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Aging, overconfidence, and portfolio choice

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ABSTRACT

Research has shown that older investors' confidence in financial skills and capability does not diminish with declining financial proficiency, and this overconfidence gap rather widens with age. Using data from the Cognitive Economics Study (CogEcon), this study examines whether and to what extent the age-related increase in overconfidence explains the riskiness of retirement portfolio. Results from the two-part models indicate that rising overconfidence is associated with a greater risky asset ownership and less share of cash equivalents, even after accounting for post-crash sentiment changes and market conditions. Further analyses find that financial advice plays an essential role in dampening the effect of overconfidence. Overall, our findings highlight the importance of cognitive bias in explaining late-life equity ownership and financial advisor as an emotional circuit breaker.

1. Introduction

A growing body of literature has explored the role of cognitive functioning in explaining late-life financial decisions.[1] One of the most plausible explanations is rising information and transaction costs due to declining cognitive skills (Christelis et al., 2010). Those with limited cognitive abilities may have to spend considerably more time to gather and process investment information, or invest in human capital to slow down cognitive aging process. In either case, cognitive aging increases the cost of risky asset ownership and thus reduces optimal exposure to financial risk.

Especially for the elderly, keeping up fast-changing financial products and investment opportunities can be particularly costly, given the increasing complexity of financial instruments and market environment. Old investors with degenerating cognitive skills would then have to bear more costs to be successful in the equity market, and in turn, reach a tipping point where information costs exceed the long-term yields on risky investments. Even for those with enough cognitive skills, their ability to make savvy financial decisions would decline gradually (Korniotis and Kumar, 2011), and preference features such as risk aversion and impatience would vary with a general aging process (Bonsang and Dohmen, 2015; Dohmen et al., 2010). Regardless of the mechanism, cognitive aging plays a major role in rebalancing retirement portfolio towards riskless assets at the end of life-cycle.

Notwithstanding the ample evidence linking cognitive decline to a less risky portfolio, the rationale behind such mechanism remains ambiguous because people are, in general, unable to judge their cognitive deficits. Finke et al. (2016), for instance, documented that old investors tend to remain confident about their financial proficiency, even though they lose financial knowledge and skills over time. In a closely related study, Gamble et al. (2014) reported a consistent decline in financial knowledge and cognitive abilities, coupled with a rising confidence in their ability to manage everyday money matters. This mismatch could reflect their beliefs about accumulating experience, reluctance to admit natural aging, or systematic deviations from a rationality rule due to cognitive aging. While recent evidence casts some doubt on the mechanism through which aging leads to biased decision-making (Kovalchik et al., 2005), it is generally accepted that older adults are more prone to overconfidence bias, particularly when they encounter cognitively demanding tasks (Bruine de Bruin et al., 2012). If these individuals show a typical investment pattern of overconfident investors (Barber and Odean, 2001), the age-related increase in overconfidence might be able to explain why some retirees still

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1 See, for instance, Christelis et al. (2010), Grinblatt et al. (2011), Kezdi and Willis (2003), and Kim et al. (2012).

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2214-6350/

hold unnecessarily risky portfolio even after accounting for bequest motives. That is, cognition-stockholding correlation is inherently multi-faceted which entails a rational motive that leads to less risky portfolio, and an irrational force that keeps old investors stay in the equity market.

Despite recent evidence calling for research on age-related increase in overconfidence, the impact such transition has on household finance is yet to be fully explored. Departing from previous analyses focused only on cognitive decline, we pay attention to a failure of realizing cognitive deficits and examine how this mismatch influences the riskiness of retirement portfolio.[2] In particular, we hypothesize that the fraction of financial wealth held in risky assets positively associate with rising overconfidence gap. To demonstrate such argument, we take advantage of data from the Cognitive Economics Study (CogEcon), which assess disparity in financial sophistication and confidence using a half-range percentage scale. The analyses begin with the replication of well-known age-related pattern in financial sophistication and confidence. The primary specification examines the extent to which this rising overconfidence affects portfolio composition, with a particular emphasis on the changes in equity ownership and conditional equity share. The models for riskless assets and indirect investments are estimated as the baseline models and then compared to the models for risky assets. This set of models reveals the substitution pattern between asset classes with different risk contents.

There are at least three pathways through which aging-driven behavioral bias can churn portfolio allocation. First, those who experienced cognitive decline but remain confident may overestimate their cognitive abilities to deal with information-intensive but risky financial instruments. This type of investors may shift their portfolio away from cash equivalents and allocate more wealth to equities with an unsupported belief of their cognitive capacity to handle the investment information. Second, although the cognitively impaired face a considerable amount of information costs, those who failed to recognize cognitive decline might be unable to identify such cost barriers. On the contrary, individuals aware of such natural degeneration may perceive the search costs correctly, and adjust the riskiness of portfolio accordingly. Third, overconfident individuals may systematically underestimate the risk involved in financial transactions while exhibiting too much optimism concerning their ability to pick winning securities (Kinari, 2016; Puri and Robinson, 2007). People who remain highly confident about cognitive skills, in this case, are likely to invest a larger fraction of savings in risky alternatives.

Collectively, our estimation results are in support of the past research and hypothesis. The CogEcon respondents display much higher confidence than their actual financial sophistication, and this lack of awareness is associated with (a) a smaller fraction of financial wealth held in cash equivalents and (b) greater likelihood of stock ownership. Those who remain overly confident about their financial acumen stay longer in the equity market, even without enough cognitive capacity to handle investment information. Our estimates from the two-part models indicate a positive association of financial sophistication with bondholding and mutual fund ownership. It seems financially sophisticated and well-calibrated individuals rebalance their financial wealth towards less risky assets (i.e., bonds) or professionally managed accounts (i.e., mutual funds), in order to minimize information costs incurred by cognitive aging. Accounting for unobserved heterogeneity, post-crash sentiment changes, and time fixed effects does not alter our findings, dismissing the potential impact of confounders. Further examination shows that financial advice significantly attenuates the overconfidence-stock holding correlation.

Although the present study does not provide conclusive evidence on the welfare outcomes, it is worth noting that these associations are not driven by actual investment skills but rather triggered by cognitive illusions. Given the general economic principles that recommend a fixed income stream after retirement, this aspect of cognitive aging might, in part, have an adverse impact on retirement well-being.

2. Literature review

Economists have long been interested in how one's economic behaviors evolve over the life cycle. In a study of credit behaviors, Agarwal et al. (2007) found that financial performance follows a hump-shaped pattern which peaks around the mid-50s. According to their estimates, individuals in their early 50s borrow financial resources at a considerably lower APR, make less rate-changing mistakes for home equity loans, and exhibit a lower propensity to pay unnecessary credit card fees. This U-shaped pattern turned out to be independent of income, education, and credit worthiness, signifying age-related drops in analytic functions as a possible mechanism. Lusardi and Mitchell (2011) also found a similar age-related pattern in Americans' financial literacy. By analyzing 2004 Health and Retirement Study, they found that financial literacy — an ability to understand and use financial information, falls sharply with age after the 50s.

Korniotis and Kumar (2011) viewed the issues from a different angle, assuming that older investors may benefit from their previous investment experiences and eventually, get wiser. That is, there might be two conflicting outcomes of aging — greater investment skills as a result of accumulating experiential capital, and less investment knowledge due to declining cognitive abilities. Investment performance and welfare outcomes would then depend on the relative sizes of potentially offsetting effects of cognitive aging. Their estimates showed that some of the investment skills indeed increase with age, but the negative impact of cognitive loss dominates the influence of accumulating experience. By examining the risk-adjusted return on household investment, they found that about 3%–5% of the annual decline in investment return is attributable to cognitive aging.

In a study of European retirees, Christelis et al. (2010) found that information-intensive assets, such as stocks or stock mutual funds which require an ability to do calculations, represents a larger fraction of financial wealth among the cognitively smart. When less information-intensive instruments such as bonds and money market funds are considered, the impact of cognitive abilities was not significant or, at best, trivial. This pattern bolsters our understanding that cognitive skills are indeed a crucial determinant of portfolio riskiness. Arguing along related lines, Banks et al. (2010) examined the extent to which cognitive ability relates to the portfolio performance and retirement income adequacy. They showed that the effect of numeracy is relatively minor when it comes to explaining broader and longer-term economic decisions such as wealth accumulation (or, decumulation).

An alternative explanation to cognition-portfolio choice nexus is proposed by Browning and Finke (2015). Unlike the previous studies emphasized the role of cognitive skills for informed choices, this study argues that deteriorating cognitive abilities lower individuals' ability to moderate negative emotional response to a loss. By analyzing portfolio reallocation during a recent financial crisis, the authors claimed that some of the portfolio reallocation away from stocks is characterized by a lower cognitive capacity and lack of ability to control emotional responses. Their findings are broadly consistent with the literature but suggest an alternative mechanism that explains portfolio reallocation during an economic downturn.

2 The basic premise of this study is that older investors are somewhat forgetful but unable to realize such loss.

Given the growing body of research highlighting the importance of financial literacy,[3] a number of studies delved into whether financial knowledge grows with experience, or decreases with cognitive resources in a manner similar to Korniotis and Kumar (2011). In Gamble et al. (2014), a unit decrease in financial literacy accompanied nearly the same amount of drop in episodic memory, perceptual speed, semantic memory, visuospatial ability, and working memory. Participants' perceptions about how much they know remained nearly unchanged or even slightly increased. A majority of participants responded that they are capable of tracking and coping with everyday money matters, despite a loss of actual cognitive capacities. Finke et al. (2016) re-affirmed this pattern by finding a consistent decline in financial proficiency coupled with rising confidence, despite a consistent decline in financial literacy and word recall ability. After the age of 80, more than 30% of the perceived financial knowledge is unjustified by their actual financial proficiency. A recent study by Robb et al. (2015) examined the welfare outcomes of this mismatch. Using 2009 and 2012 National Financial Capability Study, this study linked a gap between subjective and objective financial knowledge to the use of high-cost borrowing alternatives. The authors found that alternative financial services, such as payday loans and refund anticipation loans, are more widely used in a group of low objective financial knowledge and high subjective financial knowledge.

A notable recent finding claimed that a degeneration of brain functions carries several cognitive biases that have been widely acknowledged to lead to poor investing skills. For instance, psychology literature demonstrated that the cognitively impaired are more prone to framing effects (Finucane et al., 2005; Kim et al., 2005), tend to rely on a mental shortcut which require fewer comparisons and less cognitive loads (Johnson, 1990), and make suboptimal choices in economic issues (Besedes et al., 2012). Crawford and Stankov (1996), and Hansson et al. (2008) found that this mismatch between skills and confidence is more of a natural phenomenon, particularly when a decision-making context involves cognitively demanding tasks.

Although the evidence on older investors' overconfidence is sparse, the bold investment practice of overconfident investors has been repeatedly addressed in the finance literature (Barber and Odean, 2001; Grinblatt and Keloharju, 2009; Statman et al., 2006). In a seminal article by Odean (1999), the perceived precision of private information was significantly greater among the participants overly confident about their investment skills. Overconfident investors were more likely to misperceive the credibility of information, which make them rely on a few risky stocks with unrealistic expectations of yields. Overconfident traders earned relatively small trading profits (Gervais and Odean, 2001), and this poor performance was, in large part, attributed to the high frequency of trading (Barber and Odean, 2001). A recent study by Yang and Zhu (2016) noted that excessive trading among overconfident investors arises only in a market where historical yield is ambiguous. In a similar vein, some argued that unskilled investors are more likely to become overconfident when informed (Gregoire, 2016), and this unskilled but overconfident group makes biased savings decision over the short-term (Pak and Chatterjee, 2016).

3. Method

3.1. Data description

We utilize untapped data from the Cognitive Economics Study (CogEcon), a longitudinal study of Americans aged 50 and over and their spouses. The CogEcon was first fielded in March and July 2008 by the Survey Research Center at the University of Michigan, in order to explore the cognitive basis of economic decision-making. The 2009 survey was devoted to a post-crash study that tracks changes in income and wealth after the recession. Regular surveys continued in 2011 and 2013 with more detailed information on behavioral domains. Across the waves, participants were interviewed on cognition, preference, expectation, risk aversion, asset holdings, financial sophistication and overconfidence, and demographic characteristics.

The CogEcon respondents are recruited from the Cognition and Aging in the USA study (CogUSA), which aimed to evaluate cognitive assessment batteries for future use in the Health and Retirement Study (HRS). The baseline CogUSA survey invited 3224 individuals located in 28 primary sampling units (PSUs) across the nation, and 1514 of them completed a 40-minute telephone interview.[4] Of these 1514 participants, a total of 1230 individuals responded to a 3-hour in-person cognitive assessment within a week after the first survey. After dropping eight respondents who participated in the HRS, a total of 1222 CogUSA participants are invited to the CogEcon, and 985 of them completed the 2008 CogEcon survey by either online or mail for an overall response rate of 80.6%.[5] Of those 985 respondents, 847 participants completed a post-crash survey in 2009, followed by 772 and 708 submissions in 2011 and 2013 wave. This combined nature of sample design allows researchers to link rich cognitive performance data in the CogUSA to CogEcon. Our empirical analyses utilize (a) number series, (b) calculation, and (c) concept formation from the Woodcock–Johnson III (WJ-III) Psycho-Educational Battery, which measures quantitative reasoning, ability to perform mathematical computations, and fluid reasoning, respectively.[6]

A unique feature of the CogEcon is that financial sophistication is assessed by a half-range confidence scale (Dunning et al., 1990). When answering each question, the participants are asked to choose the most likely answer to a given financial statement, while making a judgment on how likely their response to be true by circling a pre-scaled percentage (Fig. A.1). The minimum of the scale is 50% at the left-end, reflecting a complete guess, and 100% on the opposite side, representing an absolute certainty.[7] If respondents believe a given statement is generally true but unsure that such assertion is right, they were instructed to circle a percentage that indicates 100 less a degree of reservation. Even if the respondents are completely unsure and unable to make a proper judgment, a best possible guess was made on either "guess

[3] See Lusardi and Mitchell (2014) for an extensive review of literature examining the impact of financial literacy on economic decision-making.

[4] For a validation of telephone-based cognitive tests, the first wave of CogUSA employed a condensed version of test batteries specially designed for telephone administration. This design is similar to the HRS-based episodic memory and mental status questions, and phone-adaptive version of Woodcock–Johnson III (WJ-III) number series test and retrieval fluency test.

[5] Overall response rate of the HRS ranges from 81.6% of 1992 survey to 88.6% of 2008 survey.

[6] These measures have been widely employed in the literature to explore the dividend of cognitive ability in economic choices. See Christelis et al. (2010), Kezdi and Willis (2003), and McArdle et al. (2009) for more discussions.

[7] It is assumed that a response with less than 50% certainty would switch and choose the opposite answer with 100 minus confidence.

true" or "guess false". This scale provides an opportunity to elicit domain-specific overconfidence with construct validity.[8]

Given the availability of data across waves, we analyze eight financial statements commonly available for the 2009 and 2011 survey (Table A.1). The financial sophistication score is estimated by the proportion of correct responses, without taking confidence level into account. Although respondents who made a choice with 50% certainty seem to have no clear idea of a statement, both guess false and guess true are also considered as making a conclusive judgment. Likewise, the confidence score is obtained by calculating the mean of subjective probability judgments across the questions, without assessing whether the judgment is correct or not. That is, the degree of overconfidence equals a difference between the mean confidence score and the proportion of correct responses, which ranges from −50 (extreme underconfidence) to 50 (extreme overconfidence).

3.2. Measures

Portfolio composition

The respondents in the CogEcon study were instructed to report the total value of household financial assets in and outside the tax-advantaged retirement account. Each asset class is further categorized into the five breakdowns:

(a) Short-term assets such as money market funds, CDs, and short-term Treasury bills;
(b) Bond funds, fixed income funds, or municipal, corporate or long-term government bonds;
(c) Mutual funds that hold both stocks and bonds, such as balanced or life-cycle funds;
(d) Individual stocks or stock mutual funds such as equity, index, growth, and value funds; and (e) Other financial assets.[9]

For each asset class, the participants were asked whether and how much financial wealth is held in a given financial instrument. Based on such classification, we first define a total financial wealth which equals the amount held in these five financial accounts. A set of portfolio composition measures is then constructed by dividing the amount held in each asset category by a total financial assets. We also define a set of ownership indicators, which are coded 1 if at least some of such asset is owned, and 0 if no such asset exists in a portfolio. These measures allow us to examine whether the variation in portfolio allocation is affected by relatively minor adjustments between pre-existing assets or a transition across the ownership status. Without loss of generality, we assume that category (d) represents risky, information-intensive, and direct financial investments (Christelis et al., 2010).

Control variables

The empirical models examine the extent to which asset allocation relates to financial sophistication and corresponding confidence, conditioned upon individual-specific covariates and confounding factors that correlate with our key regressors. Individual-specific covariates include age, race, gender, marital status, education history, cognitive skills, self-reported health condition, retirement status, pension income, and logged household income and net worth.[10] Demographic characteristics account for the between-individual difference in preference parameters. Self-reported health might be as important as cognitive health due to its predictive values and relevance to shaping behaviors (Miilunpalo et al., 1997). In this study, self-reported health is coded 1 if the self-rated health condition is excellent or very good, and 0 otherwise. Risk aversion is also considered to account for decreasing risk tolerance among the elderly (Riley and Chow, 1992), and its potential confounding effect on rising overconfidence. We exploit a 6-category hypothetical gamble questions in the CogEcon to impute relative risk aversion for each respondent (Barsky et al., 1995; Kimball et al., 2008). The imputed risk aversion ranges from 4.0 to 10.4 with overall mean of 8.08.[11]

Another concern is that our measure of financial sophistication and confidence might approximate investors' sentiment, or have been affected by previous stock market performances. This is of particular importance because CogEcon respondents experienced a stock market crash in 2008, and this could permanently change their perception about the stock market (Roszkowski and Davey, 2010). Respondents' perception could be influenced by either a traumatic financial experience during a recession or how much they bounced back after the crash. To ensure our findings are independent of such confounders, we control for a measure of financial loss during 2008 stock market crash and post-crash sentiment change. Since the first wave of CogEcon is fielded in mid-2008 followed by a post-crash study in May 2009, a traumatic financial experience is obtained by subtracting financial assets in wave 1 from wave 2. Post-crash sentiment change is represented by S&P 500 monthly index, assuming that external market conditions shape individuals' sentiments towards stock market. Monthly S&P 500 data is obtained from the FRED Economic Data of Federal Reserve Bank of St. Louis and matched with the data according to the survey date. This measure of stock market conditions, in conjunction with year fixed effects, is expected to net out any variation due to the temporary or permanent perception changes.

We further assume that households may have their own compensating mechanism to cope with cognitive aging. If a consumer, for instance, experiences a significant drop in cognitive functions, they may have an incentive to seek professional advisory services instead of making decisions independently. To control for such coping mechanism, we refer to the CogEcon question, "*Do you and your spouse/partner manage your own financial assets and investments, or do you use a financial planner?*", which come with the possible responses of (a) Manage own assets and (b) Use a financial planner or advisor. Our measure of financial advice equals 1 if a respondent chose response (b) and 0 otherwise. Similarly, we account for whether or not the respondent is a financial respondent who has "final say" in household finance. As cognitive capacity appears to influence who makes a financial decision in a family (Hsu and Willis, 2013), a failure to capture such variation would induce a significant bias in the estimates.

8 Several studies employed the National Financial Capability Study and compared a self-rated financial sophistication to the objective score to elicit (over)confidence (Seay and Robb, 2013; Robb et al., 2015). As discussed in Robb et al. (2015), this type of operationalization lacks validity because the scores are not measured on a comparable scale. A half-range percentage scale allows us to overcome such validity issues and yields more consistent confidence estimates.

9 Throughout the study, we take "other financial assets" into account to estimate the total financial wealth. We assume that this category represents other assets not included in these breakdowns such as life insurance.

10 See Table A.2 for more details about operationalization.

11 We identified several irregular or miscoded responses in a 6-category hypothetical gamble questions. Attrition is potentially problematic, since these responses could be related to low cognitive skills. We exploit a financial risk taking question in wave 2 of the CogUSA to further impute the risk aversion. Risk aversion based on hypothetical gamble questions is regressed on the exogenous demographic covariates and a risk-taking question in the CogUSA, and then predicted values are taken from the estimated model. These predicted values are re-scaled according to our elicitation method for comparison purposes. Consequently, a total of 36 observations are retained with the imputed risk aversion.

3.3. Empirical specifications

The portfolio outcomes are bounded between 0 and 1, and hence contain a large number of boundary values for some variables such as the share of cash equivalents and stocks. With censored outcomes, the OLS estimates are known to be biased and inconsistent even within a large sample and produce nonsensical predictions which go beyond 0 and 1 (Maddala, 1983). More importantly, with the inflations at boundary values residuals from the OLS would be heteroskedastic across the fitted values. A simple remedy, as proposed by Papke and Wooldridge (1996), is to use a transformation so that the conditional expected value of the response always lies between 0 and 1. That is, the expected value of $y_{i,t}$ conditional on the covariates is as follows.

$$E(y_{i,t}|\mathbf{X}_{i,t}) = \Lambda(\mathbf{X}_{\mathbf{i},\mathbf{t}}\boldsymbol{\beta}) = \frac{exp(\mathbf{X}_{\mathbf{i},\mathbf{t}}\boldsymbol{\beta})}{1+exp(\mathbf{X}_{\mathbf{i},\mathbf{t}}\boldsymbol{\beta})} \quad (1)$$

$\Lambda(\cdot)$ is assumed to be a logistic cumulative distribution function (CDF), but in general, it can be any function that projects arguments onto the unit interval. In this study, $\mathbf{X}_{\mathbf{i},\mathbf{t}} = [\mathbf{1}\vdots\mathbf{C}_{\mathbf{i},\mathbf{t-1}}\vdots\mathbf{Z}_{\mathbf{i},\mathbf{t}}]$ where $t \in \{2011, 2013\}$ and $t-1 \in \{2009, 2011\}$ indexes survey years; i indexes individuals; $\mathbf{C}_{\mathbf{i},\mathbf{t-1}}$ denotes a set of financial sophistication and confidence vectors; and $\mathbf{Z}_{\mathbf{i},\mathbf{t}}$ represents a covariate matrix including all other regressors in t and year fixed effects. This approach not only confines the predicted values within a unit interval but also stabilize the variance using a logit-type transformation. Following the methods of McCullagh and Nelder (1989), Papke and Wooldridge proposed to maximize the Bernoulli log-likelihood function, given by

$$\ell_{i,t}(\boldsymbol{\beta}) = y_{i,t}\cdot\log[\Lambda(\mathbf{X}_{\mathbf{i},\mathbf{t}}\boldsymbol{\beta})] + (1-y_{i,t})\cdot\log[1-\Lambda(\mathbf{X}_{\mathbf{i},\mathbf{t}}\boldsymbol{\beta})] \quad (2)$$

with respect to the parameter vector $\boldsymbol{\beta}$. This model is called "fractional logit", and yield consistent estimates as long as the model is correctly specified.[12]

An important assumption of fractional logit is that the fractional responses are generated from a single data generation process (DGP). The problem might persist if excess zeros or ones – which is a typical pattern of proportional equity data – are generated by a different DGP from nonzero outcomes. Fractional logit also ignores the fact that nonzero fractions are observed only for those holding risky assets, and that asset ownership is an endogenous choice. In other words, households would first decide whether to stay or leave the equity market, and then allocate financial wealth to risky and riskless assets. In the context of this study, it would be more plausible to assume that age-related increase in overconfidence affects the riskiness of portfolio only indirectly through its impact on ownership status because the share of wealth held in risky asset, in most cases, exhibit no life cycle pattern (Fagereng et al., 2015). Similarly, when it comes to the liquidity of portfolio, it is unrealistic to expect that households put everything into stocks and leave no cash behind due to biased decision-making. If then, rising overconfidence may affect only the relative share of cash equivalents, not the ownership status.

To jointly model both ownership and allocation changes, we consider the two-part model that allows a different DGP for each discretely and continuously distributed random variables. Among a variety of alternatives, zero-inflated beta (ZIB) model (Cook et al., 2008) is employed. The ZIB combines a logit model for binary outcomes with a beta regression for nonzero fractional responses. The beta distribution is essentially a two-parameter function that accommodates skewness and bimodality of response (Ferrari and Cribari-Neto, 2004). This distribution is very flexible and fits the bimodality of nonzero outcomes particularly well. The first part of ZIB estimates the following form of the logit model.

$$f(y_{i,t}=0|\mathbf{X}_{\mathbf{i},\mathbf{t}}) = 1-\Lambda(\mathbf{X}_{\mathbf{i},\mathbf{t}}\boldsymbol{\alpha}), \quad (3)$$

where $\Lambda(\mathbf{X}_{\mathbf{i},\mathbf{t}}\boldsymbol{\alpha})$ captures the likelihood of holding a particular asset. For nonzero proportions, we estimate a beta regression such that

$$f(y_{i,t}|\mathbf{X}_{\mathbf{i},\mathbf{t}}) = \Lambda(\mathbf{X}_{\mathbf{i},\mathbf{t}}\boldsymbol{\alpha})\left[\frac{\Gamma(\phi)}{\Gamma(\mu_{i,t}\phi)\Gamma((1-\mu_{i,t})\phi)}y_{i,t}^{\mu_{i,t}(\phi-1)}\right.$$
$$\left.(1-y_{i,t})^{(1-\mu_{i,t})(\phi-1)}\right], \quad (4)$$

where $\mu_{i,t}$ is a parameter vector of the beta distribution. The beta regression for nonzero fractions models the proportion of each asset conditional on its ownership status. Throughout the study, we report average marginal effects as in Cameron and Trivedi (2010).

4. Results

The data for empirical analysis excludes observations with no responses or miscoded values whenever such information is available. These refinements yield the analytic sample of 1044 observations. Table 1 provides descriptive statistics for the whole sample across 2011 and 2013 survey. As illustrated in Finke et al. (2016) and Gamble et al. (2014), we confirm a slight increase in confidence score coupled with a marked decline in financial sophistication over the study period. Average financial sophistication declined from 77.73 in 2009 to 70.92 in 2011, which is slightly larger than that of Hedden and Gabrieli (2004). Confidence score moved up from 78.37 to 79.48 with no statistically significant increase. A recovery of US economy is reflected in a 33% surge in S&P 500 index. Median household net worth amounts to $400,701 in 2011 and $437,600 in 2013, of which 3/5 is financial assets. About 37.7% of total financial assets is composed of less risky assets such as cash equivalents and bonds. The proportion of financial wealth held in individual stocks is 14.3% while indirect investments through mutual funds account for roughly 21.7%. Risk aversion increased slightly from 8.03 to 8.14, despite the only 2-year difference between the surveys. Financial planning service is more widely used in a later wave, and as a result, almost half of respondents in 2013 wave managed their portfolio through financial advisors.

Table 2 displays the marginal effects estimates from fractional logit models. As noted above, we present four models where the proportion of each financial asset is introduced as the response. Three clear results stand out. First, while a majority of regressors turns out to be statistically insignificant, we find a few well-described associations between socioeconomic covariates and portfolio allocation. For instance, the share of liquid and riskless assets increases with age; high-risk high-reward investments represent a larger share of the wealthy households' portfolio; and financial advice promotes less risky financial investments through bonds and mutual funds. Marginal effects estimates show that those who received financial advice allocated 14% more financial wealth to mutual funds and 17% less to short-term cash equivalents. Second, respondents' financial sophistication is generally not associated with portfolio composition. Across four models, only mutual funds share is positively related to financial sophistication at the 5% significance level. This pattern is not in support of van Rooij et al. (2011) where stockholding is more prevalent among the financially literate, but broadly in line with Parker et al. (2012) in which the influence of financial knowledge became no longer or only moderately significant as

[12] Note that this approach is essentially identical to modeling a binary response using logistic or standard normal CDF as a canonical link. The only difference is that fractional logit allows the response to be continuous in the unit interval.

Table 1
Descriptive statistics (*N=1044*).

	2011 wave	2013 wave	Full sample
Portfolio composition (%)			
Share of cash equivalents	30.9	31.2	31.0
Share of bonds	6.3	7.2	6.7
Share of mutual funds	21.2	22.3	21.7
Share of individual stocks	14.1	14.4	14.3
Share of other financial assets	10.2	8.8	9.5
Financial sophistication			
Financial sophistication$_{t-1}$ (0–100)	77.73	70.92	74.45
Confidence in fin. sophistication$_{t-1}$ (50–100)	78.37	79.48	78.91
Cognitive abilities and health condition			
Number series (0–100)			65.89
Calculation (0–100)			59.17
Fluid reasoning (0–100)			51.08
Self-reported health (0,1)	0.88	0.89	0.89
Proxies for sentiment changes			
S&P 500 index	913	1,217	1,059
Loss of financial assets during crash (real $)			5,805
Fin. asset$_t$-Fin. asset$_{t-1}$ (real $)	31,782	49,208	40,718
Socioeconomic covariates			
Age	66.8	68.2	67.5
Male (0,1)			0.45
NH White (0,1)			0.91
Other races (0,1)			0.09
Less than college (0,1)			0.21
Some college (0,1)			0.30
College graduate (0,1)			0.21
Postgraduate (0,1)			0.28
Married (0,1)	0.72	0.70	0.71
Retired (0,1)	0.44	0.51	0.47
Risk aversion (4.0–10.4)	8.03	8.14	8.08
Receiving pension (0,1)	0.37	0.40	0.38
Financial respondent (0,1)	0.78	0.79	0.79
Financial advice (0,1)	0.45	0.49	0.47
Total HH income[a] (real $)	72,495	75,000	73,672
Total HH net worth[a] (real $)	400,701	437,600	425,001

Notes: Number series, calculation, and fluid reasoning show the normalized W score defined on a scale of 0 to 100. All dollar figures are adjusted to 2013 dollars using the Consumer Price Index for all urban consumers (CPI-U).

[a] Median values are reported for total household income and net worth.

the models augment with confidence score. Third, we do find a positive association of unjustified confidence with the risky asset share. Column (4) shows that a 10 points increase in unjustified confidence on a 50–100 scale is associated with 1.83 percentage points greater proportion of stocks and stock mutual funds. This association is statistically significant at the 1% level, and a corresponding standard error estimate is also minuscule. In terms of magnitude, the estimate accounts for approximately 12.7% of the average proportion of individual stocks, which is 14.3% in the full sample. In column (1), unjustified confidence is negatively associated with the proportion of cash equivalents, although such correlation is not significant at the 10% level.

Table 3 presents the ZIB regression results. Panel A and B layout beta regression for nonzero proportions and logistic regression for binary responses respectively. As discussed above, ZIB model allows us to separate the movements along the intensive margin of asset allocation from the transitions across the extensive margin. With the ZIB models estimated, we find an interesting substitution pattern between risky and riskless assets. In column (1), a 10 points increase in unjustified confidence is associated with 2.53 percentage points decrease in the financial wealth held in cash equivalents. Such relationship is not significant in the zeroinflate model, confirming our hypothesis that overconfidence does not induce a change in riskless asset ownership. This nonsignificance is quite obvious because almost all respondents have at least some amount of short-term liquid assets. Column (4) shows that a positive link between unjustified confidence and portfolio riskiness arises due to the changes in stockholding status. According to our estimate in panel B, about 7% greater stock ownership is attributable to a 10 points increase in unjustified confidence. Conditional stock share is not responsive to both sophistication and unjustified confidence, indicating that the influence of overconfidence does not take place on the intensive margin. Along with the estimates in column (1), these results show that age-related increase in overconfidence make people stay longer in the equity market while keeping fewer cash reserves. In column (2) and (3), approximately 1.8% greater bondholding and mutual fund ownership is associated with a 10 points increase in unjustified confidence.

Table 4 re-estimates the models in Tables 2 and 3 to correct the attenuation bias in the estimates of unjustified confidence. Although the half-range scale gauges sophistication and confidence on a comparable scale, these measures can still be measured with errors. For instance, some financial statements may not have a clear-cut answer, and hence such ambiguity could affect their confidence about responses. Those who financially bounced back after the 2008 recession may have developed overconfidence, which could inflate their confidence in a later survey. It is then more appropriate to interpret that our previous estimates are plausibly the lower bound of the true relationship between confidence and portfolio choice. In order to account for the measurement error in confidence, we use the confidence estimate in $t-2$ as an instrument in the two-step IV model (2SIV), assuming that measurement error is uncorrelated over time. In this case, the variation in the cognition score in $t-1$ is isolated to the portion explained by the estimate in $t-2$. In panel A, the magnitude of the association between unjustified confidence and stock share is about twice greater than that of Table 2. In panel B,

Table 2
Models for portfolio allocation: Primary specification.

Response (0-1):	(1) Cash equivalents/FA Frac. logit	(2) Bonds/FA Frac. logit	(3) Mutual funds/FA Frac. logit	(4) Stocks/FA Frac. logit
Sophistication$_{t-1}$ (/10)	0.0039	0.0011	0.0122**	0.0032
	(0.0070)	(0.0025)	(0.0061)	(0.0040)
Confidence$_{t-1}$ (/10)	−0.0122	0.0027	0.0091	0.0183***
	(0.0115)	(0.0044)	(0.0094)	(0.0069)
Age	0.0044***	0.0002	−0.0043***	−0.0006
	(0.0017)	(0.0009)	(0.0014)	(0.0009)
Number series (/10)	−0.0085	0.0031	0.0073	0.0007
	(0.0109)	(0.0042)	(0.0099)	(0.0057)
Calculation (/10)	0.0069	−0.0002	0.0036	0.0190**
	(0.0142)	(0.0052)	(0.0111)	(0.0074)
Fluid reasoning (/10)	0.0004	−0.0037	−0.0050	−0.0005
	(0.0085)	(0.0045)	(0.0067)	(0.0046)
SR health status	−0.0326	−0.0152	0.0548	0.0292
	(0.0375)	(0.0178)	(0.0388)	(0.0265)
S&P 500 index (/100)	0.0207	0.0114	−0.0815	0.0206
	(0.0770)	(0.0280)	(0.0601)	(0.0368)
Log(loss in 2008)	−0.0021**	0.0006	0.0010	0.0018***
	(0.0010)	(0.0004)	(0.0008)	(0.0006)
Financial respondent	0.0467	−0.0109	0.0087	0.0028
	(0.0304)	(0.0124)	(0.0248)	(0.0170)
Financial advice	−0.1737***	0.0389***	0.1414***	0.0252*
	(0.0229)	(0.0103)	(0.0181)	(0.0138)
Retired	0.0736**	−0.0276**	−0.0324	0.0153
	(0.0293)	(0.0117)	(0.0235)	(0.0149)
Risk aversion	0.0106*	0.0002	0.0054	−0.0058*
	(0.0059)	(0.0023)	(0.0049)	(0.0032)
Receiving pension	−0.0022	0.0004	0.0290	−0.0286*
	(0.0276)	(0.0119)	(0.0219)	(0.0155)
Log(HH income)	0.0098*	−0.0055	0.0055	0.0047
	(0.0058)	(0.0036)	(0.0049)	(0.0045)
Log(HH net worth)	0.0004	0.0267***	0.0191***	0.0359***
	(0.0044)	(0.0047)	(0.0037)	(0.0056)
Observations	1037	1020	1036	1044

Notes: The estimates represent average marginal effects from fractional logit models and corresponding standard errors. Clustered standard errors are reported in parentheses. FA denotes household financial assets. Financial sophistication and confidence are divided by 10 for more intuitive interpretations. For instance, a one unit increase in unjustified confidence indicates a 10 percentage point increase on a 50–100 scale. The estimates on demographic covariates (gender, race, education background, and marital status) and year fixed effects are omitted.
* For 10% significance level.
** For 5% significance level.
*** For 1% significance level.

about 6.6 percentage points decrease in the conditional cash share is explained by a 10 points increase in unjustified confidence. We also find that a 10 point higher unjustified confidence is associated with almost 10% greater stock ownership. With 2SIV estimates, however, the impact of sophistication and confidence on bonds and mutual funds is less clear. Overall, Table 4 shows that the impact of growing overconfidence is not only statistically significant but also economically meaningful.

An important aspect that has not been taken into account is whether and to what extent family support network moderates the negative influence of cognitive biases. As Hsu and Willis (2013) demonstrated, if one of the spouses has enough cognitive capacity to undertake decision-making burden, such family's financial portfolio would be less responsive to a respondent's overconfidence. These families would rather reduce the share of risky assets as they age, in an attempt to avoid getting a low return on risky investments due to cognitive incapacity. The first two columns in Table 5 tests for the presence of such family support network by interacting unjustified confidence with marital status and household size. In column (2), a variable to be interacted equals 1 if household size is greater than 1, and 0 otherwise. Column (3) accounts for the use of financial planner, given the assumption that (unbiased) financial advice would weaken the link between overconfidence and portfolio riskiness. From the first two models, we reject the hypothesis that staying with other family members dampens the association of overconfidence with portfolio riskiness. In column (3), a 10 points increase in unjustified confidence is associated with nearly 10.2% greater stockholding when the portfolio is managed independently. Such association reduces down to 5.3% among those who managed their portfolio via financial planners. It seems financial advice works as an emotional circuit breaker that suppresses the influence of cognitive biases. However, this association should be interpreted with caution as a correlation between overconfidence and advice seeking behavior, if exists any, would bias the estimate of interaction term. If overconfident spouses, or more generally individuals with cognitive biases, are less likely to seek financial advice (Bachmann and Hens, 2015), the moderating impact of financial advice would be much larger than our estimate.

Table 6 tests the robustness of findings by interacting unjustified confidence with the proxy for (a) traumatic experiences during the crisis, (b) post-crash sentiment changes, and (c) overall stock market performance. If any of such changes explain a significant variation in our confidence estimate the association between unjustified confidence and stock ownership would be biased and inconsistent without such proxies. Across three different models, however, the interaction terms are not significant at the 10% level, and hence we conclude that sentiment changes do not confound the effect of unjustified confidence.

Table 3
Models for portfolio allocation: Alternative specification.

Response (0-1):	(1) Cash equivalents/FA ZIB	(2) Bonds/FA ZIB	(3) Mutual funds/FA ZIB	(4) Stocks/FA ZIB
Panel A: Proportion model (beta regression)				
Sophistication$_{t-1}$ (/10)	−0.0013	−0.0051	0.0063	0.0019
	(0.0061)	(0.0050)	(0.0068)	(0.0058)
Confidence$_{t-1}$ (/10)	−0.0253**	−0.0038	0.0031	−0.0024
	(0.0113)	(0.0082)	(0.0114)	(0.0103)
Financial advice	−0.1001***	0.0247	0.0787***	0.0162
	(0.0207)	(0.0188)	(0.0228)	(0.0214)
Retired	−0.0030	−0.0019	0.0021	0.0252
	(0.0234)	(0.0215)	(0.0283)	(0.0223)
Risk aversion	0.0080*	−0.0042	0.0002	−0.0081*
	(0.0047)	(0.0037)	(0.0054)	(0.0046)
Receiving pension	0.0424*	−0.0034	−0.0045	−0.0586**
	(0.0254)	(0.0215)	(0.0300)	(0.0243)
Log(HH income)	−0.0166**	−0.0077	0.0159**	0.0027
	(0.0067)	(0.0048)	(0.0073)	(0.0061)
Log(HH net worth)	−0.0176***	0.0153*	−0.0568***	0.0036
	(0.0054)	(0.0082)	(0.0108)	(0.0092)
Panel B: Zeroinflate model (logistic regression)				
Sophistication$_{t-1}$ (/10)	0.0144	0.0175**	0.0180**	0.0088
	(0.0093)	(0.0087)	(0.0087)	(0.0089)
Confidence$_{t-1}$ (/10)	0.0132	0.0170	0.0245*	0.0693***
	(0.0156)	(0.0156)	(0.0146)	(0.0149)
Financial advice	0.0525*	0.1821***	0.2495***	0.0839***
	(0.0300)	(0.0278)	(0.0249)	(0.0287)
Retired	0.0739*	−0.0616*	−0.0693*	−0.0255
	(0.0414)	(0.0357)	(0.0355)	(0.0359)
Risk aversion	−0.0132*	−0.0037	0.0047	−0.0091
	(0.0078)	(0.0072)	(0.0075)	(0.0074)
Receiving pension	−0.0171	−0.0512	0.0737**	−0.0017
	(0.0366)	(0.0349)	(0.0335)	(0.0335)
Log(HH income)	0.0087	0.0008	0.0059	0.0061
	(0.0083)	(0.0092)	(0.0085)	(0.0080)
Log(HH net worth)	0.0603***	0.0911***	0.0551***	0.0964***
	(0.0169)	(0.0152)	(0.0085)	(0.0138)
Observations	1037	1020	1036	1044

Notes: The estimates represent average marginal effects from zero-inflated beta models and corresponding standard errors. Clustered standard errors are reported in parentheses. Each regression model includes all RHS variables as in Table 2. Panel B models the probability of observing a nonzero response.
* For 10% significance level.
** For 5% significance level.
*** For 1% significance level.

Table 4
Correcting attenuation bias.

	(1)	(2)	(3)	(4)
Panel A: 2SIV fractional logit				
Response (0-1):	Cash equiv./FA	Bonds/FA	Mutual funds/FA	Stocks/FA
	Frac. logit	Frac. logit	Frac. logit	Frac. logit
Sophistication$_{t-1}$ (/10)	0.0023	0.0016	0.0130**	0.0000
	(0.0074)	(0.0026)	(0.0062)	(0.0042)
Confidence$_{t-1}$ (/10)	−0.0263	−0.0004	0.0364**	0.0362**
	(0.0221)	(0.0083)	(0.0163)	(0.0152)
Observations	965	948	963	971
Panel B: 2SIV beta and logit				
Response (0-1):	Cash equiv./FA			
Response (0,1):		Bond ownership	M.F. ownership	Stock ownership
	Beta	Logit	Logit	Logit
Sophistication$_{t-1}$ (/10)	0.0017	0.020*	0.027***	0.015
	(0.0063)	(0.010)	(0.009)	(0.010)
Confidence$_{t-1}$ (/10)	−0.0660***	0.058**	0.054**	0.103***
	(0.0196)	(0.029)	(0.027)	(0.031)
Observations	554	971	971	971

Notes: The estimates represent average marginal effects and corresponding standard errors. Clustered standard errors are reported in parentheses. Each regression model includes all RHS variables as in Table 2.
* For 10% significance level.
** For 5% significance level.
*** For 1% significance level.

Table 5
Models for stock ownership: Sensitivity analysis.

	(1)	(2)	(3)
Response (0,1):	Stock ownership		
	LPM	LPM	LPM
Sophistication$_{t-1}$ (/10)	0.022** (0.009)	0.022** (0.009)	0.022** (0.009)
α: Confidence$_{t-1}$ (/10)	0.048* (0.027)	0.065** (0.026)	0.102*** (0.018)
β_1: Married	−0.090 (0.240)		
β_2: HH size > 1		−0.282 (0.242)	
β_3: Financial advice			0.570*** (0.218)
γ_1: $\alpha \times \beta_1$	0.022 (0.030)		
γ_2: $\alpha \times \beta_2$		0.042 (0.030)	
γ_3: $\alpha \times \beta_3$			−0.049* (0.027)
Observations	1044	1044	1044
Linear restriction (F-test) H_0: $\alpha + \gamma_3 = 0$			0.053**

Notes: Clustered standard errors are reported in parentheses. Each regression model includes all RHS variables as in Table 2.
* For 10% significance level.
** For 5% significance level.
*** For 1% significance level.

Table 6
Models for stock ownership: Robustness checks.

	(1)	(2)	(3)
Response (0,1):	Stock ownership		
	LPM	LPM	LPM
Sophistication$_{t-1}$ (/10)	0.023** (0.009)	0.022** (0.009)	0.022** (0.009)
α: Confidence$_{t-1}$ (/10)	0.081*** (0.015)	0.080*** (0.015)	0.079 (0.083)
β_1: Log(loss in 2008)	0.016 (0.010)		
β_2: Log(Fin. asset$_t$–Fin. asset$_{t-1}$)		−0.004 (0.009)	
β_3: S&P 500 index (/100)			0.106 (0.113)
γ_1: $\alpha \times \beta_1$	−0.002 (0.001)		
γ_2: $\alpha \times \beta_2$		0.001 (0.001)	
γ_2: $\alpha \times \beta_3$			0.0003 (0.008)
Observations	1044	1044	1044

Notes: Clustered standard errors are reported in parentheses. Each regression model includes all RHS variables as in Table 2.
* For 10% significance level.
** For 5% significance level.
*** For 1% significance level.

5. Conclusions

This study is one of the first to examine the impact of the age–related increase in overconfidence on the elderly's portfolio choice. Exploiting several unique features of the data, we estimated the association of equity share/ownership with financial sophistication and unjustified confidence. Unlike the literature and conventional wisdom, we find that risky asset share is more pronounced among the respondents who lost financial proficiency but failed to realize such aging process. The proportion of cash equivalents diminishes with a rising overconfidence, indicating an interesting substitution pattern between risky and riskless assets. These patterns are in contrast to the well-known financial planning principle, advising individuals to shift away from equities and towards riskless assets as they age. In turn, age-related rise in overconfidence provides a clue about why some individuals hold risky assets, even at the very end of life cycle. The second phase of analysis shows that financial advice would moderate the negative influence of late-life cognitive bias.

The present study suggests a number of caveats that need to be addressed in future research. First, a relatively weak association between aging-induced overconfidence and portfolio allocation is, in part, due to the data limitations. With a longer panel and exhaustive information on portfolio allocation, the magnitude of the estimated link is likely to be larger than our estimates. Despite a potential downward bias in the estimates, the influence of sophistication-confidence gap on stock ownership is significantly positive across the specifications. Apart from the methodological issues, it is quite apparent that retired households are unable to adjust their portfolio within a short time frame, solely due to a failure of recognizing their cognitive limits. Second, our study does not consider whether or not the cognitive aging affects the intra-household distribution of bargaining power. Some spouse may experience a much steeper cognitive decline, while the partners cognitive abilities remain relatively intact. If then, cognitive aging may have an impact on who has the "final say" over money matters and how retirement portfolio is managed within a household. For instance, the onset of memory-related diseases such as stroke, dementia, or Alzheimer's disease, would force the other spouse who had shied away from investment decisions to undertake the management of household finance (Hsu and Willis, 2013). As overconfident individuals are unlikely to pass "final say" to the cognitively intact spouse, this could further complicate our understanding of the relationship between overconfidence and portfolio riskiness. Third, our results should be interpreted with caution because our findings are drawn from a sample collected from 2009 to 2013. While we took extra care to accounting for stock market conditions, post-crash sentiment changes, and time trends, there could still be unobserved time-varying factors that move along the aging curve and economic cycle. Further research should be conducted to develop a more nuanced understanding of whether it is a time-specific phenomenon or generalizable to other periods.

Although, the low- or moderate-income (LMI) households are not of particular interests, the consequences of the age-related increase in overconfidence can be particularly detrimental to the LMI households. The LMI households' decision-making would be more susceptible to aging-induced cognitive bias, and a proper intervention such as connecting them to a financial advisor would be able to minimize adverse consequences. Financial education aiming to inform the potential pitfalls of overconfidence or greater access to affordable financial counseling services would be able to increase retirees' financial capability. Our findings provide both a challenge and an opportunity for policy makers to develop more effective interventions to improve retirement well-being.

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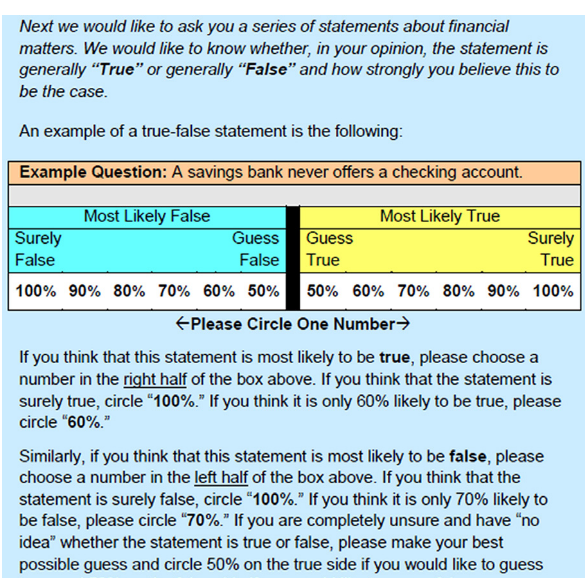
Table A.1
Wording of questions in financial sophistication module.

Question wording	Correct (%)	Confidence (%)
Financially, investing in the stock market is no better than buying lottery tickets.	87.62	84.46
A young person with $100,000 to invest should hold riskier financial investments than an older person with $100,000 to invest.	72.98	83.95
If you are smart, it is easy to pick individual company stocks that will have better than average returns.	74.76	75.55
There is no way to avoid people taking advantage of you if you invest in the stock market.	81.55	78.64
Buying a stock mutual fund usually provides a safer return than a single company stock.	90.71	82.98
An employee of a company with publicly traded stock should have little or none of his or her retirement savings in the company's stock.	56.90	77.25
It is best to avoid owning stocks of foreign companies.	59.64	76.07
Older retired people should not hold any stocks.	85.48	77.75

Table A.2
Variable descriptions.

Variables	Definition
Share of cash equivalents	Value of (MMFs, CDs, and short-term Treasury bills)/Financial wealth (0-1)
Share of bonds	Value of (bond funds, corporate funds, and municipal or long-term gov't bonds)/Financial wealth (0-1)
Share of mutual funds	Value of (less risky mutual funds such as balanced or life-cycle funds)/Financial wealth (0-1)
Share of individual stocks	Value of (individual stocks or stock mutual funds such as equity, index, or growth funds)/Financial wealth (0-1)
Financial sophistication	Number of correct responses divided by number of questions $\times$ 100 (0–100)
Confidence	Mean value of confidence in judgments regarding financial sophistication questions (50–100)
Numeracy	Number series score in Woodcock–Johnson Psycho-Educational Test Battery (0–100)
Calculation	Calculation score in Woodcock–Johnson Psycho-Educational Test Battery (0–100)
Fluid reasoning	Concept formation score in Woodcock–Johnson Psycho-Educational Test Battery (0–100)
Self-reported health condition	= 1 if self-rated health condition is very good or excellent (0,1)
S&P 500 index	Monthly average S&P 500 index
Loss of financial assets during crash	= (Real) financial asset in 2008–(real) financial asset in 2009
Fin. asset$_t$–Fin. asset$_{t-1}$	= (Real) financial asset in t–(real) financial asset in $t-1$
Age	Age of respondent (48–96)
Male	= 1 if respondent is male (0,1)
NH White	= 1 if respondent is non-Hispanic white (0,1)
Other races	= 1 if respondent is other than non-Hispanic white (0,1)
Less than college	= 1 if respondent completed less than 13 years of formal education (0,1)
Some college	= 1 if respondent completed at least 13 years but less than 16 years of formal education (0,1)
College graduate	= 1 if respondent completed 16 years of formal education (0,1)
Postgraduate	= 1 if respondent completed 17 years of formal education (0,1)
Married	= 1 if respondent is married or in a marriage-like relationship with income pooling (0,1)
Retired	= 1 if respondent is completely retired (0,1)
Receiving pension	= 1 if respondent is receiving payments from an employer-provided pension plan (0,1)
Financial respondent	= 1 if respondent is a household's financial respondent (0,1)
Financial advice	= 1 if respondent use a financial planner or advisor (0,1)
Risk aversion	Imputed 6-category relative risk aversion from hypothetical gamble questions (4.0–10.4)
Total HH income	(Real) combined income of all family members living together over the last 12 months
Total HH net worth	(Real) household net worth including housing wealth

Notes: Number series, calculation, and fluid reasoning are normalized on a scale of 0–100. See Sun (2012) for more details about scoring and scaling of cognition variables.


*Next we would like to ask you a series of statements about financial matters. We would like to know whether, in your opinion, the statement is generally **"True"** or generally **"False"** and how strongly you believe this to be the case.*

An example of a true-false statement is the following:

Example Question: A savings bank never offers a checking account.

Most Likely False						Most Likely True					
Surely False					Guess False	Guess True					Surely True
100%	90%	80%	70%	60%	50%	50%	60%	70%	80%	90%	100%

←**Please Circle One Number**→

If you think that this statement is most likely to be **true**, please choose a number in the right half of the box above. If you think that the statement is surely true, circle "**100%**." If you think it is only 60% likely to be true, please circle "**60%.**"

Similarly, if you think that this statement is most likely to be **false**, please choose a number in the left half of the box above. If you think that the statement is surely false, circle "**100%**." If you think it is only 70% likely to be false, please circle "**70%.**" If you are completely unsure and have "no idea" whether the statement is true or false, please make your best possible guess and circle 50% on the true side if you would like to guess true, and 50% on the false side if you would like to guess false.

Fig. A.1. An example of half-range scale question in CogEcon.

Appendix

See Fig. A.1 and Tables A.1 and A.2.

References

Agarwal, S., Driscoll, J.C., Gabaix, X., Laibson, D., 2007. The age of reason: Financial decisions over the lifecycle (NBER Working Paper No.13191). Cambridge, MA: National Bureau of Economic Research. http://www.nber.org/papers/w13191.

Bachmann, K., Hens, T., 2015. Investment competence and advice seeking. J. Behav. Exp. Finance 6, 27–41.

Banks, J., O'Dea, C., Oldfield, Z., 2010. Cognitive function, numeracy and retirement saving trajectories. Econom. J. 120 (548), F381–F410.

Barber, B.M., Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. Quart. J. Econ. 116 (1), 261–292.

Barsky, R.B., Kimball, M.S., Juster, F.T., Shapiro, M.D., 1995. Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement survey (NBER Working Paper No.5213). Cambridge, MA: National Bureau of Economic Research. http://www.nber.org/papers/w5213.

Besedes, T., Cary, D., Sudipta, S., Mikhael, S., 2012. Age effects and heuristics in decision making. Rev. Econ. Stat. 94 (2), 580–595.

Bonsang, E., Dohmen, T., 2015. Risk attitude and cognitive ageing. J. Econ. Behav. Organ. 112, 112–126.

Browning, C., Finke, M., 2015. Cognitive ability and the stock reallocations of retirees during the Great Recession. J. Consum. Aff. 49 (2), 356–375.

Bruine de Bruin, W., Parker, A.M., Fischhoff, B., 2012. Explaining adult age differences in decision-making competence. J. Behav. Decis. Mak. 25 (4), 352–360.

Cameron, A.C., Trivedi, P.K., 2010. Microeconometrics Using Stata. Stata Press, College Station, TX.
Christelis, D., Jappelli, T., Padula, M., 2010. Cognitive abilities and portfolio choice. Eur. Econ. Rev. 54 (1), 18–38.
Cook, D.O., Kieschnick, R., McCullough, B.D., 2008. Regression analysis of proportions in finance with self selection. J. Empir. Finance 15 (5), 860–867.
Crawford, J.D., Stankov, L., 1996. Age differences in the realism of confidence judgements: A calibration study using tests of fluid and crystallized intelligence. Learn. Individ. Differ. 8 (2), 83–103.
Dohmen, T., Falk, A., Huffman, D., Sunde, U., 2010. Are risk aversion and impatience related to cognitive ability?. Amer. Econ. Rev. 100 (3), 1238–1260.
Dunning, D., Griffin, D.W., Milojkovic, J.D., Ross, L., 1990. The overconfidence effect in social prediction. J. Pers. Soc. Psychol. 58 (4), 568–581.
Fagereng, A., Gottlieb, C., Guiso, L., 2015. Asset market participation and portfolio choice over the life-cycle (SAFE Working Paper No. 115). Frankfurt, Germany: Goethe University Frankfurt. http://www.econstor.eu/bitstream/10419/120931/1/836434900.pdf.
Ferrari, S., Cribari-Neto, F., 2004. Beta regression for modelling rates and proportions. J. Appl. Stat. 31 (7), 799–815.
Finke, M.S., Howe, J.S., Huston, S.J., 2016. Old age and the decline in financial literacy. Manage. Sci..
Finucane, M.L., Mertz, C.K., Slovic, P., Schmidt, E.S., 2005. Task complexity and older adults' decision-making competence. Psychol. Aging 20 (1), 71–84.
Gamble, K.J., Boyle, P.A., Yu, L., Bennett, D.A., 2014. Aging and financial decision making. Manage. Sci. 61 (11), 2603–2610.
Gervais, S., Odean, T., 2001. Learning to be overconfident. Rev. Financ. Stud. 14 (1), 1–27.
Gregoire, P., 2016. Unskilled traders, overconfidence and information acquisition. J. Behav. Exp. Finance 9, 1–5.
Grinblatt, M., Keloharju, M., 2009. Sensation seeking, overconfidence, and trading activity. J. Finance 64 (2), 549–578.
Grinblatt, M., Keloharju, M., Linnainmaa, J., 2011. IQ and stock market participation. J. Finance 66 (6), 2121–2164.
Hansson, P., Ronnlund, M., Juslin, P., Nilsson, L.G., 2008. Adult age differences in the realism of confidence judgments: Overconfidence, format dependence, and cognitive predictors. Psychol. Aging 23 (3), 531–544.
Hedden, T., Gabrieli, J.D., 2004. Insights into the ageing mind: a view from cognitive neuroscience. Nat. Rev. Neurosci. 5 (2), 87–96.
Hsu, J.W., Willis, R., 2013. Dementia risk and financial decision making by older households: The impact of information. J. Human Capital 7 (4), 340–377.
Johnson, M.M.S., 1990. Age differences in decision making: A process methodology for examining strategic information processing. J. Gerontol. 45 (2), 75–78.
Kezdi, G., Willis, R.J., 2003. Who becomes a stockholder? Expectations, subjective uncertainty, and asset allocation (MRRC Working Paper No.2003–039). Ann Arbor, MI: Michigan Retirement Research Center. http://www.mrrc.isr.umich.edu/publications/papers/pdf/wp039.pdf.
Kim, S., Goldstein, D., Hasher, L., Zacks, R.T., 2005. Framing effects in younger and older adults. J. Gerontol. B: Psychol. Sci. Soc. Sci. 60 (4), P215–P218.
Kim, E.J., Hanna, S.D., Chatterjee, S., Lindamood, S., 2012. Who among the elderly owns stocks? The role of cognitive ability and bequest motive. J. Family Econ. Issues 33 (3), 338–352.
Kimball, M.S., Sahm, C.R., Shapiro, M.D., 2008. Imputing risk tolerance from survey responses. J. Amer. Statist. Assoc. 103 (483), 1028–1038.
Kinari, Y., 2016. Properties of expectation biases: Optimism and overconfidence. J. Behav. Exp. Finance 10, 32–49.
Korniotis, G.M., Kumar, A., 2011. Do older investors make better investment decisions?. Rev. Econ. Stat. 93 (1), 244–265.
Kovalchik, S., Camerer, C.F., Grether, D.M., Plott, C.R., Allman, J.M., 2005. Aging and decision making: A comparison between neurologically healthy elderly and young individuals. J. Econ. Behav. Organ. 58 (1), 79–94.
Lusardi, A., Mitchell, O.S., 2011. Financial literacy and planning: Implications for retirement wellbeing (NBER Working Paper No.17078). Cambridge, MA: National Bureau of Economic Research. http://www.nber.org/papers/w17078.
Lusardi, A., Mitchell, O.S., 2014. The economic importance of financial literacy: Theory and evidence. J. Econom. Lit. 52 (1), 5–44.
Maddala, G., 1983. Limited Dependent and Qualitative Variables in Econometrics. Cambridge University Press, Cambridge, UK.
McArdle, J.J., Smith, J.P., Willis, R., 2009. Cognition and economic outcomes in the Health and Retirement Survey (NBER Working Paper No. 15266). Cambridge, MA: National Bureau of Economic Research. http://www.nber.org/papers/w15266.
McCullagh, P., Nelder, J.A., 1989. Generalized Linear Models. CRC press, Boca Raton, FL.
Miilunpalo, S., Vuori, I., Oja, P., Pasanen, M., Urponen, H., 1997. Self-rated health status as a health measure: The predictive value of self-reported health status on the use of physician services and on mortality in the working-age population. J. Clin. Epidemiol. 50 (5), 517–528.
Odean, T., 1999. Do investors trade too much? Amer. Econ. Rev. 89 (5), 1279–1298.
Pak, T.Y., Chatterjee, S., 2016. Savings decisions of American households: The roles of financial literacy and financial practice. Econ. Bull. 36 (3), 1486–1496.
Papke, L.E., Wooldridge, J.M., 1996. Econometric methods for fractional response variables with an application to 401(K) plan participation rates. J. Appl. Econometrics 11 (6), 619–632.
Parker, A.M., Bruin, W.B., Yoong, J., Willis, R., 2012. Inappropriate confidence and retirement planning: Four studies with a national sample. J. Behav. Decis. Mak. 25 (4), 382–389.
Puri, M., Robinson, D.T., 2007. Optimism and economic choice. J. Financ. Econ. 86 (1), 71–99.
Riley Jr., W.B., Chow, K.V., 1992. Asset allocation and individual risk aversion. Financ. Anal. J. 48 (6), 32–37.
Robb, C.A., Babiarz, P., Woodyard, A., Seay, M.C., 2015. Bounded rationality and use of alternative financial services. J. Consum. Aff. 49 (2), 407–435.
Roszkowski, M.J., Davey, G., 2010. Risk perception and risk tolerance changes attributable to the 2008 economic crisis: A subtle but critical difference. J. Financ. Serv. Prof. 64 (4), 42–53.
Seay, M.C., Robb, C.A., 2013. The effect of objective and subjective financial knowledge on high-cost borrowing behavior. Financ. Plan. Rev. 6 (4), 1–19.
Statman, M., Thorley, S., Vorkink, K., 2006. Investor overconfidence and trading volume. Rev. Financ. Stud. 19 (4), 1531–1565.
Sun, R., 2012. Grounding Social Sciences in Cognitive Sciences. MIT Press, Cambridge, MA.
van Rooij, M., Lusardi, A., Alessie, R., 2011. Financial literacy and stock market participation. J. Financ. Econ. 101 (2), 449–472.
Yang, X., Zhu, L., 2016. Ambiguity vs risk: An experimental study of overconfidence, gender and trading activity. J. Behav. Exp. Finance 9, 125–131.