Effects of Over and Under-Confidence on Asset Holdings and Net Worth

Abstract

Previous measures that proxy for overconfidence tend to deal with perceptions about knowledge pertaining to economic conditions and financial markets since the research often deals with economic and financial decisions. Our objective is to contribute to this literature by considering a more general proxy of overconfidence. We do so by operationalizing measures of subjective and objective cognitive ability in the Health and Retirement Study to estimate a proxy for over confidence. This proxy is the remaining variation of subjective cognition not explained by an objective cognitive score. We then explore differences in financial asset holdings and overall net worth holdings by people we characterize as over or under-confident, and those of average confidence. We find that overconfident individuals are less likely to hold most types of financial assets, and have lower net worth than average and under-confident individuals. Conditional on ownership, overconfident individuals hold a greater share of financial wealth in liquid assets and other financial assets. Under-confident individuals invest similarly to people with average confidence.

Keywords: overconfidence; asset holdings; net worth; investment

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Highlights

- We estimate the effect of over and under-confidence on asset holdings and net worth.
- Our measure for overconfidence in cognition is unique and more general than previous measures.
- We find asymmetry in asset holdings by the level of overconfidence.

1. Introduction

People differ in saving and investing behavior for multiple reasons. Some people have high discount rates and even overweight current and near-term consumption (see O'Donoghue and Rabin, 1999) or lack the will power to continue with a savings plan (e.g., Choi et al. 2004). Others procrastinate investing for various reasons, including the complexity of financial markets (see O'Donoghue and Rabin, 2001, Della Vigna, 2009). Our objective is to examine whether and to what extent people differ in asset holdings and net worth based on *perceptions* of their own cognitive ability.

This topic is of interest because a person's cognitive abilities affect his/her economic and financial decisions. Individuals with greater cognitive ability may be better able to acquire and process relevant information, especially for complex decisions. Extant literature has found that individuals with greater cognitive ability are less likely to exhibit behavioral biases such as conjunction fallacy – assuming specific events are more likely to occur than general events – and conservatism bias – the tendency to insufficiently update beliefs when presented with new evidence – when they estimate probabilities of certain events (Oechssler et al., 2009). Current evidence also shows that people with greater cognitive ability make fewer financial mistakes (Agarwal and Mazumder, 2013) and are more likely to participate in the stock market (Christelis et al., 2010; Grinblatt et al., 2011; Cole et al., 2014). Moreover, given the complexity of financial markets, it is no surprise that people with greater cognition allocate more to stocks (Browing and Finke, 2015) and earn higher risk-adjusted returns (Grinblatt et al., 2012). Moreover, researchers have also found evidence that cognitive abilities relate to risk aversion, impatience, and time preferences (Dohemen et al., 2010; Benjamin et al., 2013; Bonsang and Dohemen, 2015).

To illustrate the association between cognition and performance in financial markets, Ginkblatt et al. (2011, 2012) use IQ test scores, which are mandatory for joining in the Finnish Armed Forces (FAF), as a measure of an individual' cognitive ability. They found that even after controlling for income, wealth, age, and other characteristics, those with a higher IQ are more likely to participate in the stock market, to diversify their portfolio, to earn higher risk-adjusted returns, and to display trading behavior that is consistent with better-than-average ability, e.g., they are less affected by the disposition effect and actively sell stocks to realize losses with the purpose of minimizing taxes.

Researchers have relied on various measures to study middle age to older people's cognitive ability and their financial choices. In the Survey on Health, Ageing, and Retirement in Europe (SHARE) and the Health and Retirement Study (HRS), which both sample people 50 or older, cognitive ability is measured in terms of memory (word recalls), planning and executive skills (verbal fluency skills), and numeracy (Christelis et al., 2010; Bonsang and Dohmen, 2015; Browing and Finke, 2015). Christelis et al. (2010) finds that those who suffer from cognitive impairment are less likely to hold stocks, and this relation is robust even when they use sub-dimensions for the cognition measure. They do not find the same relation for the propensity to hold bonds, since bonds arguably require less intellectual ability to manage. This result supports the idea that cognitive ability may especially influence those decisions that require gathering and processing large amounts of information.

While cognitive ability plays an important role in financial markets and decision making, a closely related strain of literature shows how self-evaluation of performance, ability, or perceived precision of information or knowledge possessed consequently affects decisions. In this strain of literature, researchers define the concept of overconfidence in three ways (Moore and Healy, 2008). The first type of overconfidence is *overestimation*, which indicates that individuals overestimate their own ability, performance, or odds of success. Illusion of control is also a type of overestimation in that people overestimate their control over events (Langer, 1975). The second category of overconfidence is referred to as *overplacement*. People affected by overplacement tend to rate themselves better than others (Svenson, 1981). The last classification of overconfidence is *overprecision*, also known as miscalibration (Lichtenstein and Fischhoff, 1977). This type of overconfidence occurs when people erroneously believe that the information they possess is more accurate than it actually is. In the current study, we focus on the first definition of overconfidence, overestimation, to study whether and to what extent overconfidence has an effect on asset holdings of people fifty years or older.

Overconfidence is a common behavior and certain personal characteristics correlate with it. Using a sample of approximately 2,000 Canadians who participate in a defined contribution (DC) plan, Bhandari and Deaves (2006) find that people are more likely to overestimate their knowledge about asset returns (i.e., to be overconfident) if they are male, highly-educated, close to retirement, have ever received advice from professionals, and have experience investing for themselves. Financial professionals are also more likely to overestimate their financial knowledge, to believe that their knowledge/investment skills are better than others, and to be overconfident about the precision of their knowledge even though they do not actually know better (Deaves et al., 2010; Menkhoff et al., 2013; Pikulina et al., 2017).

Overconfidence is important to study because it may lead to suboptimal decisions and outcomes. Theoretical models predict that overconfident investors trade more than rational investors, and thus obtain lower expected utility (Daniel et al., 1998; Odean, 1998; Gervais and Odean, 2001). In these models, investors who experience high returns in the past tend to be more overconfident because they mistakenly believe that past success in investment is driven by the precision of their information or knowledge about the investments even though the high return is simply due to good overall market conditions. Furthermore, authors of several empirical studies find that overconfident investors trade excessively (Barber and Odean, 2001; Statman et al., 2006; Glaser and Weber, 2007; Deaves et al., 2009; Grinblatt and Keloharju, 2009; Chuang and Susmel, 2011; Abreu and Mendes, 2012; Fellner-Röhling and Krügel, 2014), under-diversify their portfolio (Merkle, 2017), earn a lower risk-adjusted return (Guiso and Jappelli, 2006), and are more willing to take risks (Nosić and Weber, 2010; Merkle, 2017).

Researchers have used various methods to proxy for overconfidence. For example, Barber and Odean (2001) use gender as a proxy for overconfidence under the assumption that males are more overconfident and females. Consistent with their study, Jacobsen et al. (2014) find that men are more likely to be more optimistic about the economy and the performance of the stock market, and that the gender gap in risky asset holdings disappears after controlling for optimism. Inspired by Gervais and Odean's (2001) theoretical model, empirical studies also utilize past stock performance as a trigger of overconfidence (Statman et al., 2006; Chuang and Susmel, 2011; Lui et al., 2016).

More direct measures of overconfidence rely on self-perceptions of cognitive ability instead of observed behavior in the market place. These measures usually stem from responses in surveys and questionnaires. They include the degree of how well people *think* they know financial matters (Guiso and Japelli, 2006; Nosić and Weber, 2010; Abreu and Mendes, 2012; Menkhoff et al., 2013), the *perception* of current and future economic conditions (both general and personal) (Jacobsen et al., 2014), the discrepancy between people's *beliefs* about their own ability/knowledge/skills and actual performance in general and financial domains (Bhandari and Deaves, 2006; Deaves et al., 2009; Grinblatt and Keloharju, 2009; Merkle, 2017; Pikulina et al., 2017), the extent to which people *consider* themselves better than others (Deaves et al., 2009; Nosić and Weber, 2010; Menkhoff et al., 2013; Merkle, 2017; Pikulina et al., 2017), and the degree of *overestimation* of the precision of one's knowledge/information (Glaser and Weber, 2007; Nosić and Weber, 2010; Menkhoff et al., 2013; Fellner-Röhling & Krügel, 2014; Merkle, 2017).

Our main contribution is our use of a measure of overconfidence that is more general than measures developed in previous research that focus on financial literacy and economic knowledge. This measure relies on objective measures of cognition, measured through tasks that test memory and mental status, and a subjective measure of cognition, measured as self-reported memory status. To capture variation in the subjective measure that is not explained by cognitive ability we regress the self-reported memory status on our objective measures. Notably, to eliminate the potential endogeneity of the objective measures we use Polygenic Scores for General Cognition and individual age as instruments, then we use predicted values of the cognitive measure as a variable in the regression with subjective cognition, that is subjective memory status, as a dependent variable. We then create measures of over and under-confidence based on the residuals from the latter regression and use these measures as explanatory variables for asset holdings. In sections 2 and 3 we provide details about our data and methods.

We recognize that cognition and memory are different but we leverage their inter-related nature to justify calling the measure we generate overconfidence. Notably research in psychology suggests a strong relationship between memory and cognition. Some researchers describe the two concepts as interdependent such that memory relies on cognition, and vice versa (Heit et al., 2012). In another sense, lines of research in memory and cognition describe both as part of a cognitive architecture (Charter et al. 2010; Rogers and McClelland 2004) or even a hierarchical system (Fodor 1983). Furthermore, researchers measure memory and cognition through various questions, and tasks and these questions and tasks may rely on multiple cognitive processes (Medin et al., 1995; Ross 1996) such that understanding one (memory or cognition) provides insights into the other.

In addition to our contribution of a different measure of overconfidence, we also include a measure of under-confidence and evaluate its impact on asset holdings and net worth. Furthermore, we build on previous work by estimating the effect of overconfidence on a variety of asset classes including stocks, bonds, cash-equivalent accounts, individual retirement accounts (IRAs), and certificate of deposits (CDs). The manner in which a person handles these asset holdings will strongly affect overall net worth, which affects life after retirement.

By using a unique approach to proxy for overconfidence described above, our results provide evidence that people in our sample exhibit asymmetric behavior in asset holdings and net worth by their level of overconfidence – over-, average-, and under-confidence. Specifically, relative to average and under-confident people, overconfident individuals are *less likely* to hold most asset classes and to have positive net worth. These findings are robust to different definitions of overconfidence. We also find that, conditional on ownership, under-confident individuals have higher stock allocations than average confidence individuals.

2. Data

For our data analyses, we use a biennial longitudinal dataset comprised of the 1996-2012 waves of the Health and Retirement Study (HRS), which surveys over 22,000 Americans aged 50 and older, as well as their spouses. The survey contains detailed information regarding demographics, physical and mental health including cognition, disability, family structure, income, assets, insurance, past and current employment, and psycho-social factors. Servais (2004) provides more detailed information about the survey.

Our primary objective is to study how an individual's overconfidence in cognitive ability affects financial decisions. We proxy overconfidence in cognition by using objective and subjective cognition measures from the HRS. Specifically, in this survey, respondents answer a series of questions designed to measure cognitive ability. These questions fall into two categories: total word recall and mental status. We rely on these categories because they appear in each waves of our sample. For total word recall (memory), interviewers test a respondent's ability for immediate and delayed word recall. First, interviewers read 10 words and ask respondents to write down as many they can remember. Then after about five minutes of answering other survey questions, the interviewer again asks respondents to list as many words as they can remember. This particular score measures “fluid intelligence,” or the mechanism that allows a respondent’s mind to process information and store it (Craik, 1999). These memory skills are known to decline as people advance to old age (Colsher and Wallace, 1991; Hultsch et al., 1992; Poon, 1985).

To test mental status, interviewers ask respondents to perform several tasks reflecting “crystallized intelligence,” which is based on knowledge, language, and orientation, and could grow through formal education and experience (Salthouse, 1999). Notably, age is less likely to negatively affect a person’s mental status. In the survey, respondents perform a series of tasks, and the overall mental status score is the sum of the outcome from each task. For these tasks respondents count backwards 10 numbers starting at either 20 or 86, subtract 7 from a prior number for five trials and they begin with the number 100, report the day’s date including the day of the month, the year, and day of the week, recall the correct object based on a simple and concise verbal description (the objects are scissors and cactus), name the current president and vice-president of the United States, and provide the definition of five specific words read by the interviewer.

Ofstedal et al. (2005) documents the validity and reliability of the cognitive measures described above. As proxies for an individual’s cognition we use the total word recall and mental status scores separately and as a composite cognitive ability score. In other words, we use three measures of cognition to generate three different measures of over-confidence: one based on memory score, one based on mental status score, and one based on total cognitive score. As a robustness check, we additionally use a factor score of cognition estimated by a factor analyses using eight items of cognitive tests.

We expect subjective and objective cognitive ability to be jointly determined, thus, we need to instrument for cognitive ability. For instruments, we use polygenic scores for general cognition collected from a sample of respondents. Specifically, in 2006, 2008, and 2010 the HRS collected saliva samples from a randomly selected sub-sample of HRS respondents and their spouses (Ware et al., 2017). The HRS constructed polygenic risk scores (PGSs) for a large set of phenotypes. To do this, they used a genome-wide association study (GWAS) in which they correlated genetic variants in individuals with a given trait (Faul & Smith, 2017). The PGSs consist of the weighted sum of the genotype (the number of reference alleles for individuals at each single nucleotide polymorphism, SNP). The PGS for general cognition combines the 13 SNPs associated with neuropsychiatric phenotypes (Ware et al., 2017).

Following the literature, we restrict our sample to HRS respondents who are from European ancestry because researchers derived the SNP weights from a sample that was almost exclusively of European ancestry. PGSs of individuals who are from other ancestry groups may not have the same predictive capability of the outcome of interest (Martin et al., 2017; Ware et al., 2017). Given this restriction our final sample only includes respondents with European ancestry.

An issue to consider is that missing data in this series of cognition tests are systematically related to the survey participants' actual and subjective cognitive ability. Because the occurrence of missing data is arguably not random, the HRS imputes data to provide a more complete dataset. Only for self-reported respondents (proxy responses are not imputed), the HRS performs the imputations by using a regression-based procedure accounting for demographics, economic and health status, and past and current period cognition variables. Then based on individual characteristics reported in the survey, HRS administrators impute scores to the cognitive ability tests. The detailed information about the imputations is documented in Fisher et al. (2017). For our data analyses, we use these imputed cognition scores provided by the HRS.

The single question in the HRS we use as proxy for subjective cognitive ability asks the respondent to report memory capacity. In the survey, the specific question for the memory measure reads as follows: "How would you rate your memory at the present time? Would you say it is excellent, very good, good, fair, or poor? " While this measure most closely relates to the cognitive tests for memory, we utilize it as a general subjective cognitive score since it is the only question that captures a respondent's subjective belief about his/her cognitive ability. By using the composite score and a perceived level of cognition, we construct a measure for overconfidence. We describe the process in the empirical model section below. We note that respondents answer questions for all of the measures we use for subjective and objective cognitive ability in each wave of the survey, and thus the measure spans across time.

Outcomes we use in this study measure ownership, amount, and share of different types of financial assets respondents use for saving and investing. We also use ownership and amount of total financial assets and net worth as outcome variables. The financial assets we use are cash-equivalent accounts (checking, savings, or money market accounts), stocks (stocks and mutual funds), individual retirement accounts (IRAs – any amount in IRA or Keogh accounts), certificates of deposit (CDs – CDs, government savings bonds, or treasury bills), bonds (corporate, municipal, government, foreign, and other bond funds), and other assets such as money owed, annuities, trusts, and jewelry.

Even if the HRS records detailed information about household financial status, some information is not available or not consistently collected in every wave. For example, the HRS does not provide detailed portfolio compositions of the assets saved in IRAs and employer-sponsored pension accounts. We use financial information provided by the RAND HRS wealth file to deal with missing values. We also adjust the values (expressed in 2014 dollars) by using the consumer price index (CPI).

As control variables, we include several factors, some which are time-variant and some which are not. These include gender, age, educational attainment, perceived health status, medical condition, employment status, marital status, number of living children, number of years of work, household income, and birth cohort. We code medical conditions as the number of conditions a respondent has from the following list: high blood pressure or hypertension, diabetes, cancer or malignant tumor, chronic lung problems, heart problems, stroke victim, psychological ailments such as depression, and arthritis or rheumatism. For birth cohorts, we include four birth year cohorts: AHEAD, people born before 1924; the Children of Depression (CODA), those who born 1924-1930; HRS, individuals born 1931-1941; and War Babies (WB), people born 1942-1947.

We restrict our sample to respondents who claim they are the primary person responsible for financial decisions in the household since the financial variables are gathered in the household level as opposed to the individual level. After this restriction and the restriction for the PGS for general cognition, our final sample includes 4,893 individuals and 16,740 observations. More than half of our sample is female (56.15%) and married or partnered (56.81%). A majority of the individuals have at least a high school degree (84.57%), report at least good health status (80.83%), own private and/or public health insurance (96.61%), and are retired or not working (84.49%). On average, individuals are 72 years-old, have 3 living children, and have worked for 36 years. We report these sample characteristics in Table 1.

3. Empirical Model

To estimate the impact of overconfidence on asset contributions and holdings, we carry out multiple steps in our analytical plan. We proxy overconfidence using residuals from a regression of subjective cognitive ability on objective cognitive ability. Residuals from this estimation procedure include the variation in subjective cognitive ability that is not explained by the objective measures, thus we consider these residuals as a proxy for overconfidence.

Objective measures of cognition, however, are most likely endogenous because both objective and subjective cognitive ability are likely jointly determined. Thus, our first step is to use the instrumental variables approach to remove the endogeneity from the measures of objective cognition (Greene 2012). As instruments, we use age and PGS for general cognition which is available for a portion of the HRS sample.

We expect that these genetic markers correlate with cognitive ability since at least a portion of cognition is genetic (Plomin 1999; Plomin and Spinath 2002). While evidence does not substantiate that cognitive decline is heritable (Harris and Deary 2011), there is strong evidence that cognition declines with age and that this decline may begin before age 60 (Salthouse 2009). Thus genetic markers and age are good candidates for instruments for cognition. We note that in this first and second stage we use the sample of adults with European ancestry so that our parameter estimates are not biased. In our asset equations, however, we restrict the sample to only include respondents who are the primary financial decision makers.

Our first stage equation is the following:

$$CA_{it} = \delta_0 + \delta_1 AGE + \delta_2 PGS_i + \varepsilon_{it} \quad (1)$$

Where CA_{it} is cognitive ability measured for respondent i at time period t. Independent variables in this regression are the age and PGS instruments. We also impose the distributional assumption on the error term: $\varepsilon_{ist} \sim \text{iid } N(0, \sigma)$.

From this first regression we generate predicted values for objective cognitive ability, $\widehat{CA}_{it}$ and use them as the explanatory variables for subjective cognitive ability:

$$SCA_{it} = \gamma_0 + \gamma_1 \widehat{CA}_{it} + \gamma_2 AGE + \nu_{ist} \quad (2)$$

For this study we use variation in subjective cognitive ability not explained by cognitive ability – estimated residuals – to proxy for overconfidence. Positive values for this residual indicate subjective cognition is greater than measured cognition, and vice versa for negative values. With these residuals, we create three indicator variables. The first indicator equals 1 for all values of the overconfidence measure that are greater than positive one, and zero otherwise. The second indicator, which we use as baseline, equals one for all values of the measure between, and including, negative one and positive one, and zero otherwise. We classify these people as having average confidence. Notably, someone with average confidence could have above or below average cognitive ability. The distinguishing factor is that the person is accurately gauges his/her ability. The third indicator equals one for values of the measure less than negative one, and zero otherwise. We classify these people as under-confident.

To assess the robustness of our results we generate four different measures for over and under-confidence. We develop the first three measures by using total word recall, mental status, and total cognition score (combination of first two scores) each in separate equations. For our fourth measure we estimate a factor model by using all the cognitive test measures from the HRS as factors in the subjective memory equation. Then we use residuals from this method as a proxy for overconfidence. In our tables of results, we label regressions based on these variations as Specification I-IV.

Then to measure the effect of perceived cognitive ability on asset holdings we employ a double hurdle model (Cragg 1971) which jointly estimates the probability of a respondent holding an asset and the effect of explanatory variables on asset holdings, given that the respondent holds the asset. We use a double hurdle model because the zeros in the data are corner solutions from the respondent's decision process. Since these zeros are not censored a traditional Tobit estimation procedure is not appropriate (though Cragg's (1971) method is based on the Tobit method). Also, a Heckman Two-Step approach is not appropriate because we actually know that the zero is from a consumer decision so we actually observe the market outcome. Specifically, the equations we jointly estimate in the double hurdle model are:

$$P(y_{it} > 0|X_{it}) = \Phi(\alpha_0 + \alpha_1 Over_{it} + \alpha_2 Under_{it} + X_{it}\Delta + T_t + W_i) \quad (3a)$$

which measures the probability of holding the asset and

$$E(y_{it}|y_{it} > 0, X_{it}) = \beta_0 + \beta_1 Over_{it} + \beta_2 Under_{it} + X_{it}\mathrm{K} + T_t + W_i. \quad (3b)$$

For the double hurdle method, we use amount and share of assets as outcome variables, and as regressors we include the indicators for levels of confidence, individual level covariates (X), year fixed effects (T), and cohort fixed effects (W). Individual covariates that we include in the model are gender, age, age-squared, educational attainment, marital status (never married, separated/widowed/divorced vs. married), perceived health condition (poor, fair, good, very good, excellent), number of medical health condition, number of living children, log of income, health insurance ownership, employment status (retired vs. employed, not employed), and years employed.

We hypothesize that in each asset class and for total net worth, people labeled as overconfident will have different asset holdings than those we consider as having average confidence. Our test for overconfidence is whether the coefficient β_1 is statistically different from zero for each asset class, total financial assets, and net worth. Since we are dealing with total asset holdings and not contributions to the assets, portfolio balances, returns, or trading volume, we do not attempt to hypothesize the direction of the difference. In other words, we only observe total account values which include contributions plus dividends, interest earnings, and asset returns. Thus we will rely on the data to provide the direction of the effect.

On the other hand, we expect that under-confident people may reflect those who are aware of a cognitive impairment and respond accordingly, that is they possibly seek help. Thus, we expect their holdings to be similar to those of people in the average confidence group. As a result we hypothesize that we will fail to reject the null that β_2 is different from zero.

4. Results

Table 2 provides summary statistics for total financial assets, net worth, and each financial instruments. The mean amounts owned by individuals in net worth, financial assets, equity, cash-equivalent, IRAs, CDs, bonds, and other financial assets are \$504,045, \$281,993, \$104,090, \$39,195,

$79,032, $26,669, $16,436, and $16,572, respectively. Percentage allocations differ considerably across asset types. A majority of the old individuals have positive net worth (97.18%), and own at least one form of financial assets (95.14%) and cash-equivalent (91.53%). Approximately half of the individuals save in IRAs (47.25%). The least popular types of financial assets are bonds (10.26%) and other financial assets (18.58%).

In Table 3 we provide estimates from our IV regression models. Our main instrument, polygenic score for general cognition, is positively associated with all measures for objective cognition at the 99% significance level. This shows that genetic traits predict individuals' cognitive ability. Age is also significantly correlated with objective cognition in all specifications. As expected, older people exhibit lower cognitive ability than relatively younger individuals. In the second stage we find that the predicted objective cognition measure positively correlates with subjective cognition. Age has a much smaller effect, and even insignificant effect.

In order to test whether our instruments are weakly correlated with the endogenous regressors, we present F statistic for all specifications. For Wooldridge's score test for endogeneity we reject the null hypothesis at the 5% level that the variables are exogenous in all specifications except for IV, which suggests that we should treat objective cognitive score as endogenous. In addition, our test statistics exceed the critical value of 10, and thus we reject the null hypothesis of weak instruments (Stock and Yogo 2005). We also present the estimate from Wooldridge's robust score test of overidentifying restrictions (1995). In all specifications, test statistics are significant at the 5% test level, which means that our instruments are overidentified, and thus we reject the null hypothesis that our instruments are valid or our structural model is correctly specified. This case of over-identification does not concern us for two reasons. First, the literature establishes that PGS and age strongly correlate with cognition which justifies our use of both. Next, our second equation, in which we regress subjective cognition on the predicted values of cognition as well as age is not designed to be a structural model, rather a way in which we isolate variation in subjective cognition that is not explained by objective cognition. Thus it is not a structural equation but rather a method to generate an overconfidence measure.

We use estimated residuals from the IV regression models presented in Table 3 as proxy measures for overconfidence. In Figure 1 we plot histograms for each of the four measures for overconfidence. The mean of the measures is equal to zero by construction, and the values range from negative four to positive four (except for the third measure). All measures seem to be normally distributed (though the third measure looks slightly different from the distributions of the other measures). Our results are not likely to be sensitive to the particular shape of the distribution of each measure because we use two dummy variables indicating high and low level of overconfidence in cognition.

In Table 4 we provide summary statistics for net worth, total financial assets, and each financial instrument by subgroups categorized based on the level of overconfidence. On average people with average confidence hold the greatest amount of net worth, total financial assets, cash-equivalent, IRAs, CDs, and bonds. Under-confident individuals tend to hold the least amount of net worth, total financial assets, stocks, cash-equivalent, bonds, and other financial assets. Even though the unconditional mean values of asset holdings in more risky assets such as stocks and other financial assets are the greatest among overconfidence individuals, the mean difference in such values between overconfident and people with average confidence do not seem to be large enough to be statistically significant. Among average-confidence individuals, 40.18%, 92.29%, 49.13%, 33.73%, 10.65%, 19.02 %, 95.78%, and 97.85% of them hold stocks, cash-equivalent, IRAs, CDs, bonds, other financial assets, any financial assets, and positive net worth. The percentage of people who hold each asset and positive net worth is lower among under- and over-confident individuals compared to average confidence individuals.

In Table 5 we present the results from double-hurdle models for ownership and actual amount of positive net worth. We truncate negative values to zero (324 out of 16,740 and minimum value is -$8683), and take a log transformation for positive values. The results show that, in all specifications except for Specification IV, overconfident individuals are less likely to have positive net worth compared to people with average confidence. In specifications II, III, and IV, overconfident individuals have a lower net worth than people with average confidence. Specifically, conditional on having positive net worth, the overconfidence group has 12 percent, 19 percent, and 15 percent lower net worth than those who are in the reference group. It is interesting to observe that under-confident individuals are not more or less likely to have positive net worth, and do not have a significantly different amount of positive net worth from those with average confidence. Hence, the effect of overconfidence on net worth appears to be asymmetric.

In Table 6 we present the estimates from double hurdle models for ownership and amount of financial assets. In all specifications, overconfident individuals are less likely to hold any financial asset, and hold less amount of financial assets compared to people with average confidence. Conditional on ownership, overconfident individuals hold 32 percent, 26 percent, 31 percent, and 35 percent less financial assets in each specification. They may save or invest less because they believe that they already save or invest enough. Again, under-confident individuals are not systematically different from the group of people with average confidence when they decide whether and how much to hold in financial assets.

Table 7 presents the estimates for whether overconfidence affects ownership, amount, and share of equity. In all specifications, overconfident individuals are less likely to hold equity in their portfolio. The interesting results are that, in all specifications conditional on the stock market participation, under-confident individuals hold a greater equity share than people with average confidence by 5.23 to 6.44

percent. Overconfident individuals do not have a statistically different equity share compared to the group of individuals with average confidence. This result may reflect a stylized fact in finance that people with average confidence earn greater risk-adjusted returns and diversify their portfolio more than more overconfident individuals (Statman et al., 2006; Glaser and Weber, 2007; Deaves, Lüders, & Luo, 2009; Grinblatt and Keloharju, 2009; Chuang and Susmel, 2011; Abreu and Mendes, 2012; Fellner-Röhling and Krügel, 2014).

Table 8 presents the estimates from double-hurdle models of ownership, total amount, and share of cash-equivalent in financial assets. In all specifications, overconfident individuals are less likely to hold cash-equivalent, hold lower amounts of cash-equivalent, but hold a greater share of cash-equivalent to total financial assets compared to the reference group. This may suggest that, on average, overconfident individuals save less in an absolute term, and conditional on asset holdings they choose investments in assets that they can easily convert to cash.

In Table 9, we present the results from double-hurdle models of ownership, total amount, and share of investments in IRAs. Overconfident individuals are less likely to hold investment in IRAs, and conditional on ownership they hold fewer assets in IRAs, specifically, from 13.77 to 15.16 percent less. The percentage share of investments in IRAs that overconfident individuals hold is not different from the percentage share held by the group of people with average confidence. The finding that overconfident individuals save or invest less in IRAs is consistent with a misperception of their own financial situation. As they overestimate their cognitive ability, they may also overestimate their financial status, and thus they save or invest less. Or, they may prefer to hold an extremely risky asset (riskier than stocks) because the overconfidence in their ability makes them underestimate the risk of doing so (Nosić and Weber, 2010; Merkle, 2017).

We then proceed to test whether overconfidence influences ownership, amount, and share of CDs that individuals hold (Table 10). We find that overconfident individuals are less likely to hold CDs than individuals with average confidence. Interestingly, overconfident individuals hold a greater share of CDs in their portfolios compared to the group of people with average confidence. This result is similar to what we observe in Table 7. Conditional on ownership of CDs, overconfident individuals hold a greater share of safe assets in their portfolios supporting our hypothesis that a share of CDs of overconfident individuals are different from that of people with average confidence. This result is rather surprising because the previous literature suggests that overconfident individuals are more willing to take risk (Nosić and Weber, 2010; Merkle, 2017). The potential explanation might be that overconfident individuals prefer to hold liquid assets so that they can quickly access the funds for risky investment.

In Table 11, we test whether overconfident individuals are more or less likely to invest in bonds or hold more or less bonds. In specifications I, III, and IV, overconfident individuals are less likely to hold their assets in bonds, and conditional on their ownership they hold a lower share of their assets in bonds by 3.42 to 4.24 percent. However, our results should be interpreted cautiously because only a few overconfident individuals hold bonds in their portfolios (192 observations based on the overconfidence measure using total cognition score).

Finally, we present the results from double-hurdle models estimating ownership, amount, and share of other financial assets in Table 12. In Specification III, overconfident individuals hold a greater share of other financial assets compared to the group of people with average confidence group by 4.53 percent, conditional on ownership of other financial assets. This result is consistent with our hypothesis and previous research that overconfident individuals are more likely to take risks (Nosić and Weber, 2010; Merkle, 2017), and thus hold more risky assets.

In sum, overconfident individuals are less likely to own stocks, cash-equivalent, IRAs, CDs, bonds, total financial assets, and positive net worth, and conditional on ownership hold a greater share of cash-equivalent, CDs, and other financial assets but a lower share of bonds to total financial assets. On average, overconfident individuals hold fewer financial assets and have lower net worth.

5. Conclusions

We find a strong asymmetry in asset holdings between overconfident, average confident, and under-confident people. Most striking is that in each asset class, overconfident people are less likely to hold the asset and have holdings less than those in the average confidence and under-confident group. This asymmetry highlights that the overconfidence trait can have negative long-term effects on net worth which can result in later retirements or a greater need for government assistance.

Interestingly, conditional on ownership, overconfident people hold a greater share of cash-equivalent, certificates of deposits, and other financial assets but a smaller share of bonds than average confidence individuals. We do not observe any difference in asset holdings in these assets between under- and average confidence individuals. Overconfident individuals may choose to hold assets that can be readily converted into liquid assets in case they need to purchase risky investments when they desired to do so or to hold extremely risky assets (i.e., other financial assets) because they underestimate the risks associated with such investment.

Our results suggest that under-confident people in our sample may, in part, be similar to those with mild cognitive impairment. These people are generally aware of their state and may recognize their need for assistance to manage their money and assets (see Cook and Marsiske 2006; Podewils et al. 2003). We show virtually no differences in asset holdings between under-confident and having average confidence, which suggests that they may seek help, that both groups seek help in similar ways, or manage their assets in similar ways. Overall our results indicate that under-confidence is not necessarily a negative attribute, at least in terms of financial health. Notably, relative to overconfident people, under-confident individuals may have a greater share of stocks in their portfolio because they earn higher returns from their investment (potentially by diversifying more and trading less excessively) as illustrated in previous research (Statman et al., 2006; Glaser and Weber, 2007; Grinblatt and Keloharju, 2009; Chuang and Susmel, 2011; Fellner-Röhling and Krügel, 2014).

These findings differ from the literature showing that optimism, measured by the discrepancy between self-reported life expectancy and the value compared to the actuarial statistical table, is positively related to stock holdings, total wealth holdings, and the likelihood to save (Puri and Robinson, 2007). However, our results are driven by extremely over- or under-confident individuals, and these are consistent with extant literature in finance and economics that overconfidence may lead to decisions that are not rational (Guiso and Jappelli, 2006; Statman et al., 2006; Glaser and Weber, 2007; Deaves, Lüders, & Luo, 2009; Grinblatt and Keloharju, 2009; Chuang and Susmel, 2011; Abreu and Mendes, 2012; Fellner-Röhling and Krügel, 2014; Merkle, 2017).

This asymmetry in asset holdings between those of different levels of confidence is one of the contributions of our research. This asymmetry highlights the stark differences in behavior between those who are over confident and those who are under-confident. We also generate a more general measure of overconfidence that measures memory status, which is closely linked to cognition. Previous research focuses on overconfidence primarily in financial settings. In addition, we study more asset categories which provides a broader understanding of the ways in which overconfidence affects net worth and the individual measures that contribute to net worth. Lastly, our approach with the double hurdle model allows us to jointly determine the likelihood of holding an asset and the impact of overconfidence on asset holdings, conditional on respondents holding it.

We recognize that our results are based on data with various limitations. First, asset holding data do not include actual contributions, returns, or portfolio information. We also recognize that our sample is limited to those of European ancestry since we use the PGS as an instrument. While our measure of confidence is novel, it is also limited because our subjective cognitive measure relies on a question about memory, making the measure noisy.

We expect our work to contribute to the literature on overconfidence in meaningful ways. Most important is that overconfidence has a negative impact on net worth while under-confident people experience no negative effects. This asymmetry highlights the need to provide financial planning assistance in ways that overconfident people will feel comfortable and build their net worth in good ways.

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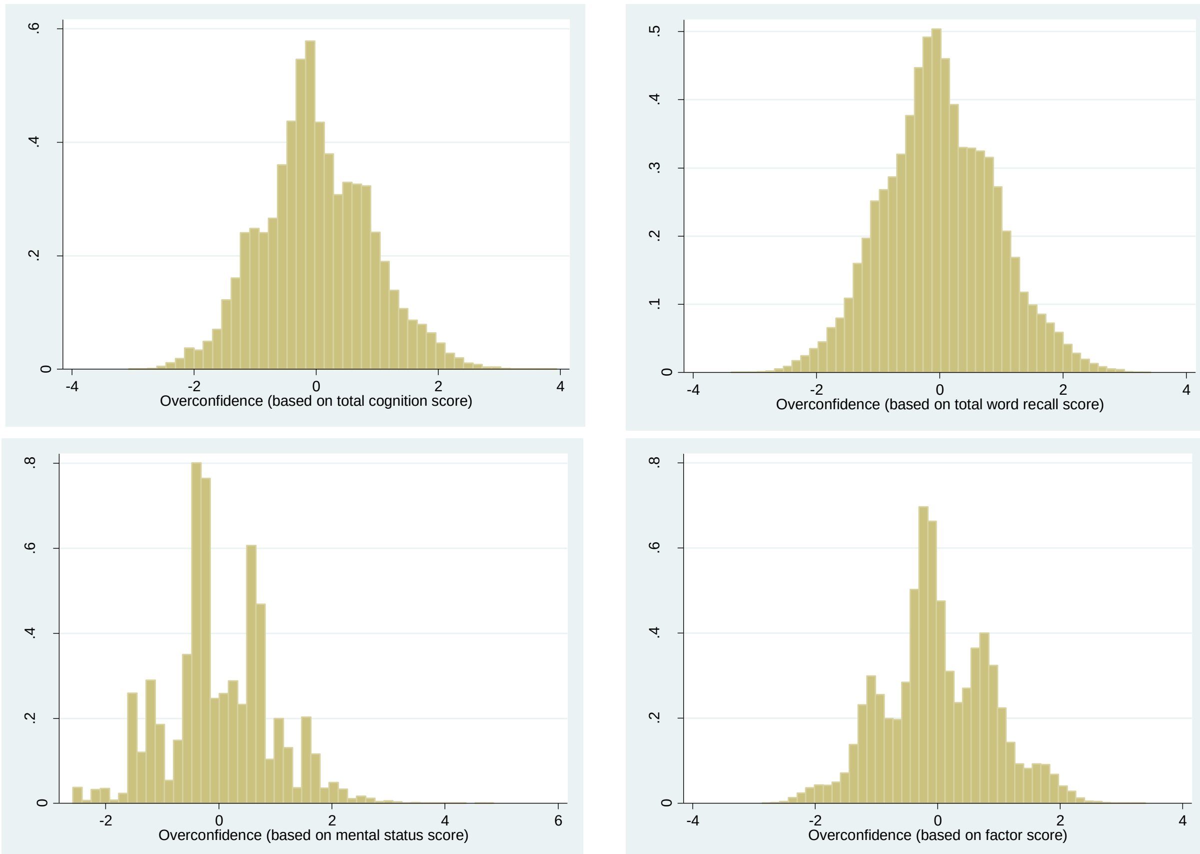

Figure 1. Histogram of Different Measures for Overconfidence.

Table 1. Sample Characteristics

Variables	%/mean (S.D.)	Variables	%/ mean (S.D.)
Gender		No. of medical conditions	
Female	56.16	Mean	0.22
Educational attainment		(S.D.)	(0.31)
Less than high school degree	15.43	No. of children	
High school degree	40.1	Mean	3.22
Some college	21.99	(S.D.)	(2.02)
College graduate +	22.48	Health insurance ownership	
Age		Owner	96.61
Mean	72.27	Household income (2014 $)	
(S.D.)	(7.34)	Mean	64,726
Marital status		(S.D.)	(86,688)
Married/Partnered	56.81	Employment status	
Separated/divorced/widowed	40.52	Employed	15.51
Never married	2.67	Retired	76.03
Health status		Not working	8.46
Poor	4.49	Total years worked	
Fair	14.68	Mean	36.10
Good	32.07	(S.D.)	(15.34)
Very good	35.38		
Excellent	13.39		

Note. The estimates are unweighted. The sample includes 4,893 individuals and 16,740 observations.

Table 2. Summary Statistics of Financial Assets and Net Worth (2014$)

	10%	25%	50%	75%	90%	Mean	S.D.	% of Sample
Stocks	0	0	0	41,103	259,650	104,090	388,288	38.75
Cash-equivalent	72	2,349	10,997	36,302	97,688	39,195	91,782	91.53
IRAs	0	0	0	65,555	214,134	79,032	198,704	47.25
CDs	0	0	0	9,048	68,733	26,669	77,849	32.71
Bonds	0	0	0	0	1,277	16,436	94,869	10.26
Other financial assets	0	0	0	0	21,708	16,572	74,372	18.58
Total financial assets	658	11,940	84,494	11,940	713,279	281,993	612,440	95.14
Net worth	19,719	98,190	236,700	526,343	1,111,702	504,045	966,201	97.19

Note. All values are expressed in 2014 dollars. The estimates are not weighted. The sample includes 4,893 individuals and 16,740 observations.

Table 3. Instrumental Variable Approach for Overconfidence

	Specification I		Specification II		Specification III		Specification IV	
	1st DV= CA_{it} Coef. (Robust S.E.)	2nd DV= SCA_{it} Coef. (Robust S.E.)	1st DV= CA_{it} Coef. (Robust S.E.)	2nd DV= SCA_{it} Coef. (Robust S.E.)	1st DV= CA_{it} Coef. (Robust S.E.)	2nd DV= SCA_{it} Coef. (Robust S.E.)	1st DV= CA_{it} Coef. (Robust S.E.)	2nd DV= SCA_{it} Coef. (Robust S.E.)
Age	-0.1698*** (0.0021)	0.0043 (0.0026)	-0.1250*** (0.0012)	0.0056* (0.0022)	-0.0377*** (0.0010)	-0.0032* (0.0014)	-0.0241*** (0.0004)	-0.0013 (0.0024)
General cognition PGS (Z_i)	0.2837*** (0.0210)		0.1896*** (0.0127)		0.1092*** (0.0099)		0.0514*** (0.0042)	
Predicted Cognition score ($\widehat{CA}_{it}$)		0.0962*** (0.0149)		0.1372 (0.0176)***		0.2347*** (0.0351)		0.4191*** (0.0982)
N	45,449		69,081		45,449		29,657	
First-stage F	18.37		24.62		16.10		15.73	
Chi 2 (test of overidentifying restrictions)	80.76 (p<0.001)		123.86 (p<0.001)		70.45 (p<0.001)		56.31 (p<0.001)	
Chi 2 (test of endogeneity)	12.02 (p<0.001)		24.69 (p<0.001)		22.75 (p<0.001)		1.73 (p=0.1885)	

Note. For all specifications, we use an instrumental variable regression. The instruments are polygenic score for general cognition and the ten principle components for general genetic traits specific to a European ancestry group. The dependent variables of the first stage in specification I, II, III, and IV are total cognition score, total word recall score, mental status score, and factor scores estimated using all items of cognition tests, respectively. The dependent variable of the second stage in all specifications is subjective cognitive ability. The predicted cognition score obtained from the first stage model is used as a predictor of subjective cognitive ability in the second stage. * p<0.05, ** p<0.01, *** p<0.001

Table 4. Summary Statistics of Financial Assets and Net Worth by Levels of Overconfidence

	Under-confident			Average-confident			Over-confident		
	Mean	S.D.	% of sample	Mean	S.D.	% of sample	Mean	S.D.	% of sample
Stocks	87,181	241,490	34.30	105,037	396,710	40.18	116,902	496,598	35.17
Cash-equivalent	35,389	68,306	90.42	40,238	102,079	92.29	37,205	83,623	88.26
IRAs	68,712	163,492	44.14	83,295	207,359	49.13	65,221	200,021	39.59
CDs	23,104	72,165	30.84	27,373	94,589	33.73	26,411	96,056	28.75
Bonds	11,167	68,643	9.19	18,020	111,997	10.65	12,866	71,729	9.13
Other financial assets	13,680	71,632	16.54	17,007	81,093	19.02	17,155	82,765	18.25
Total financial assets	239,233	403,583	94.23	290,970	640,122	95.78	275,761	676,468	92.35
Net worth	448,555	850,133	96.76	513,230	960,934	97.45	510,421	1,017,894	96.15
No of obs. (%)		2,286 (13.66)			12,350 (73.78)			2,104 (12.57)	

Note. The estimates are unweighted. The sample includes 4,893 individuals and 16,740 observations. We classify individuals based on the first overconfidence measure using total cognition score.

Table 5. Ownership and Amount of Positive Net worth

Positive net worth	Specification I 1st DV= positive NW Coef. (Robust S.E.)	Specification I 2nd DV= ln(amt) Coef. (Robust S.E.)	Specification II 1st DV= positive NW Coef. (Robust S.E.)	Specification II 2nd DV= ln(amt) Coef. (Robust S.E.)	Specification III 1st DV= positive NW Coef. (Robust S.E.)	Specification III 2nd DV= ln(amt) Coef. (Robust S.E.)	Specification IV 1st DV= positive NW Coef. (Robust S.E.)	Specification IV 2nd DV= ln(amt) Coef. (Robust S.E.)
Overconfident	-0.1730** (0.0638)	-0.1145 (0.0665)	-0.1799*** (0.0416)	-0.1187** (0.0379)	-0.2387*** (0.0640)	-0.1875*** (0.0429)	-0.1116 (0.0657)	-0.1529*** (0.0436)
Under-confident	0.0210 (0.0721)	0.0222 (0.0687)	0.0133 (0.0375)	-0.0075 (0.0390)	0.0275 (0.0754)	0.0156 (0.0371)	0.0290 (0.0699)	-0.0048 (0.0378)
Age	0.1183* (0.0501)	0.1206* (0.0501)	0.1169*** (0.0261)	0.1187*** (0.0260)	0.1165* (0.0501)	0.1162*** (0.0261)	0.1197* (0.0502)	0.1180*** (0.0261)
$Age^2/100$	-0.0529 (0.0335)	-0.0545 (0.0335)	-0.0624*** (0.0175)	-0.0638*** (0.0175)	-0.0516 (0.0334)	-0.0620*** (0.0175)	-0.0540 (0.0336)	-0.0631*** (0.0175)

Note. The sample includes 4,893 individuals and 16,740 observations. For all specifications, we use double hurdle models. The first-stage dependent variable is whether individuals hold positive net worth or not. The second-stage dependent variable is natural log of the value of net worth. Control variables include gender, age, age-squared, educational attainment, health status, employment status, marital status, number of living children, number of medical conditions, total number years of work, household income, health insurance ownership, cohort effect, and year-fixed effects. Standard errors are clustered at individual levels. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 6. Ownership and Amount of Financial Assets

Financial assets	Specification I		Specification II		Specification III		Specification IV	
	1st	2nd	1st	2nd	1st	2nd	1st	2nd
	DV= ownership	DV= ln(amt)	DV= ownership	DV= ln(amt)	DV= ownership	DV= ln(amt)	DV= ownership	DV= ln(amt)
	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)
Overconfident	-0.2781***	-0.3169***	-0.1706**	-0.2569***	-0.3043***	-0.3146***	-0.2514***	-0.3472***
	(0.0539)	(0.0570)	(0.0551)	(0.0527)	(0.0541)	(0.0586)	(0.0545)	(0.0599)
Under-confident	-0.0584	-0.0154	-0.0670	-0.0612	-0.0371	-0.0347	-0.0818	-0.0438
	(0.0542)	(0.0597)	(0.0542)	(0.0624)	(0.0564)	(0.0577)	(0.0531)	(0.0599)
Age	0.0887*	0.1020**	0.0912*	0.1046**	0.0856*	0.1014**	0.0907*	0.1028**
	(0.0409)	(0.0362)	(0.0407)	(0.0361)	(0.0409)	(0.0362)	(0.0409)	(0.0362)
$Age^2/100$	-0.0416	-0.0383	-0.0435	-0.0402	-0.0397	-0.0380	-0.0430	-0.0386
	(0.0272)	(0.0237)	(0.0271)	(0.0237)	(0.0272)	(0.0237)	(0.0272)	(0.0237)

Note. The sample includes 4,893 individuals and 16,740 observations. For all specifications, we use double hurdle models. The first-stage dependent variable is whether individuals hold any financial asset. The second-stage dependent variable is natural log of the value of financial assets. Control variables include gender, age, age-squared, educational attainment, health status, employment status, marital status, number of living children, number of medical conditions, total number years of work, household income, health insurance ownership, cohort effect, and year-fixed effects. Standard errors are clustered at individual levels. * p<0.05, ** p<0.01, *** p<0.001

Table 7. Ownership, Amount, and Share of Directly-held Stocks

Stocks	Specification I			Specification II			Specification III			Specification IV		
	1st	2nd		1st	2nd		1st	2nd		1st	2nd	
	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)
Over-confident	-0.1431*** (0.0385)	-0.0492 (0.0834)	0.0318 (0.0248)	-0.1398*** (0.0368)	-0.0319 (0.0763)	0.0304 (0.0237)	-0.1515*** (0.0389)	-0.0595 (0.0813)	0.0271 (0.0253)	-0.1747*** (0.0402)	-0.0686 (0.0889)	0.0195 (0.0264)
Under-confident	-0.0494 (0.0369)	0.1632* (0.0799)	0.0644* (0.0256)	-0.0522 (0.0368)	0.1332 (0.0804)	0.0629 (0.0249)*	-0.0544 (0.0363)	0.1382 (0.0755)	0.0530* (0.0252)	-0.0403 (0.0363)	0.1160 (0.0793)	0.0523* (0.0255)
Age	-0.0080 (0.0245)	0.0311 (0.0491)	-0.0277 (0.0164)	-0.0070 (0.0244)	0.0321 (0.0491)	-0.0274 (0.0164)	-0.0085 (0.0245)	0.0305 (0.0491)	-0.0275 (0.0165)	-0.0075 (0.0244)	0.0310 (0.0491)	-0.0279 (0.0164)
$Age^2/100$	0.0187 (0.0162)	0.0023 (0.0328)	0.0258* (0.0106)	0.0180 (0.0162)	0.0016 (0.0328)	0.0257* (0.0106)	0.0190 (0.0162)	0.0026 (0.0328)	0.0257* (0.0107)	0.0185 (0.0162)	0.0025 (0.0328)	0.0260* (0.0106)

Note. The sample includes 4,893 individuals and 16,740 observations. For all specifications, we use double hurdle models. The first-stage dependent variable is whether individuals hold any directly-held stocks. The second-stage dependent variables are 1) natural log of the value of stocks and 2) percentage share of stocks to total financial assets. Control variables include gender, age, age-squared, educational attainment, health status, employment status, marital status, number of living children, number of medical conditions, total number years of work, household income, health insurance ownership, cohort effect, and year-fixed effects. Standard errors are clustered at individual levels. * p<0.05, ** p<0.01, *** p<0.001

Table 8. Ownership, Amount, and Share of Cash-equivalent

Cash-equivalent	Specification I			Specification II			Specification III			Specification IV		
	1st	2nd		1st	2nd		1st	2nd		1st	2nd	
	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)
Over-confident	-0.2060*** (0.0431)	-0.1556** (0.0491)	0.2378*** (0.0466)	-0.1498*** (0.0430)	-0.1030* (0.0453)	0.2323*** (0.0456)	-0.2071*** (0.0445)	-0.1479** (0.0507)	0.2190*** (0.0457)	-0.2003*** (0.0442)	-0.1529** (0.0513)	0.2723*** (0.0476)
Under-confident	-0.0454 (0.0435)	-0.0157 (0.0501)	0.0458 (0.0463)	-0.0676 (0.0431)	-0.0460 (0.0523)	0.0682 (0.0447)	-0.0503 (0.0443)	-0.0576 (0.0477)	0.0204 (0.0467)	-0.0857* (0.0425)	-0.0474 (0.0503)	0.0567 (0.0460)
Age	0.0144 (0.0321)	0.0992** (0.0322)	-0.0116 (0.0319)	0.0163 (0.0321)	0.1007** (0.0322)	-0.0133 (0.0318)	0.0124 (0.0321)	0.0993** (0.0322)	-0.0117 (0.0319)	0.0155 (0.0321)	0.0999** (0.0322)	-0.0124 (0.0318)
$Age^2/100$	0.0012 (0.0210)	-0.0337 (0.0211)	0.0054 (0.0208)	-0.0002 (0.0210)	-0.0349 (0.0211)	0.0065 (0.0208)	0.0023 (0.0210)	-0.0338 (0.0211)	0.0056 (0.0208)	0.0004 (0.0210)	-0.0341 (0.0211)	0.0057 (0.0208)

Note. The sample includes 4,893 individuals and 16,740 observations. For all specifications, we use double hurdle models. The first-stage dependent variable is whether individuals hold any cash-equivalent. The second-stage dependent variables are 1) natural log of the value of cash-equivalent and 2) percentage share of cash-equivalent to total financial assets. Control variables include gender, age, age-squared, educational attainment, health status, employment status, marital status, number of living children, number of medical conditions, total number years of work, household income, health insurance ownership, cohort effect, and year-fixed effects. Standard errors are clustered at individual levels. * p<0.05, ** p<0.01, *** p<0.001

Table 9. Ownership, Amount, and Share of Investments in IRAs

IRAs	Specification I			Specification II			Specification III			Specification IV		
	1st	2nd		1st	2nd		1st	2nd		1st	2nd	
	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)
Over-confident	-0.1719*** (0.0387)	-0.1377* (0.0621)	-0.0159 (0.0225)	-0.1379*** (0.0369)	-0.0957 (0.0554)	-0.0156 (0.0210)	-0.1948*** (0.0391)	-0.1454* (0.0646)	-0.0226 (0.0225)	-0.1654*** (0.0401)	-0.1516* (0.0649)	-0.0114 (0.0228)
Under-confident	-0.0438 (0.0375)	-0.0373 (0.0552)	-0.0134 (0.0205)	-0.0424 (0.0377)	-0.0166 (0.0559)	-0.0009 (0.0201)	-0.0340 (0.0371)	-0.0349 (0.0539)	-0.0117 (0.0198)	-0.0353 (0.0373)	-0.0171 (0.0543)	-0.0019 (0.0201)
Age	0.1224*** (0.0245)	0.2136*** (0.0391)	0.0405* (0.0162)	0.1235*** (0.0244)	0.2154*** (0.0391)	0.0407* (0.0162)	0.1219*** (0.0245)	0.2152*** (0.0391)	0.0407* (0.0162)	0.1229*** (0.0244)	0.2145*** (0.0391)	0.0407* (0.0162)
Age^2/100	-0.1024*** (0.0163)	-0.1619*** (0.0272)	-0.0430*** (0.0114)	-0.1032*** (0.0163)	-0.1632*** (0.0271)	-0.0431*** (0.0114)	-0.1021*** (0.0163)	-0.1631*** (0.0272)	-0.0431*** (0.0114)	-0.1027*** (0.0163)	-0.1624*** (0.0272)	-0.0431*** (0.0114)

Note. The sample includes 4,893 individuals and 16,740 observations. For all specifications, we use double hurdle models. The first-stage dependent variable is whether individuals hold any investment in IRAs. The second-stage dependent variables are 1) natural log of the value of investments in IRAs and 2) percentage share of investments in IRAs to total financial assets. Control variables include gender, age, age-squared, educational attainment, health status, employment status, marital status, number of living children, number of medical conditions, total number years of work, household income, health insurance ownership, cohort effect, and year-fixed effects. Standard errors are clustered at individual levels. * p<0.05, ** p<0.01, *** p<0.001

Table 10. Ownership, Amount, and Share of CDs

CDs	Specification I			Specification II			Specification III			Specification IV		
	1st	2nd		1st	2nd		1st	2nd		1st	2nd	
	DV= ownership	DV= ln(amt)	DV= % share	DV= ownership	DV= ln(amt)	DV= % share	DV= ownership	DV= ln(amt)	DV= % share	DV= ownership	DV= ln(amt)	DV= % share
	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)
Over-confident	-0.1594*** (0.0363)	-0.0524 (0.0791)	0.1533* (0.0599)	-0.1440*** (0.0348)	-0.0730 (0.0755)	0.0981 (0.0600)	-0.1941*** (0.0367)	0.0550 (0.0801)	0.1685** (0.0591)	-0.1586*** (0.0376)	-0.0591 (0.0814)	0.1508* (0.0604)
Under-confident	-0.0169 (0.0350)	0.0315 (0.0755)	-0.0126 (0.0611)	-0.0696* (0.0346)	-0.0357 (0.0750)	-0.0237 (0.0630)	-0.0068 (0.0349)	0.1258 (0.0734)	0.0554 (0.0596)	-0.0332 (0.0345)	0.0429 (0.0757)	-0.0233 (0.0609)
Age	0.0345 (0.0243)	0.2509*** (0.0534)	0.1265** (0.0453)	0.0356 (0.0243)	0.2505*** (0.0534)	0.1254** (0.0455)	0.0333 (0.0243)	0.2528*** (0.0534)	0.1273** (0.0453)	0.0352 (0.0242)	0.2508*** (0.0534)	0.1255** (0.0454)
$Age^2/100$	-0.0059 (0.0162)	-0.1333*** (0.0346)	-0.0660* (0.0279)	-0.0067 (0.0162)	-0.1330*** (0.0346)	-0.0651* (0.0280)	-0.0051 (0.0162)	-0.1349*** (0.0345)	-0.0666* (0.0279)	-0.0063 (0.0161)	-0.1332*** (0.0346)	-0.0655* (0.0279)

Note. The sample includes 4,893 individuals and 16,740 observations. For all specifications, we use double hurdle models. The first-stage dependent variable is whether individuals hold any CDs. The second-stage dependent variables are 1) natural log of the value of CDs and 2) percentage share of CDs to total financial assets. Control variables include gender, age, age-squared, educational attainment, health status, employment status, marital status, number of living children, number of medical conditions, total number years of work, household income, health insurance ownership, cohort effect, and year-fixed effects. Standard errors are clustered at individual levels. * p<0.05, ** p<0.01, *** p<0.001

Table 11. Ownership, Amount, and Share of Bonds

	Specification I			Specification II			Specification III			Specification IV		
	1st	2nd		1st	2nd		1st	2nd		1st	2nd	
Bonds	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)	DV= ownership Coef. (Robust S.E.)	DV= ln(amt) Coef. (Robust S.E.)	DV= % share Coef. (Robust S.E.)
Over-confident	-0.1243* (0.0491)	-0.1593 (0.1281)	-0.0383* (0.0155)	-0.0739 (0.0457)	-0.1537 (0.1239)	-0.0183 (0.0153)	-0.1719*** (0.0515)	-0.2034 (0.1395)	-0.0424** (0.0158)	-0.1375** (0.0510)	-0.2184 (0.1410)	-0.0342* (0.0166)
Under-confident	-0.0082 (0.0500)	-0.0547 (0.1210)	-0.0073 (0.0175)	-0.0508 (0.0485)	0.0022 (0.1168)	0.0024 (0.0169)	0.0066 (0.0476)	-0.0309 (0.1207)	0.0034 (0.0170)	-0.0207 (0.0489)	-0.0913 (0.1202)	-0.0097 (0.0170)
Age	0.0339 (0.0335)	0.2543** (0.0953)	0.0165 (0.0117)	0.0347 (0.0335)	0.2519** (0.0954)	0.0161 (0.0117)	0.0330 (0.0336)	0.2538** (0.0954)	0.0163 (0.0117)	0.0340 (0.0335)	0.2524** (0.0953)	0.0161 (0.0117)
$Age^2/100$	-0.0114 (0.0219)	-0.1456* (0.0618)	-0.0093 (0.0079)	-0.0121 (0.0219)	-0.1443* (0.0619)	-0.0091 (0.0079)	-0.0107 (0.0220)	-0.1450* (0.0619)	-0.0091 (0.0079)	-0.0113 (0.0219)	-0.1438* (0.0618)	-0.0090 (0.0079)

Note. The sample includes 4,893 individuals and 16,740 observations. For all specifications, we use double hurdle models. The first-stage dependent variable is whether individuals hold any bonds. The second-stage dependent variables are 1) natural log of the value of bonds and 2) percentage share of bonds to total financial assets. Control variables include gender, age, age-squared, educational attainment, health status, employment status, marital status, number of living children, number of medical conditions, total number years of work, household income, health insurance ownership, cohort effect, and year-fixed effects. Standard errors are clustered at individual levels. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 12. Ownership, Amount, and Share of Other Financial Assets

Other financial assets	Specification I			Specification II			Specification III			Specification IV		
	1st	2nd		1st	2nd		1st	2nd		1st	2nd	
	DV= ownership	DV=ln	DV=%	DV= ownership	DV=ln	DV=%	DV= ownership	DV=ln	DV=%	DV= ownership	DV=ln	DV=%
	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)
Over-confident	0.0055 (0.0387)	-0.0094 (0.0874)	0.0265 (0.0176)	0.0266 (0.0358)	-0.0684 (0.0830)	0.0212 (0.0160)	0.0716 (0.0392)	0.0677 (0.0865)	0.0453* (0.0181)	0.0048 (0.0397)	-0.0483 (0.0925)	0.0163 (0.0181)
Under-confident	-0.0207 (0.0416)	0.1211 (0.0908)	-0.0110 (0.0186)	-0.0578 (0.0412)	0.0901 (0.0895)	-0.0025 (0.0187)	-0.0245 (0.0411)	0.0994 (0.0871)	-0.0067 (0.0182)	-0.0325 (0.0413)	0.0884 (0.0879)	-0.0067 (0.0184)
Age	0.0251 (0.0257)	0.1813** (0.0650)	0.0055 (0.0124)	0.0249 (0.0257)	0.1807** (0.0649)	0.0052 (0.0124)	0.0261 (0.0257)	0.1813** (0.0649)	0.0050 (0.0124)	0.0250 (0.0257)	0.1811** (0.0650)	0.0051 (0.0125)
$Age^2/100$	-0.0239 (0.0172)	-0.1153* (0.0450)	-0.0064 (0.0084)	-0.0238 (0.0172)	-0.1149* (0.0449)	-0.0062 (0.0084)	-0.0247 (0.0171)	-0.1156* (0.0449)	-0.0061 (0.0084)	-0.0238 (0.0172)	-0.1150* (0.0450)	-0.0061 (0.0085)

Note. The sample includes 4,893 individuals and 16,740 observations. For all specifications, we use double hurdle models. The first-stage dependent variable is whether individuals hold any other financial assets. The second-stage dependent variables are 1) natural log of the value of other financial assets and 2) percentage share of other financial assets to total financial assets. Control variables include gender, age, age-squared, educational attainment, health status, employment status, marital status, number of living children, number of medical conditions, total number years of work, household income, health insurance ownership, cohort effect, and year-fixed effects. Standard errors are clustered at individual levels. * p<0.05, ** p<0.01, *** p<0.001