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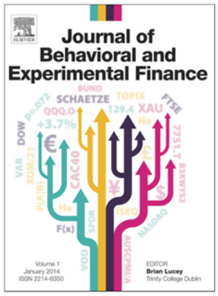

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Aging, Overconfidence, and Portfolio Choice

Tae-Young Pak* Swarn Chatterjee†

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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 as they age. This study examines whether and to what extent the age-driven increase in overconfidence explains the riskiness of retirement portfolio. Using data from 2011 and 2013 Cognitive Economics Study (CogEcon), we examine the behavioral aspect of portfolio allocation by estimating the impact of unjustified confidence, conditioned upon actual financial sophistication and cognitive skills. 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 external market conditions. Further analysis finds much weaker association among those who use a financial planner, indicating a moderating role of financial advice. Overall, our findings highlight the importance of cognitive bias in explaining late-life stock ownership and financial advisor as an emotional circuit breaker.

Keywords: Cognitive Aging, Cognitive Bias, Overconfidence, Financial Sophistication, Portfolio Choice, and Two-Part model

JEL Classification Codes: E2, D8, G1

*Assistant Professor (corresponding author), Department of Consumer Sciences, University of Alabama, Address: 303A Adams Hall, Box 870158, Tuscaloosa, AL 35487, phone: +1-205-348-4068, e-mail: `tpak@ches.ua.edu`.

†Associate Professor, Department of FHCE, University of Georgia, Address: 106 Housing Research Center, 407 Sanford Dr., Athens, GA 30602, USA, phone: +1-706-542-4722, e-mail: `swarn@uga.edu`.

1 Introduction

The relationship between cognitive capacity and financial decisions at the end of life-cycle has been the subject of intense exploration, with a general finding that investments in risky assets increase with intelligence.[1] This strand of research documented that individuals with poor cognitive skills tend to stay away from information-intensive assets, and in turn, form a less risky financial portfolio. One of the most plausible explanations is rising information costs due to declining cognitive skills (Christelis, Jappelli, and Padula, 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 improve/maintain cognitive skills. In either case, cognitive loss increases the cost of risky asset ownership and thus lowers optimal risk exposure.

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. The 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 from risky investments. Even for those with enough cognitive skills, their ability to make savvy financial decisions would decline gradually (Korniotis and Kumar, 2011), and their risk preference would be lower with the cognitive loss (Bonsang and Dohmen, 2015; Dohmen, Falk, Huffman, and Sunde, 2010). Regardless of the mechanism, cognitive aging plays a major role in shaping the late-life shift of portfolio towards riskless assets.

Despite the abundance of empirical evidence, the impact of cognitive aging on risky asset ownership is theoretically ambiguous because people are, in general, unable to judge their cognitive skills/loss. Finke, Howe, and Huston (2016), for instance, documented that older investors tend to remain confident about their financial proficiency, even though they lose financial knowledge and skills as they reach the end of life. In a closely related study, Gamble, Boyle, Yu, and Bennett (2014) documented 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 be because of their beliefs about the experience, reluctance to admit natural aging process, or systematic deviations from a rationality rule due to cognitive aging process. While recent evidence casts some doubt on the mechanism through which aging leads to overconfidence (Kovalchik, Camerer, Grether, Plott, and Allman, 2005), it is generally accepted that older adults are more prone to overconfidence bias, particularly

[1]See, for instance, Christelis, Jappelli, and Padula, (2010), Grinblatt, Keloharju, and Linnainmaa (2011), Kezdi and Willis (2003), and Kim, Hanna, Chatterjee, and Lindamood (2012).

when they encounter cognitively demanding tasks (Bruine de Bruin, Parker, and Fischhoff, 2012). If these individuals show the typical investment practices of overconfident investors (Barber and Odean, 2001), the age-related increase in overconfidence might be able to explain why some retirees still hold unnecessarily risky portfolio even after accounting for bequest motives. That is, cognition-stock holding 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.

In spite of recent evidence calling for research on age-related increase in behavioral biases, the impact such transition has on personal finance is yet to be fully explored. Departing from previous analyses focused only on cognitive decline, we pay attention to a failure of realizing such cognitive deficits and examine how this mismatch affects 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 scale of overconfidence. This study begins the analyses by replicating the well-known age-related pattern in financial sophistication and confidence among the elderly. The primary specification examines the extent to which growing overconfidence affects portfolio composition, with a particular emphasis on the changes in risky asset shares and ownership status. 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 allows us to reveal the substitution pattern between financial assets with different risk contents.

Following the literature, we provide several 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 that require substantial information processing. This type of investors may shift the portfolio away from cash equivalents, which require less cognitive abilities, to more information-intensive assets with an unsupported belief that they have enough cognitive capacity to handle the investment information. Second, although the less sophisticated face a considerable amount of information and transaction costs, those who failed to recognize cognitive decline might be unable to identify such cost barriers. On the contrary, those who do aware of such natural decline may perceive the search costs correctly, and adjust the risk contents of portfolio accordingly. Third, as will be discussed later in the paper, overconfident individuals may systematically underestimate the risk involved in

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

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 literature and research questions. The CogEcon respondents have much higher confidence than their actual financial sophistication, and this lack of awareness is associated with (a) a less share of financial wealth held in cash equivalents and (b) greater likelihood of stock ownership. Those who remain overly confident about their financial acumen seem to stay longer in the equity market, even though they have no enough cognitive skills and face higher information costs. Meanwhile, financial sophistication is positively associated with a greater bondholding and mutual fund ownership. This might indicate that financially sophisticated and well-calibrated individuals would 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, indicating that age-related increase in overconfidence indeed drives the results. Further examination shows that financial advice significantly attenuates overconfidence-stock ownership 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 over the remaining life years, 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 market behaviors, Agarwal, Driscoll, Gabaix, and Laibson (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 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-driven declines 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 noted 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 in turn, get wiser as they grow older. 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 whether and how much negative impact of cognitive aging is offset by the age-driven increase in experience. Their estimates showed that some of the investment skills indeed increase with age, but the negative impact of cognitive loss dominates the positive influence of accumulating investment 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) linked cognitive skills to direct and indirect stock market participation. In this study, holding information-intensive assets, such as stocks or stock mutual funds which require an ability to do calculations, was more prevalent among the respondents with higher numeracy, verbal fluency, and recall abilities. When less information-intensive financial instruments such as bonds and money market funds are considered, the relationship between cognitive capacity and risky asset ownership was not significant or, at best, trivial. This pattern bolsters our understanding that cognitive skills to process financial information are a crucial factor that determines the riskiness of retirement portfolio. Arguing along related lines, Banks, O'Dea, and Oldfield (2010) examined the extent to which cognitive ability related to the performance of a retirement portfolio and retirement income adequacy. They showed that, in general, the effect of numeracy is relatively minor when it comes to explaining broader and longer-term economic decisions. In particular, the pattern of wealth accumulation (or, decumulation) of those with higher numeracy was not significantly different from their less numerate counterparts.

An alternative explanation to portfolio choice-cognition correlation is proposed by Browning and Finke (2015). Unlike the previous studies emphasizing the role of cognitive abilities for informed choices, the authors argued that deteriorating cognitive abilities lower individuals' ability to moderate negative emotional response to a loss, and this affects their exposure to financial risks. By analyzing portfolio reallocation during a recent financial crisis, the authors claimed that some of the portfolio reallocation away from stocks is attributable to lower cognitive skills and lack of ability to control negative emotional responses. In turn, their findings are broadly consistent with the literature but suggest an alternative mechanism that determines portfolio reallocation during an economic downturn.

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 cognition score encompassing episodic memory, perceptual speed, semantic memory, visuospatial ability, and working memory. Survey participants' perceptions about how much they know remained unchanged or even increased due to a lack of awareness of cognitive loss. Not surprisingly, a majority of participants responded that they are capable of tracking and coping with everyday money matters, although their actual cognitive capacities were far from what they recognized. Similarly, Finke et al. (2016) found that individuals do not lose confidence in financial decision-making ability, despite a consistent decline in financial literacy and word recall ability. After the age of 80, more than 30% of the perceived financial knowledge was not justified by their actual financial proficiency. A recent study by Robb, Babiarz, Woodyard, and Seay (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 methods. The authors found that alternative financial services, such as payday loans and refund anticipation loans, are more widely used among those with low objective financial knowledge and high subjective financial knowledge.

A notable recent finding argues that a degeneration of brain functions carries several cognitive biases that have been widely acknowledged to result in poor investing skills. For instance, psychology literature demonstrated that the elderly who experienced a sharp decline in cognitive abilities are more prone to framing effects (Finucane, Mertz, Slovic, and Schmidt, 2005; Kim, Goldstein, Hasher, and Zacks, 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, Deck, Sarangi, and Shor, 2009). Crawford and Stankov (1996), and Hansson, Ronnlund, Juslin, and Nilsson (2008) found that a 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, Thorley, and Vorkink, 2012). In a seminal article by Odean (1999), the perceived precision of private information was significantly greater among those who were overly confident about their investment skills.

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

The study found that overconfident investors are more likely to misperceive the strength and credibility of private information, which make them rely on a few risky stocks with expectations of above-average yield. Overconfident traders, as a result, earned relatively small trading profits (Gervais and Odean, 2001), and this poor performance among overconfident traders 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 dividend 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, and financial sophistication and overconfidence, as well as 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 3,224 individuals located in 28 primary sampling units (PSUs) across the nation, and 1,514 of them completed a 40-minute telephone interview.[4] Of these 1,514 participants, a total of 1,230 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 1,222 CogUSA participants are invited to the CogEcon, and 985 of them completed 2008 CogEcon survey

[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.

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 from 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, Griffin, Milojkovic, and Ross, 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 (Figure 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 the 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 true" or "guess false". Since subjective belief is measured with judgment, 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

[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, Smith, and Willis, (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.

[8]Several studies employed the National Financial Capability Study and compared a self-rated financial sophistication to the objective score from test battery 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 due to a disparity in the measurement scales. A half-range confidence scale allows us to overcome such validity issues and yields more consistent confidence estimates.

(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 by aggregating the amount of 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 the fourth category 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, and pension income, as well as logged household income, and net worth.[10] Demographic characteristics account for the between-individual difference in preference parameters. Self-reported health status might be as important as cognitive health due to its predictive values and relevance to shaping behaviors (Miilunpalo, Vuori,

[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.

Oja, Pasanen, and Urponen, 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, Kimball, Juster, and Shapiro, 1995; Kimball, Sahm, and Shapiro, 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 confounding covariates, we construct 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 the variation due to any 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 (a) Manage own assets and (b) Use a financial planner or advisor. Our measure of financial

[11] We identified several irregular or miscoded responses in a 6-category hypothetical gamble questions due to a lack of understanding of survey instruments. As these responses are systematically related to low cognitive skills, we exploit a financial risk taking question in wave 2 of the CogUSA to further impute the risk aversion and retain the missing values. 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 imputed risk aversion.

advice equals 1 if a respondent chose response (b) and 0 otherwise. Similarly, we account for whether the individuals is a financial respondent who has "final say" about everyday money matters. 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 estimated models.

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.

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

$\Lambda(\cdot)$ 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, $\mathbf{X_{i,t}} = [\mathbf{1}\vdots\mathbf{C_{i,t-1}}\vdots\mathbf{Z_{i,t}}]$ where $t \in \{2011, 2013\}$ and $t-1 \in \{2009, 2011\}$ indexes survey years; i indexes individuals; $\mathbf{C_{i,t-1}}$ denotes a set of financial sophistication and confidence vectors; and $\mathbf{Z_{i,t}}$ represents a covariate matrix that includes all other variables 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

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

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

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

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, Gottlieb, & Guiso, 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, I 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, Kieschnick, and McCullough, 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.

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

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

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

, where $\mu_{i,t}$ is a parameter vector of the beta distribution. The beta regression for nonzero fractions models the share 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 final sample for empirical analysis excludes observations with no responses or miscoded values whenever such information is available. These refinements yield the analytic sample of 1,044 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. The overall degree of financial sophistication declined from 77.73 to 70.92, 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 difference. A recovery of U.S. economy is reflected in a 33% surge in S&P 500 index during the study period. 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 mean share of risky assets is 14.3% while indirect investments through mutual funds account for 21.7% of the total financial wealth. Risk aversion increased slightly from 8.03 to 8.14, despite only 2-year difference between the surveys. Financial planning service is more widely used as individuals age, and as a result, almost half of respondents in 2013 wave managed their portfolio through financial planners.

[Insert Table 1 about here]

Table 2 displays the marginal effects estimates from fractional logit models. As discussed above, we present four models where the proportion of each financial asset is introduced as an outcome variable. Three clear results stand out. First, while a majority of variables 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 safe assets increases with age; high-risk high-reward investments are more pronounced among the wealthy households; and investments in bonds and mutual funds represent a larger portion of financial wealth with the advice from a financial planner. Those who received financial advice allocate 14% more financial wealth to mutual funds and 17% less to short-term cash equivalents. Second, respondents financial sophistication is not associated with portfolio composition. Across the models, only the share of mutual funds is positively related to financial sophistication at the 5% significance level. This pattern is not in support of van Rooij, Lusardi, and Alessie (2011) where stockholding is more prevalent among the financially literate, but broadly in line with Parker, Bruine de Bruin, Yoong, and Willis (2012) in which the influence of financial knowledge became no longer or only moderately significant as the models augment with confidence score. Third, we do find a positive association of unjustified confidence with risky investments. Column (4) shows that a 10 points increase in unjustified confidence on a 50-100 scale is associated with a 1.83 percentage points greater proportion of stocks and stock mutual funds. Unjustified confidence is negatively associated with the proportion of cash equivalents, but such correlation is not significant at the 10% level.

[Insert Table 2 about here]

Table 3 presents the ZIB regression results. Beta regression for nonzero proportions and logistic regression for binary responses are laid out in Panel A and B, respectively. As discussed above, ZIB model allows us to separate the changes in intensive margin of asset allocation from other variations across the extensive margin of ownership changes. With 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 a 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 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 in Table 2 arises on the extensive rather than on the intensive margin. Specifically, about 7% greater stock ownership is explained by a 10 points increase in unjustified confidence. Risky asset share conditional on ownership 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), we find that about 1.8% greater likelihood of bondholding and mutual fund ownership is associated with a 10 points increase in unjustified confidence.

[Insert Table 3 about here]

Table 4 re-estimates the models in Table 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. Some financial statements, for instance, may not have a clear-cut answer, and this 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. Such proxy measured with error is subject to attenuation bias, and thus the previous estimates could be downward biased. Our identification strategy is to 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 one in $t-2$. In panel A, the magnitude of the association between unjustified confidence and risky asset share is about twice greater than that of Table 2. In panel B, about 6.6 percentage points decrease in the share of cash equivalents is explained by a 10 points increase in unjustified confidence. We also find that those with 10 points higher overconfidence are 10% more likely to own stocks. 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 increasing overconfidence is not only statistically significant but also economically meaningful.

[Insert Table 4 about here]

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) alluded to, if the spouse has enough cognitive capacity to make unbiased choices and the household make financial decisions jointly, such family's financial portfolio would not change with 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 translation of overconfidence bias into risky portfolio. From the first two models, we reject the hypothesis that staying with other family members dampens the association of overconfidence with portfolio riskiness. In the third model, among those using financial planning service a 10 points increase in unjustified confidence is associated with only 5.3% greater likelihood of stock ownership, which is significantly smaller than 10.2% of those managing portfolio via financial planners. However, this association should be interpreted with caution as a correlation between overconfidence and advice seeking behavior 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. That is, a 5% difference by the use of financial advice would plausibly be a lower bound of true difference.

[Insert Table 5 about here]

Table 6 further 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. As discussed above, if any of such changes explain a significant variation in our confidence estimate the association between unjustified confidence and stock ownership would be significantly underestimated. 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.

[Insert Table 6 about here]

5 Conclusions

This study is one of the first to examine the impact of the age-driven increase in overconfidence, which is discovered by Finke et al. (2016) and Gamble et al. (2014), on portfolio allocation among the elderly. Exploiting several unique features of the data, we constructed the household portfolio models that link asset allocation and ownership status to 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 this rising overconfidence, indicating an interesting substitution pattern between risky and riskless assets in response to aging-driven cognitive bias. Considering a gradual loss of cognitive skills during retirement, our findings suggest that older investors who do not recognize their cognitive deficits tend to hold risky assets longer than the well-calibrated. This is in contrast to the well-known financial planning principle that advises individuals to stay away from equities and hold more riskless assets as they age. In another side, this positive association between stock ownership and rising overconfidence provides a clue about why some individuals with no bequest motives still hold stocks, even at the very end of life cycle. The second phase of analysis showed the possibility that an unbiased financial advice could 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 likely to be a reflection of data limitations. With a longer panel and exhaustive information on portfolio allocation, the magnitude of the hypothesized link is likely to be larger than our estimates. But despite a potential downward bias, the influence of overconfidence gap on stock ownership is significantly positive across the specifications. Apart from the methodological problems, 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, the current study does not take into account whether the cognitive aging affects the intra-household distribution of decision-making power. Some spouse may experience a sharp decline in memory ability and financial sophistication, while the partners cognitive abilities remain relatively intact. If then, cognitive aging may have an impact on who has the "final say" over everyday money matters and how retirement portfolio is managed within the household. For instance, the onset of particular health conditions such as stroke, dementia, or Alzheimers disease, which carry a substantial loss of cognitive abilities, would force the other spouse who had shied away from the equity market to take charge 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 issue. Third, our results should be interpreted with caution as our study covered post-crash periods when the economy was recovering. While we paid particular attention to capturing 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 the primary focus of this study, the consequences of the age-related increase in overconfidence can be particularly detrimental to the LMI households. In particular, our findings signify that the LMI households who used to have no investment assets would be more susceptible to aging-induced cognitive bias, and a proper intervention such as connecting them to a financial planner would be able to minimize adverse consequences. Considering the lower economic status of the LMI households, late-life financial education aiming to inform the potential pitfalls of overconfidence or greater access to affordable financial counseling services at the community level would be able to increase retirees' financial capability. Our findings, overall, 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 1: Descriptive Statistics (*N=1,044*)

	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			
Numbere 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 controls			
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[§] (real $)	72,495	75,000	73,672
Total HH net worth[§] (real $)	400,701	437,600	425,001

Notes: Numbere 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). [§]Median values are reported for total household income and net worth.

Table 2: Models for Portfolio Allocation: Primary Specification

	(1)	(2)	(3)	(4)
Response (0-1):	Cash equivalents / FA	Bonds / FA	Mutual funds / FA	Stocks / FA
	Frac. Logit	Frac. Logit	Frac. Logit	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)
Numbere 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	1,037	1,020	1,036	1,044

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 controls (age, gender, race, education background, and marital status) and year fixed effects are omitted. Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent significance level, respectively.

Table 3: Models for Portfolio Allocation: Alternative Specification

	(1)	(2)	(3)	(4)
Response (0-1):	Cash equivalents / FA	Bonds / FA	Mutual funds / FA	Stocks / FA
	ZIB	ZIB	ZIB	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	1,037	1,020	1,036	1,044

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 having a nonzero response. Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent significance level, respectively.

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. Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent significance level, respectively.

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**	0.022**	0.022**
	(0.009)	(0.009)	(0.009)
α: Confidence$_{t-1}$ (/10)	0.048*	0.065**	0.102***
	(0.027)	(0.026)	(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	1,044	1,044	1,044
Linear restrictions (t-test)			
H_0: $\alpha+\gamma_3=0$			0.053**

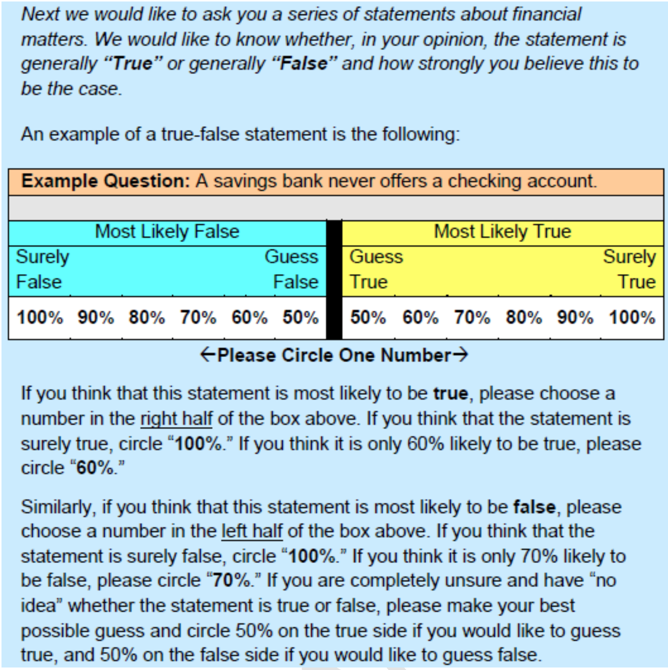
Notes: Clustered standard errors are reported in parentheses. Each regression model includes all RHS variables as in Table 2. Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent significance level, respectively.

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**	0.022**	0.022**
	(0.009)	(0.009)	(0.009)
α: Confidence$_{t-1}$ (/10)	0.081***	0.080***	0.079
	(0.015)	(0.015)	(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	1,044	1,044	1,044

Notes: Clustered standard errors are reported in parentheses. Each regression model includes all RHS variables as in Table 2. Significance levels are indicated by *, **, and *** for 10, 5, and 1 percent significance level, respectively.

Appendix A



*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.

Figure A.1: An Example of Half-range Scale Question in CogEcon

Table A.1: Question Wording of 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 companys 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 × 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: §Numbere series, calculation, and fluid reasoning are normalized on a scale of 0 to 100. See Sun (2012) for more details about scoring and scaling of cognition variables.