Chicago Press, 2009.
- Bricker, Jesse, Lisa J. Dettling, Alice Henriques, Joanne W. Hsu, Kevin B. Moore, John Sabelhaus, Jeffrey Thompson, and Richard A. Windle**, “Changes in U.S. Family Finances from 2010 to 2013: Evidence from the Survey of Consumer Finances,” Federal Reserve Bulletin 4, Board of Governors of the Federal Reserve System 2014.

- Brown, Jeffrey and Alessandro Previtro**, “Procrastination, Present-Biased Preferences, and Financial Behaviors,” August 2014. Working Paper.
- Brown, Jeffrey R., Gopi Shah Goda, and Kathleen McGarry**, “Heterogeneity in State-Dependent Utility: Evidence from Strategic Surveys,” *Economic Inquiry*, 2011, *54* (2), 847–861.
- Carroll, Raymond J., David Ruppert, and Leonard A. Stefanski**, *Measurement Error in Nonlinear Models*, Chapman & Hall, 1995.
- Chuang, Yating and Laura Schechter**, “Stability of Experimental and Survey Measures of Risk, Time, and Social Preferences: A Review and Some New Results,” *Journal of Development Economics*, November 2015, *117*.
- Condon, David M. and William Revelle**, “The international cognitive ability resource: Development and initial validation of a public-domain measure,” *Intelligence*, 2014, *43*, 52 – 64.
- Diamond, Peter and Botond Köszegi**, “Quasi-hyperbolic Discounting and Retirement,” *Journal of Public Economics*, 2003, *87* (9), 1839–1872.
- Eisenhauer, Joseph G. and Luigi Ventura**, “The prevalence of hyperbolic discounting: some European evidence,” *Applied Economics*, 2006, *38*, 1223–1234.
- Eisenstein, Eric M. and Stephen J. Hoch**, “Intuitive Compounding: Framing, Temporal Perspective, and Expertise,” Working Paper, Cornell University 2007.
- Falk, Armin, Anke Becker, Thomas Dohmen, David Huffman, and Uwe Sunde**, “An Experimentally-Validated Survey Module of Economic Preferences,” February 2014. Working Paper.
- Gaudecker, Hans-Martin Von**, “How Does Household Portfolio Diversification Vary with Financial Literacy and Financial Advice,” *Journal of Finance*, April 2015, *70* (2), 489–507.
- Goda, Gopi Shah, Colleen Flaherty Manchester, and Aaron Sojourner**, “What Will My Account Really Be Worth? Experimental Evidence on How Retirement Income Projections Affect Saving,” *Journal of Public Economics*, 2014, *119*, 80–92.
- Grinblatt, Mark, Matti Keloharju, and Juhani Linnainmaa**, “IQ and Stock Market Participation,” *Journal of Finance*, 2011, *66* (6), 2121–2164.
- Heutel, Garth, David Bradford, Charles Courtemanche, Patrick McAlvanah, and Christopher Ruhm**, “Time Preferences and Consumer Behavior,” July 2014. NBER Working Paper 20320.
- Hung, Angela A., Andrew M. Parker, and Joanne K. Yoong**, “Defining and Measuring Financial Literacy,” September 2009. RAND Labor and Population Working Paper Series.
- Investment Company Institute**, [urlhttps://www.ici.org/research/stats/retirement/ret_17_q3](https://www.ici.org/research/stats/retirement/ret_17_q3) 2017.
- Keren, Gideon**, “Cultural Differences in the Misperception of Exponential Growth,” *Perception and Psychophysics*, 1983, *34* (3), 289–293.
- Laibson, David**, “Golden Eggs and Hyperbolic Discounting,” *Quarterly Journal of Economics*,

- 1997, *62* (2), 443–477.
- , “Life-cycle Consumption and Hyperbolic Discount Functions,” *European Economic Review*, 1998, *42* (3), 861–871.
- , **Andrea Repetto**, and **Jeremy Tobacman**, “Self-Control and Saving for Retirement,” *Brookings Papers on Economic Activity*, 1998, *1*, 91–196.
- Levy, Matthew R. and Joshua Tasoff**, “Exponential Growth Bias and Lifecycle Consumption,” *Journal of the European Economic Association*, 2016, *14* (3).
- and – , “Exponential-Growth Bias and Overconfidence,” *Journal of Economic Psychology*, 2017, *58*, 1–14.
- Lusardi, Annamaria and Olivia Mitchell**, “Financial Literacy and Retirement Preparedness: Evidence and Implications for Financial Education,” *Business Economics*, 2007, *42* (1), 35–44.
- and **Olivia S. Mitchell**, “Planning and Financial Literacy: How Do Women Fare?,” *American Economic Review*, 2011, *98* (2), 413–417.
- and – , “The Economic Importance of Financial Literacy: Theory and Evidence,” *Journal of Economic Literature*, March 2014, *52* (1), 5–44.
- , **Pierre-Carl Michaud**, and **Olivia Mitchell**, “Optimal Financial Knowledge and Wealth Inequality,” January 2013. NBER Working Paper 18669.
- , – , and **Olivia S Mitchell**, “Optimal financial literacy and saving for retirement,” 2011. RAND Working Paper Series No. WR-905-SSA.
- McKenzie, Craig R.M. and Michael J. Liersch**, “Misunderstanding Savings Growth: Implications for Retirement Savings Behavior,” *Journal of Marketing Research*, 2011, *48*, S1–S13.
- Meier, Stephan and Charles Sprenger**, “Present-Biased Preferences and Credit Card Borrowing,” *American Economic Journal: Applied Economics*, 2010, *2* (1), 193–210.
- and – , “Temporal Stability of Time Preferences,” *Review of Economics and Statistics*, 2015, *97* (2), 273–286.
- O’Donoghue, Ted and Matthew Rabin**, “Doing It Now or Later,” *American Economic Review*, March 1999, *89* (1), 103–124.
- and – , “Procrastination in Preparing for Retirement,” in Henry Aaron, ed., *Behavioral Dimensions of Retirement Economics*, Brookings Institution Press & Russell Sage Foundation, 1999, pp. 125–156.
- and – , “Choice and Procrastination,” *Quarterly Journal of Economics*, 2001, *116* (1), 121–160.
- Phelps, Edmund S and Robert A Pollak**, “On Second-Best National Saving and Game-Equilibrium Growth,” *Review of Economic Studies*, 1968, *35* (2), 185–199.
- Skinner, Jonathan**, “Are You Sure You’re Saving Enough for Retirement?,” *Journal of Economic Perspectives*, 2007, *21* (3), 59–80.
- Song, Changcheng**, “Financial Illiteracy and Pension Contributions: A Field Experiment on Compound Interest in China,” January 2012. Working Paper.

- Stango, Victor and Jonathan Zinman**, “Exponential Growth Bias and Household Finance,” *Journal of Finance*, December 2009, *64* (6), 2807–2849.
- , **Joanne Yoong, and Jonathan Zinman**, “We are all behavioral, more or less: Measuring the prevalence, heterogeneity and importance of multiple behavioral factors,” Dartmouth Economics working paper, Dartmouth University 2016.
- , – , and – , “Quicksand or Bedrock for Behavioral Economics? Assessing Foundational Empirical Questions,” July 2017. NBER Working Paper 23625.
- Strotz, Robert H.**, “Myopia and Inconsistency in Dynamic Utility Maximization,” *Review of Economic Studies*, 1956, *23*, 165–180.
- van Rooij, Maarten, Annamaria Lusardi, and Rob Alessie**, “Financial Literacy and Stock Market Participation,” *Journal of Financial Economics*, 2011, *101* (2), 449–472.
- van Rooij, Maarten C.J., Annamaria Lusardi, and Rob J.M. Alessie**, “Financial Literacy, Retirement Planning and Household Wealth,” *Economic Journal*, May 2012, *122*, 449–478.
- Wagenaar, Willem A. and Han Timmers**, “The Pond-and-Duckweed Problem: Three Experiments on the Misperception of Exponential Growth,” *Acta Psychologica*, 1979, *43*, 239–251.
- and **Sabato D. Sagaria**, “Misperception of Exponential Growth,” *Perception and Psychophysics*, 1975, *18* (6), 416–422.
- Westat**, “Data Set Aggregation,” Appendix B, U.S. Department of Health and Human Services December 2006.
- Zhang, Lin**, “Saving and retirement behavior under quasi-hyperbolic discounting,” *Journal of Economics*, 2013, *109* (57–71).

Appendix A Survey Design [for online publication only]

Table A.1 describes the content of each module contained in the two surveys, which were administered several weeks apart.³⁸ We collected data from four cohorts (cohort 1, 2, and 3 from the RAND ALP sample, and 4 from the UAS sample) based on date invited to complete Survey 1. Each cohort subsample was selected at random from the respective survey sample. The number of invitations, completions, and usable responses are described in Table A.2.

While not the focus of this paper, we also construct a measure of self-awareness of each biases. In the EGB elicitation, we measure self-awareness of EGB given that awareness may result in behaviors that mitigate the effects of EGB on retirement savings, such as hiring a financial advisor or using tools. We use a new and intuitive method for assessing one’s self-awareness of EGB. After completing the five compound-interest questions, we asked subjects to choose between their performance earnings or an automatic specified payment using a multiple-price list. We define overconfidence as the difference between a subjects’ minimum acceptable payment and their performance earnings, as a fraction of possible earnings: $(\text{certain payment} - \text{performance earnings})/(\text{max earnings})$. This measure takes on the value of 0 when a person’s evaluation of their performance earnings is equal to their true performance earnings. The measure takes on the value of 1 when a person values her performance earnings maximally but true performance earnings are zero, and -1 when a person values her performance earnings at 0 when the true performance earnings are maximal.³⁹ Empirically, we find that self-awareness of one’s (mis)understanding of exponential growth is low: the mean value of overconfidence for the sample is 0.33, indicating that individuals are overconfident on average. In the PB elicitation, we construct a measure of one’s self-awareness of time-inconsistent tendencies. For this, we use an additional time staircase:

Prediction Staircase: Suppose that 12 months from now, you are going to be given the choice between the following: receiving a payment on that day (that is, 12 months from today) or a payment 12 months later (that is, 24 months from today) ... Do you think you would rather choose to receive \$110 on that day or \$[Z] 12 months later?

We construct a measure $\widehat{\text{Beta}}_i$ from the Prediction Staircase such that $\widehat{\text{Beta}}_i = 110/(\text{Delta}_i Z_{\text{cutoff}})$. We construct a binary measure of sophistication that equals 1 if an individual’s $\widehat{\text{Beta}}_i \leq \text{Beta}_i$

³⁸We used two different elicitation procedures to identify the time-preference parameters: asking for preferences regarding real-effort tasks for real stakes (Survey 1), and asking for preferences for different sums of money over time in a hypothetical choice paradigm (Survey 2). Despite careful design and piloting, the former appear to have measured calendar effects rather than a behavioral time-preference parameter.

³⁹Risk aversion will cause a person to value the certain money over the risky performance earnings. This will bias down a person’s elicited overconfidence; thus our measure is a lower bound. In our empirical analysis of retirement savings, we control for risk preferences.

and 0 otherwise.⁴⁰ For the sample, 33% of the sample is sophisticated. Results on the relationship between self-awareness of each bias and retirement savings are reported in Table C.2.

We attempted a real-effort time-preference elicitation in addition to our monetary time-preference elicitation. However, the fundamental assumption necessary for identification — that people would be available to do real-effort tasks over the course of three consecutive weeks — largely failed despite requiring this for participation. The open-ended text responses indicate that people’s choices for engaging in tasks over time was primarily influenced by how busy they were over the subsequent three weeks. We iterated a total of six combination lab and Amazon MTurk pilot experiments to achieve an implementable survey design, but despite this serious attempt “calendar effects” still confounded our final elicitation. In contrast, [Augenblick, Niederle and Sprenger \(2015\)](#) had several design differences that reduced this issue. Since it was a lab experiment they could make it clear to subjects that they needed to participate on multiple occasions. The physical presence of professor-experimenters with student subjects makes this requirement more emphatic relative to our text-based requirement of participating in multiple scheduled surveys, which was highly unusual for ALP participants. [Augenblick, Niederle and Sprenger \(2015\)](#) were also able to pay contingent on full participation but we were not. Even still in [Augenblick, Niederle and Sprenger \(2015\)](#) 12% of subjects may have exhibited some calendar effects as they dropped over the course of the multiple-week experiment. Our calendar effects were much more severe.

⁴⁰We use an indicator variable instead of including $\widehat{\text{Beta}}_i$ directly in the regression because $\widehat{\text{Beta}}_i$ is near collinear with Beta_i with a correlation of $r = 0.61$. For the future-biased, our binary measure of sophistication is 1 if $\text{Beta}_i \leq \widehat{\text{Beta}}_i$ and 0 otherwise.

Table A.1: Survey Design

Survey	Module	Description
1	Retirement Saving Scenario 1	Elicits a baseline hypothetical 401(k) contribution with and without a matching contribution from an employer.
	Background Characteristics 1	Includes measures of income, marital status, retirement savings, non-retirement savings, asset allocation, primary residence value, mortgage, secured debts, unsecured debts, 3-question financial literacy, unincentivized compounding interest question, self-reported financial knowledge.
	EG Bias Elicitation	Elicits subjects' α and subjects' overconfidence regarding their ability to accurately compute solutions to questions that involve compounding interest (<i>incentivized</i>).
	Real-Effort PB Elicitation	Elicits subjects' $\beta_R, \hat{\beta}_R, \delta_R$. Subjects choose how to allocate effort over time periods: today, next week, two weeks. Subjects must also predict their future WTA for more effortful tasks (<i>incentivized</i>).
	Risk Elicitation	Elicits subjects' coefficient of absolute risk aversion r_A . Subjects choose one binary lottery from a menu of binary lotteries that have a risk-return tradeoff (<i>incentivized</i>).
2	Retirement Saving Scenario 2	Subjects are randomized into EGB and PB Treatment groups, each with two treatment conditions and one control, for a total of 3X3 experimental groups. The pure control condition is identical to Retirement Savings Scenario 1.
	Hypothetical Monetary PB Elicitation	Elicits subjects' $\beta_M, \hat{\beta}_M, \delta_M$. Subjects choose between two hypothetical sums of money to be received at two different points in time.
	Background Characteristics 2	Includes number of children, household well-being, self-reported procrastination tendencies, financial decision maker, income tax behavior, beliefs about active vs. passive investment strategies, when they plan to collect retirement benefits, use of payday loans and bankruptcy.
	Intelligence Test	Five-question cognitive and reasoning test: three questions are alpha-numeric/mathematical, one question is on pattern-matching, and one question is on mental rotation.

Table A.2: Survey Invitations and Responses

Cohort	Source	Survey	Launch Date	Invites	Completions	Usable
1	ALP Panel	1	8/29/14	1,500	1,008	911
		2	10/17/14			
2	ALP Panel	1	10/24/14	1,500	692	625
		2	11/21/14			
3	ALP Panel	1	12/1/14	5,00	201	178
		2	12/29/14			
4	UAS Panel	1	4/29/15	1,200	700	603
		2	5/30/2015			

A.1 Survey Instructions

A.1.1 EG Bias Elicitation Module

Hypothetical Investment Questions

The closer your response is to the correct answer, the more you will earn. You may use whatever approaches you would like to answer these questions.

Each time your answer is within 10% of the correct answer, you will receive \$3; responses within 25% will receive \$2; and responses within 50% will receive \$1. Responses more than 50% away from the correct answer will not receive a payment for that question.

*Example: An asset has an initial value of \$0 but its value increases by \$10 every period. What is the value of the asset after **6 periods**?*

The correct answer is \$60. Earnings for different responses are shown below:

Response	Below \$30	\$30–\$44	\$45–\$53	\$54–\$66	\$67–\$75	\$76–\$90	Above \$90
Earnings	\$0	\$1	\$2	\$3	\$2	\$1	\$0

[Question 1: An asset has an initial value of **\$100** and grows at an interest rate of **10%** each period. What is the value of the asset after **20 periods**?]

[Question 2: An asset has an initial value of **\$100** and grows at an interest rate of **5%** each period. What is the value of the asset after **50 periods**?]

[Question 3: An asset has an initial value of **\$100** and grows at an interest rate of **-20% in odd periods** (starting with the first) and at **25% in even periods**. What is the value of the asset after **24 periods**?]

[Question 4: An asset has an initial value of **\$100** and grows at an interest rate of **-40% in odd periods** (starting with the first) and at **80% in even periods**. What is the value of the asset after **14 periods**?]

[Question 5: Asset A has an initial value of **\$100** and grows at an interest rate of **8%** each period. Asset B has an initial value of **\$X**, and grows at an interest rate of **8%** each period. Asset A grows for **10 periods**, and Asset B grows for **24 periods**. What value of **X** will cause the two assets to be of equal value?]

A.1.2 Hypothetical Monetary PB Elicitation Module

- ***Hypothetical Payment Choices***

Here are some questions that will ask you when you would prefer to receive payments. There are three sets of five questions each. The timing of the payments differs in each set, and the amounts of money differ in each question.

[Present-Future Tradeoff]

- *Suppose you were given the choice between the following:*
 - *Receiving a payment **today***
 - *Receiving a different payment **in 12 months***

We will now present five situations. The payment today is the same in each of these situations. The payment in 12 months is different in every situation.

For each of these situations, we would like to know which you would choose.

- *Would you rather receive \$100 today or \$153.80 in 12 months?*
 - *\$100.00 today*
 - *\$153.80 in 12 months*

[Future-Future Tradeoff]

- *Suppose you were given the choice between the following:*
 - *Receiving a payment **in 12 months***
 - *Receiving a different payment **in 24 months***

We will now present five situations. The payment in 12 months is the same in each of these situations. The payment in 24 months is different in every situation.

For each of these situations, we would like to know which you would choose.

- *Would you rather receive \$120 in 12 months or \$184.60 in 24 months?*
 - *\$120.00 in 12 months*
 - *\$184.60 in 24 months*

[Prediction Tradeoff]

- Suppose that **12 months from now**, you are going to be given the choice between the following:
 - Receiving a payment on that day (that is, 12 months from now)
 - Receiving a different payment 12 months later (that is, 24 months from today).

We will now present five situations. The payment on that day (12 months from now) is the same in each of these situations. The payment 12 months later (24 months from today) is different in each of these situations.

For each of these situations, we would like to know which you think you would choose if you were asked 12 months from today.

- Do you think you would rather choose to receive \$110 on that day or \$169.20 in another 12 months?
 - \$110 on that day
 - \$169.20 12 months later

A.1.3 Risk Elicitation Module

- **Risk Question**

This question is for real stakes. This question may be selected to count, possibly increasing your payment.

The following question asks you to pick between 6 possible pairs of outcomes. If this question is selected for payment, then the computer will flip a virtual coin. There is a 50% chance it will come up “heads” and a 50% chance it will come up “tails”. You will receive the amount indicated by the pair you choose.

For example, if you choose Pair 4 and the virtual coin comes up heads, you will receive \$11. If you choose Pair 4 and the virtual coin comes up tails, you will receive \$2.

- Pair 1: \$5 if heads, \$5 if tails.
- Pair 2: \$7 if heads, \$4 if tails
- Pair 3: \$9 if heads, \$3 if tails
- Pair 4: \$11 if heads, \$2 if tails
- Pair 5: \$13 if heads, \$1 if tails
- Pair 6: \$15 if heads, \$0 if tails

**Appendix B Sample Selection, Additional Descriptive
Statistics [for online publication only]**

Table B.1: Demographic Controls, All Invitees

	Non-Responder/Incomplete	Estimation Sample
Age	49.67 (17.12)	46.83 (16.80)
Female	0.565 (0.497)	0.516 (0.500)
Family Income	64706.7 (49413.3)	64139.8 (46968.7)
<i>Education</i>		
HS or Less	0.394 (0.490)	0.420 (0.494)
Some College	0.228 (0.421)	0.199 (0.399)
Assoc Degree	0.0655 (0.248)	0.0889 (0.285)
BA/BS Degree	0.220 (0.415)	0.177 (0.382)
Post BA/BS	0.0921 (0.290)	0.115 (0.320)
<i>Marital Status</i>		
Married/Partnered	0.579 (0.495)	0.624 (0.485)
Separated	0.0177 (0.132)	0.0191 (0.137)
Divorced	0.109 (0.312)	0.107 (0.309)
Widowed	0.0756 (0.265)	0.0398 (0.196)
Never Married	0.219 (0.415)	0.211 (0.408)
Add'l HH Members	1.092 (1.044)	1.290 (1.155)
Hispanic/Latino	0.241 (0.429)	0.173 (0.378)
<i>Race</i>		
White/Caucasian	0.784 (0.413)	0.774 (0.418)
Black/African American	0.126 (0.333)	0.121 (0.326)
American Indian	0.00394 (0.0628)	0.0127 (0.112)
Asian	0.0331 (0.179)	0.0272 (0.163)
Other	0.0525 (0.224)	0.0648 (0.246)
Missing	0 (0)	0.000108 (0.0104)
N	2436 (0)	2315 (0)

Note: Family income is midpoint of 17 income categories. Non-responder/incomplete include 1,850 invitees who did not begin the survey, 300 who began but did not complete, and 284 who completed but are missing data.

Table B.2: Correlations And Reliability From Reliability Sample

	Alpha	RAlpha	Beta	RBeta	Delta	RDelta	Beta × Delta	R(Beta × Delta)
Alpha	1.00							
RAlpha	0.21 (0.01)	1.00						
Beta	-0.04 (0.07)	0.24 (0.01)	1.00					
RBeta	0.10 (0.26)	0.04 (0.66)	0.09 (0.31)	1.00				
Delta	0.11 (0.00)	-0.08 (0.33)	-0.36 (0.00)	-0.07 (0.44)	1.00			
RDelta	0.07 (0.40)	-0.01 (0.92)	-0.04 (0.67)	-0.35 (0.00)	0.40 (0.00)	1.00		
Beta × Delta	0.09 (0.00)	0.09 (0.29)	0.37 (0.00)	0.02 (0.85)	0.72 (0.00)	0.42 (0.00)	1.00	
R(Beta × Delta)	0.12 (0.17)	0.00 (0.98)	0.01 (0.91)	0.26 (0.00)	0.38 (0.00)	0.80 (0.00)	0.45 (0.00)	1.00
Reliability: Alpha	0.27							
Reliability: Beta	0.11							
Reliability: Delta	0.55							
Reliability: Beta*Delta	0.58							

Note: Pairwise correlation coefficients between behavioral parameters. Measures beginning with R denotes parameter values measured from reliability survey (n = 135). P-values in parentheses. Reliability coefficient is Cronbach's reliability based on test-retest correlation.

Figure B.1: Relationship Between Income and Beta

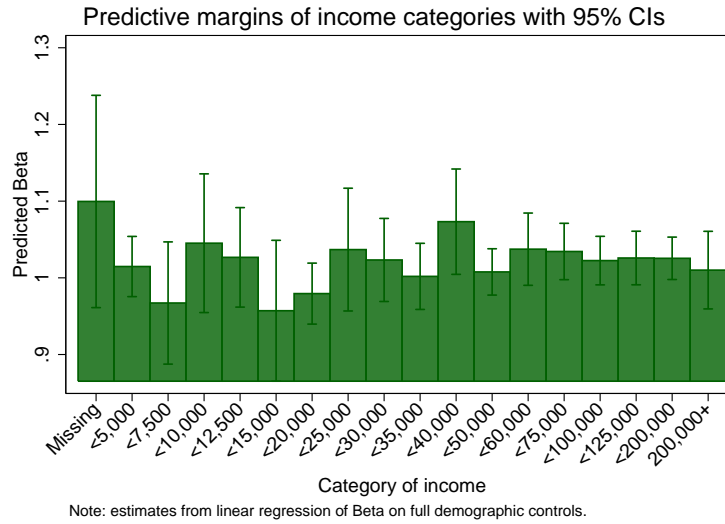


Figure B.2: Relationship Between Income and Delta

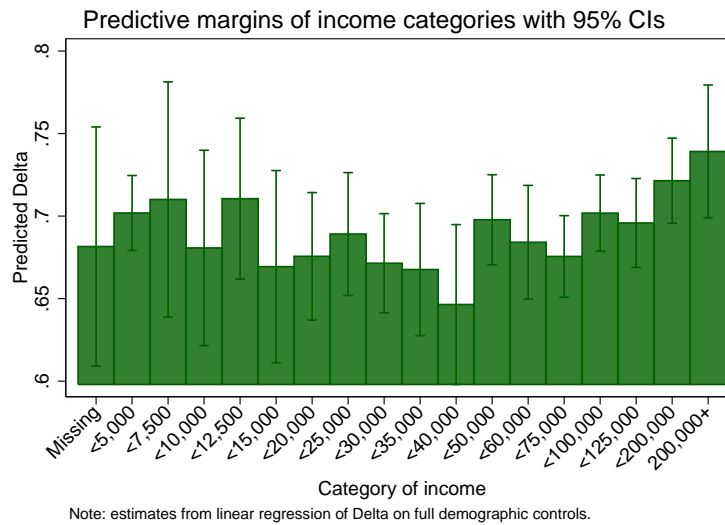


Table B.3: Predictors of Alpha, Beta, Delta, Overconfidence, Sophistication and Financial Literacy Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Alpha	Beta	Delta	Beta \times Delta	Overconf.	Sophis.	Fin Lit
IQ Measure (Std.)	0.088*** (0.015)	0.001 (0.008)	0.017*** (0.004)	0.018*** (0.005)	-0.050*** (0.011)	-0.056*** (0.014)	0.239*** (0.027)
Fin Lit (Std.)	0.011 (0.016)	0.008 (0.008)	-0.005 (0.005)	0.001 (0.005)	-0.018 (0.012)	-0.009 (0.015)	
Some Coll	0.047 (0.038)	-0.020 (0.017)	0.000 (0.011)	-0.010 (0.011)	-0.021 (0.030)	0.014 (0.035)	0.119* (0.070)
Assoc Degree	-0.004 (0.044)	-0.032* (0.018)	0.017 (0.012)	0.001 (0.012)	-0.006 (0.034)	0.036 (0.040)	0.243*** (0.073)
BA/BS Degree	0.085** (0.039)	-0.025 (0.016)	0.025** (0.012)	0.011 (0.012)	-0.033 (0.030)	0.071* (0.037)	0.291*** (0.071)
Post BA/BS	0.091 (0.058)	0.003 (0.021)	0.033** (0.014)	0.039*** (0.014)	-0.096*** (0.032)	0.023 (0.041)	0.374*** (0.075)
Female=1	-0.043 (0.027)	0.003 (0.012)	-0.002 (0.008)	-0.004 (0.008)	0.014 (0.021)	-0.028 (0.026)	-0.149*** (0.051)
Black/Afr American	-0.022 (0.045)	-0.001 (0.022)	0.007 (0.016)	-0.002 (0.015)	0.139*** (0.036)	0.003 (0.047)	-0.289*** (0.081)
American Indian	-0.198* (0.101)	0.017 (0.071)	-0.013 (0.036)	-0.012 (0.027)	0.067 (0.079)	-0.143* (0.083)	-0.126 (0.272)
Asian	-0.066 (0.089)	-0.066*** (0.022)	0.002 (0.026)	-0.043 (0.027)	0.024 (0.076)	0.017 (0.078)	0.221* (0.124)
Other Race	0.003 (0.067)	-0.024 (0.029)	0.013 (0.019)	-0.007 (0.017)	-0.007 (0.049)	0.043 (0.062)	-0.188 (0.141)
Hispanic/Latino	-0.014 (0.057)	0.053** (0.024)	-0.026* (0.015)	0.006 (0.014)	0.127*** (0.035)	-0.029 (0.045)	-0.324*** (0.098)
Adj R ²	.081	.127	.314	.325	.145	.124	.341
N	2,315	2,315	2,315	2,315	2,315	2,315	2,315

Notes: Models are estimated using Weighted Least Squares. Controls also include indicator variables for marital status, number of household members, number of children, state of residence, risk aversion category, 10-year age groups, and 17 income categories. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table B.4: Summary Statistics for Additional Robustness Checks

	mean	sd	min	max	count
5Q Fin Lit (Std.)	0.006	0.997	-3.195	1.273	706
IQ - Number	529.632	24.167	411.600	568.000	1,287
IQ - Picture	553.552	23.992	476.000	602.000	1,287
IQ - Analogy	520.207	24.643	435.000	560.000	1,287
Alt. IQ Measure (Std.)	0.008	0.985	-4.826	2.012	1,287
<i>Retirement Characteristics</i>					
Empl. Offers Ret. Plan	0.478	0.500	0.000	1.000	2,314
Empl. Offers Match	0.293	0.455	0.000	1.000	2,314
Empl. Offers Non-Match Contr.	0.156	0.363	0.000	1.000	2,314
Exp. Ret. Age	74.219	15.241	50.000	99.000	2,315
<i>Wealth Measures</i>					
Ret Savings (ALP FC)	1.13e+05	2.37e+05	0.000	1.50e+06	1,091
Housing Equity	1.30e+05	8.87e+05	-2.25e+05	3.43e+07	2,315
<i>FICO Score</i>					
FICO Score	536.866	317.651	7.000	825.000	1,136
Don't Know Score	0.247	0.431	0.000	1.000	1,136
<i>Subj. Health Measures</i>					
RateHealthIndex	2.494	0.859	1.000	5.000	1,388
Prob(Live to 75)	61.200	23.910	0.000	100.000	1,211
Prob(Live to 85)	45.064	24.262	0.000	100.000	1,368

Notes: First Fin Lit are normalized performance on first attempt on the 3-item and 5-item financial literacy batteries across any linkable survey, respectively. IQ measures are scores on Number Series, Picture Vocabulary, and Verbal Analogy modules of ALP Well Being Survey 286. Retirement characteristics are dummies for whether employer offers: any retirement plan, a matching contribution, and a non-matching contribution, as well as expected retirement age. ALP FC asset measures are matched from ALP "Effects of the Financial Crisis" surveys, matching to a respondent's most recent answer. FICO score is midpoint of 6-bin response if known, or indicator if respondent does not know. Subjective health measures are self-rated overall health and probability of living to indicated age, matched from same FC surveys.

Table B.5: Summary Statistics for Instruments

	mean	sd	min	max
Spreadsheet	0.046	0.209	0.000	1.000
Patience SPQ	3.692	0.950	1.000	5.000
Self-Assessed Fin Awareness	3.907	1.398	1.000	7.000

Notes: SPQs scored on 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Question text for SPQ is I am willing to give up something that is beneficial today in order to receive a larger reward in the future.

Appendix C Additional Results [for online publication only]

Table C.1: Relationship between Bias Measures and Retirement Assets

	(1)	(2)	(3)	(4)	(5)
Alpha	41,542*** (10,102)	19,791** (8,637)		18,048** (8,714)	27,247** (10,609)
Beta	87,749*** (29,072)	43,508** (21,679)		42,083* (21,630)	57,117** (23,181)
Delta	202,185*** (39,603)	77,456** (35,991)	59,436* (35,347)	74,231** (36,320)	118,426*** (39,488)
IQ Measure (Std.)			6,708 (4,502)	4,797 (4,500)	8,909* (5,185)
Fin Lit (Std.)			3,620 (4,222)	3,309 (4,244)	3,886 (4,785)
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	Yes	Yes	Yes	Yes
Mean of DV	97,185	97,185	97,185	97,185	132,821
Adj R ²	0.166	0.377	0.375	0.377	0.368
N	2,315	2,315	2,315	2,315	2,315

Notes: This table is identical to Table 4 except with age interactions removed. Dependent variable is Winsorized retirement assets. Models reported in Columns (1) to (4) are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit. Demographic controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, and 10-year age groups. Additional controls include indicator variables for highest level of education, 17 income categories, and 10-year age groups \times income category interactions. Column (5) reports unweighted results using OLS. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table C.2: Relationship between Overconfidence, Sophistication and Retirement Assets

	(1)	(2)	(3)	(4)
Alpha	34,588** (17,049)	40,891** (16,319)	35,083** (17,125)	
Overconfidence	-24,150 (20,928)		-23,975 (21,008)	-47,682** (19,524)
Beta	88,823*** (32,959)	91,876*** (33,479)	91,173*** (33,396)	88,249*** (33,298)
Sophisticated		14,140 (16,877)	13,936 (16,922)	8,996 (16,975)
Delta	130,621** (53,109)	142,773*** (54,859)	140,229** (54,574)	153,541*** (54,372)
IQ Measure (Std.)	10,425 (7,910)	11,768 (7,801)	10,932 (7,971)	
Fin Lit (Std.)	17,220** (8,137)	17,862** (8,263)	17,410** (8,177)	
Controls	Yes	Yes	Yes	Yes
Mean of DV	97,185	97,185	97,185	97,185
Mean of DV for Ages 60-69	187,202	187,202	187,202	187,202
Adj R ²	0.384	0.384	0.384	0.380
N	2,315	2,315	2,315	2,315

Notes: Dependent variable is Winsorized retirement assets. Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table C.3: Heterogeneity in Effect of Biases Across Observable Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Inc < Med	Inc > Med	Fin Head	Not Fin Head	Married	Unmarried	Age < 65	Age > 65
Alpha	2,050 (6,647)	54,677* (28,573)	45,526** (21,654)	28,162 (27,240)	36,677 (23,394)	13,235 (24,185)	36,896* (19,742)	78,096 (54,055)
Beta	45,946* (24,922)	125,110** (57,660)	70,636 (46,688)	186,653*** (72,135)	131,670*** (48,616)	18,899 (48,243)	57,959 (44,886)	-4,656 (107,259)
Delta	29,331 (28,659)	170,183* (97,657)	243,695*** (61,305)	156,219 (112,004)	114,728 (80,155)	117,659* (70,270)	81,218 (73,363)	504,114*** (162,981)
IQ Measure (Std.)	3,457 (4,041)	10,504 (14,509)	3,276 (10,182)	22,700 (13,852)	15,734 (11,734)	755 (10,392)	20,601** (10,310)	-58,994* (31,960)
Fin Lit (Std.)	11,411** (4,771)	22,114 (16,449)	20,401* (11,185)	8,020 (16,215)	16,952 (12,080)	4,116 (11,338)	5,022 (10,715)	72,024** (33,964)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of DV	19,723	171,272	95,910	98,792	123,850	52,964	77,134	187,678
Mean of DV for Ages 60-69	46,447	292,315	166,034	224,119	227,349	112,676	147,420	218,085
<i>p</i> -value for Equality								
Across Groups								
Alpha		0.077		0.614		0.483		0.437
Beta		0.212		0.170		0.098		0.561
All		0.091		0.452		0.238		0.022
Adj R ²	0.312	0.333	0.362	0.401	0.399	0.392	0.410	0.299
N	1,051,000	1,264,000	1,438,000	877,000	1,389,000	926,000	1,820,000	495,000

Notes: Dependent variable is Winsorized retirement assets. Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table C.3: Heterogeneity in Effect of Biases Across Observable Characteristics (*cont.*)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Women	Men	Low Educ	High Educ	Emp S Plan	No Emp Plan	Enrolled	Not Enrolled
Alpha	18,270 (19,469)	60,326** (26,396)	2,740 (13,253)	104,029** (40,353)	52,396 (31,963)	19,454 (15,533)	46,462 (40,684)	30,164* (17,102)
Beta	23,304 (38,129)	184,390*** (63,824)	19,422 (32,942)	141,184* (75,563)	87,599 (62,493)	109,738*** (35,816)	57,308 (71,267)	143,094*** (33,191)
Delta	145,297* (76,577)	204,891** (81,101)	-28,369 (55,132)	415,829*** (128,550)	258,558** (105,713)	92,157* (52,285)	227,785* (122,760)	112,803** (46,817)
IQ Measure (Std.)	27,435** (11,037)	-300 (12,709)	3,919 (8,026)	-7,938 (18,509)	15,775 (15,635)	5,650 (7,383)	16,527 (19,382)	6,528 (6,882)
Fin Lit (Std.)	8,136 (9,665)	23,236* (13,121)	12,257* (6,969)	29,084 (23,245)	22,566 (18,237)	17,100*** (6,497)	20,718 (22,035)	20,589*** (7,063)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of DV	83,090	112,197	55,551	197,989	145,735	52,884	173,296	55,300
Mean of DV for Ages 60-69	154,643	225,835	100,644	372,130	236,499	141,632	275,263	137,454
<i>p</i> -value for Equality								
Across Groups								
Alpha		0.198		0.016		0.355		0.707
Beta		0.029		0.137		0.759		0.267
All		0.113		0.004		0.469		0.483
Adj R ²	0.408	0.415	0.419	0.396	0.359	0.419	0.361	0.382
N	1,274,000	1,041,000	1,274,000	1,041,000	1,144,000	1,171,000	880,000	1,435,000

Notes: Dependent variable is Winsorized retirement assets. Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table C.4: Alternative Specifications of Retirement Assets

	(1)	(2)	(3)	(4)	(5)
main					
Alpha	40,448** (16,283)	23,842** (10,844)	42,871** (18,809)	.0027 (.0292)	39,773* (21,506)
Beta	89,523*** (33,049)	59,147** (25,394)	127,777*** (40,718)	.118 (.0752)	86,313* (45,552)
Delta	133,060** (53,450)	106,893*** (37,706)	164,843*** (63,278)	.0877 (.105)	141,287* (72,276)
IQ Measure (Std.)	11,256 (7,754)	8,493 (5,685)	17,635* (9,389)	.0251 (.0174)	9,273 (10,873)
Fin Lit (Std.)	17,663** (8,220)	16,607*** (5,796)	32,412*** (10,545)	.0507** (.0197)	17,487 (11,667)
Controls	Yes	Yes	Yes	Yes	Yes
Mean of DV	97,185	84,168	97,185	.654	148,626
Mean of DV for Ages 60-69	187,202	148,660	187,202	.709	263,977
Adj R ²	0.384	0.448		0.346	0.355
N	2,315	2,315	2,315	2,315	1,608

Notes: Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Dependent variable in Column (1) is Winsorized retirement assets at 1%. Dependent variable in Column (2) is Winsorized retirement assets at 5%. Specification in Column (3) is a Tobit with bottom-censoring at \$0. Dependent variable in Column (4) is indicator of any retirement assets. Sample in Column (5) is conditional on having retirement assets. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table C.5: Alternative Specifications of Alpha, Beta, and Delta

	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	40,448**	18,048**	104,312*	-22,100	39,847**	39,552**
	(16,283)	(8,714)	(63,078)	(37,589)	(16,232)	(16,242)
Beta	89,523***	42,083*	118,573***	228,908	281,879***	
	(33,049)	(21,630)	(44,461)	(203,360)	(98,757)	
Delta	133,060**	74,231**	131,351**	-680,511	128,157**	107,852**
	(53,450)	(36,320)	(53,428)	(530,531)	(52,619)	(53,883)
Alpha \times Beta			-59,888			
			(59,206)			
Alpha \times Alpha				45,380		
				(27,669)		
Beta \times Beta				-60,496		
				(78,664)		
Delta \times Delta				557,856		
				(369,516)		
FB=1 \times Beta					-228,413**	
					(103,405)	
FB=1					226,772**	
					(101,682)	
Top-Coded Beta						299,536***
						(89,047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age Interactions	Yes	No	Yes	Yes	Yes	Yes
Mean of DV	97,185	97,185	97,185	97,185	97,185	97,185
Mean of DV for Ages 60-69	187,202	187,202	187,202	187,202	187,202	187,202
Adj R ²	0.384	0.377	0.384	0.386	0.385	0.385
N	2,315	2,315	2,315	2,315	2,315	2,315

Notes: Dependent variable is Winsorized retirement assets. Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table C.6: Robustness to Adding Employment, Retirement Plan, Liquidity Measures, and Expectations about Health and Retirement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alpha	40,448** (16,283)	38,852** (16,379)	37,156** (16,373)	37,192** (16,373)	38,478** (15,959)	53,858** (23,687)	59,420** (29,464)
Beta	89,523*** (33,049)	89,176*** (32,405)	87,608*** (32,747)	86,955*** (32,807)	78,262** (32,272)	96,131** (46,837)	99,615 (68,764)
Delta	133,060** (53,450)	125,806** (52,904)	136,555*** (52,379)	135,866*** (52,476)	114,116** (50,266)	72,311 (78,639)	97,489 (100,884)
IQ Measure (Std.)	11,256 (7,754)	9,909 (7,628)	10,163 (7,699)	10,292 (7,695)	7,662 (7,725)	1,413 (12,032)	10,867 (16,085)
Fin Lit (Std.)	17,663** (8,220)	15,670* (8,325)	15,666* (8,330)	15,769* (8,330)	14,445* (8,016)	14,756 (12,044)	9,541 (16,701)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation	No	Yes	Yes	Yes	Yes	Yes	Yes
ER Ret Plan Characteristics	No	No	Yes	Yes	Yes	Yes	Yes
Exp Retirement Age	No	No	No	Yes	Yes	Yes	Yes
Liquidity Measures	No	No	No	No	Yes	Yes	Yes
FICO Score	No	No	No	No	No	Yes	Yes
Subj. Health Measures	No	No	No	No	No	No	Yes
Mean of DV	97,185	97,185	97,261	97,261	97,261	119,091	117,870
Mean of DV for Ages 60-69	187,202	187,202	188,322	188,322	188,322	216,398	229,174
Adj R ²	0.384	0.391	0.397	0.397	0.424	0.467	0.489
N	2,315	2,315	2,314	2,314	2,314	1,135	966

Notes: Dependent variable is Winsorized retirement assets. Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table C.7: Relationship between Alpha, Beta, Delta, and Alternative Survey Asset Measures

	(1)	(2)	(3)
	Ret Savings (Us)	Ret Savings (Us)	Ret Savings (ALP FC)
Alpha	40,448** (16,283)	48,392* (26,337)	48,087* (27,154)
Beta	89,523*** (33,049)	84,793* (44,775)	72,068 (59,670)
Delta	133,060** (53,450)	64,007 (83,948)	110,181 (75,741)
IQ Measure (Std.)	11,256 (7,754)	12,958 (12,459)	17,425 (12,812)
Fin Lit (Std.)	17,663** (8,220)	21,415* (12,441)	25,033* (13,252)
Controls	Yes	Yes	Yes
Mean of DV	97,185	109,587	112,694
Mean of DV for Ages 60-69	187,202	193,294	206,091
Adj R ²	0.384	0.389	0.407
N	2,315	1,091	1,091

Notes: Dependent variable is as indicated in table. Models are estimated using Weighted Least Squares. All specifications interact Alpha, Beta, Delta, IQ, and Fin Lit with age (represented linearly and centered at 65). Coefficients on the non-interacted parameter represent the relationship between the parameter and retirement assets at age 65. Ret Savings (ALP FC) represents Winsorized retirement savings from ALP Financial Crisis surveys from 2014–2015. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. Column (2) and (3) restrict to same sample. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.

Table C.8: First Stage Results

	Panel A: No Age Interactions		
	(1) Alpha	(2) Beta \times Delta	(3) Fin Lit (Std.)
Spreadsheet=1	.378*** (.0453)		
Patience SPQ		.0332*** (.00431)	
Self-Assessed Fin Awareness			.0855*** (.0211)
Controls	Yes	Yes	Yes
Mean of Dep Var	.547	.697	-.00864
Adj R ²	0.090	0.379	0.334
N	2,315	2,315	2,315
	Panel B: With Age Interactions		
	(4) Alpha	(5) Beta \times Delta	(6) Fin Lit. (Std.)
Spreadsheet=1 \times (Age - 65)	.371*** (.0766)		
Patience SPQ \times (Age - 65)		.035*** (.0122)	
Self-Assessed Fin Awareness \times (Age - 65)			.152*** (.0478)
Controls	Yes	Yes	Yes
Mean of Dep Var	-9.85	-12.3	4.46
Adj R ²	0.437	0.918	0.346
N	2,315	2,315	2,315

Notes: Dependent variable is as indicated in table. Models are estimated using Weighted Least Squares. Column (1) regresses Alpha on spreadsheet indicator and controls. Column (2) regresses Beta \times Delta on Patience SPQ and controls. Column (3) regresses Fin Lit on Self-Assessed Financial Awareness and controls. Columns (4), (5) and (6) report analogous specifications with age-interacted dependent variables and age-interacted instruments. Controls include indicator variables for female, marital status, number of household members, number of children, race, ethnicity, state of residence, risk aversion category, 10-year age groups, highest level of education, 17 income categories, and 10-year age groups \times income category interactions. * Significant at the 10% level; ** at the 5% level; *** at the 1% level.