Are older people aware of their cognitive decline? Misperception and financial decision making*

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Abstract

We investigate whether older people correctly perceive their own cognitive decline, and the potential financial consequences of misperception. First, we provide evidence that older people tend to underestimate their cognitive decline. We then show that those who experience a severe decline, but are unaware of it, are more likely to suffer wealth losses compared to those who are aware or did not experience such decline. These losses largely reflect decreases in financial wealth and are mainly experienced by wealthier people who were previously active on the stock market. Our findings support the view that financial losses among older people unaware of their cognitive decline are the result of bad financial decisions, not of rational disinvestment strategies.

Keywords: Aging; cognitive ability; household finance; HRS.

JEL codes: J14, J24, C23.

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1 Introduction

A key feature of the process of human aging is the decline of cognitive ability, a complex phenomenon whose causes and economic consequences are still not well understood. Our limited understanding of cognitive decline, and of human capital decumulation more generally, is unfortunate because cognitive functioning influences one's ability to process information and to make the right choices. This is becoming even more relevant in the light of the recent trend to scale back publicly-provided safety nets that require relatively little individual decision-making – such as public social security and healthcare systems – and to rely more on private providers that require much higher decision-making skills. For instance, the pension landscape in the U.S. and many other countries has changed dramatically in the last three decades, with a major shift away from defined benefit systems towards defined contribution systems (Poterba et al., 2009). At the same time, the cohorts currently near retirement are expected to live longer and to manage after retirement larger amounts of wealth than previous cohorts. As a result, they will need to make more complex financial decisions, and these decisions will crucially affect their lifetime resources and welfare.

If older people lack the skills required to properly manage their wealth, they are more likely to make mistakes that can end up eroding their retirement security and lowering their own welfare (Mitchell et al., 2021). In the aggregate, this can have broader consequences for the whole economy (Campbell, 2016). Because of the significant amount of assets they hold, older people are also more likely to be victimized by investment fraud (Kim et al., 2018; Egan et al., 2019). These observations motivate a growing body of research in economics on the causes and consequences of financial (il)literacy (Agarwal and Mazumder, 2013) and its relationship with the process of cognitive aging (Agarwal et al., 2009; Korniotis and Kumar, 2011; Finke et al., 2016). They also raise fundamental questions about the best policy response.

While financial education is clearly important for younger cohorts, two largely neglected issues arise for older people facing a risk of cognitive decline that increases with age. The first is whether they are able to recognize their own cognitive decline. The second is how they protect themselves. For example, those who perceive or can predict their own decline may delegate financial decisions to someone they trust, such as their spouse (Hsu and Willis, 2013), another family member, or a financial advisor. On the contrary, those who are unaware of their decline may incur financial losses because of bad investments or financial frauds. The consequences of cognitive decline may be even worse for those with high initial levels of cognitive ability, who tend to manage directly their finances and do not seek advice due to a higher level of confidence (von Gaudecker, 2015; Kim et al., 2018).

In this paper we use data from the Health and Retirement Study (HRS), a representative panel of the U.S. population aged 50+, to explore the relationships between self-ratings of memory changes, assessed changes in memory performance, and changes in reported wealth across waves of the survey. To avoid the issues arising from institutionalization, mortality or proxy interviewing, we restrict the sample to people aged 80 years or less. We define a severe memory loss as a decline of 20% or more between adjacent survey waves in the total score from the HRS word recall tests. Nearly 60% of the people in our sample experience at least one severe memory loss event over their observation period (about 7 years on average), but these cognitive losses tend to occur earlier and to be milder than the extreme cognitive decline typical of Alzheimer's disease and related dementias (AD/ADRD).

We establish three important facts, some of which are new. First, consistent with the evidence from other studies (see, e.g., Gamble et al. 2015), we show that older people are often unaware of their cognitive decline, even when severe. Second, we analyze the financial consequences of this underestimation and show that respondents who experience a severe memory loss and are unaware of it are more likely to suffer large wealth losses (negative wealth changes between adjacent survey waves) relative to respondents who either are aware or do not experience a severe memory loss. Third, we show that wealth losses are mainly reported by unaware respondents in the upper quartile of the wealth distribution, mainly reflect large decreases – equal on average to about 10% of initial financial wealth – in the real value of financial wealth, and are much larger among respondents who were active on the stock market in the previous two years.

To investigate the dynamics around the first severe memory loss event, and to provide a more convincing causal interpretation of our findings, we estimate difference-in-differences (DiD) and event-study models of wealth changes, focusing on the different wealth profiles of aware and unaware respondents. We show that being unaware of own severe memory losses helps predict future wealth losses, but past wealth losses do not help predict severe memory losses in the future or awareness of these events. Moreover, estimated wealth losses for unaware respondents are similar to those estimated in the baseline static model. Reverse causality concerns may still arise if, during the 2-year window between survey waves, wealth shocks negatively affect health and cognition, perhaps via increasing stress (Schwandt, 2018). We address these concerns by constructing an arguably exogenous measure of wealth shocks that only depends on the initial portfolio composition of each household and on exogenous stock market fluctuations. Although our measure strongly predicts wealth changes, it does not significantly affect the probability of experiencing a severe memory loss or the probability of being aware of it. We also find no evidence of depression or stress driven by financial concerns among unaware respondents.

Our findings suggest that unawareness of own cognitive decline may cause wealth losses. Since wealth losses among the unaware mainly reflect a decrease in the value of riskier financial assets, they might result from bad financial investments. Indeed, we find no such decrease among respondents who are aware of their declining memory, or are unaware and either are inactive on the stock market or are unlikely to make financial decisions in the household. We also find that wealthier unaware respondents tend to display better memory performance before a severe memory loss. Thus, bad financial investments may reflect "overconfidence", that is, the case when individuals overestimate their performance in tasks requiring ability. As argued by Barber and Odean (2001), overconfident investors incur larger return losses because they trade too much, hold unrealistic expectations about their investments and the accuracy of their estimates, and invest too much on information acquisition. The fact that the unaware also present a nonnegligible drop in the value of liquid assets, and assets such as jewelry, collections, etc., suggests that money and other assets may also be given away, possibly because of financial frauds or scams. The two interpretations – bad financial investments and financial frauds or scams – are not mutually exclusive and are indistinguishable in our data because we only observe the results of financial decisions, not how they were made.

To explore other interpretations of our findings, we ask whether differences in health or other personal characteristics might provide an explanation. For example, if unaware respondents have lower subjective life expectancy, they might optimally decide to disinvest more, which would explain their different wealth profiles. In fact, we find that they are on average in better physical health than aware respondents and do not report lower self-assessed life expectancy. For them, the standard life-cycle model would predict smaller disinvestment, which is just the opposite of what we observe. Further, we find no differences between aware and unaware respondents in financial transfers to children or, using additional data from the HRS Consumption and Activities Mail Survey (HRS CAMS), in consumption expenditure patterns. Finally, we cannot explain our findings with differences between aware and unaware respondents in portfolio composition or differential misreporting of wealth.

Our paper speaks to a growing literature that investigates the determinants of the large wealth dispersion observed in the U.S. and other developed economies (see Campbell, 2016 for a review), especially around the age of retirement. While earlier works attempt to explain the large cross-sectional wealth inequality through heterogeneity in saving rates (Dynan et al., 2004) or risk aversion (Calvet et al., 2009), recently attention has been devoted to cross-sectional heterogeneity in the rates of returns (Fagereng et al., 2016), possibly arising from differences in financial knowledge (Lusardi et al., 2017). We contribute to this line of research by proposing yet another channel that may affect the longitudinal variation in wealth, namely differences in cognitive deterioration and awareness of own decline. While the existing literature provides clear evidence of a U-shaped age-profile of financial mistakes (Agarwal et al., 2009; Korniotis and Kumar, 2011), to the best of our knowledge we are the first to use nationally-representative longitudinal data to explore the link between age-related cognitive decline, awareness of this decline, and financial performance. Our findings suggest the importance of interventions aimed at detecting deterioration of financial decision-making skills among older wealth owners and encouraging pre-commitment to financial delegation in case of failure of some financial “driving licence” test.

The remainder of this paper is organized as follows. Section 2 reviews the literature on cognitive aging and decision making. Section 3 introduces our data and presents some descriptive statistics. Section 4 outlines our modeling strategy. Section 5 presents our empirical results and discusses some alternative explanations. Section 6 concludes. Finally, Appendix A provides more detail on key features of the HRS and includes summary information on financial returns during the period considered, while Appendix B contains additional tables and figures.

2 Cognitive aging and decision making

Cognitive ability is the ability to perform the mental processes required in a variety of tasks. It is generally regarded as a multidimensional latent trait, only imperfectly measured by different types of tests.

As people get older, their cognitive ability tends to deteriorate, albeit with large differences across individuals in both the nature and the sources of cognitive decline (see for example Schaie, 1996). The nature of the decline ranges from normal aging – in which a person may occasionally forget names and words, or misplace things – to mild cognitive impairment (MCI) – in which a person experiences noticeable declines in mental abilities that are not severe enough to interfere with normal daily life – to drops in cognitive function, due to neurological pathologies such as AD/ADRD, that are severe enough to interfere with daily living. For most cases, MCI is just a stage in the continuum between the mental decline seen in normal aging and overt dementia (Scheltens et al., 2021). A person with dementia is no longer fully independent, and this is the primary feature differentiating dementia from MCI. As for the sources of cognitive decline, these include emotional shocks, such as the loss of an immediate kin or a close friend; brain or other physical injuries from accidents; exposure to pollution, pesticides or toxins; and treatable conditions, such as thyroid, kidney or liver problems, sleep disorders, infections, diseases/conditions that affect blood flow in the brain, etc.

The psychological literature usually draws a distinction between two different forms of intelligence, fluid and crystallized (Horn and Cattell, 1967). Fluid intelligence comprises fundamental skills, such as memory, executive functioning, abstract reasoning and processing speed, which are more closely related to biological factors. It is generally related to the performance on new tasks and is characterized by a steady decline over one’s adult life starting already from the age of 20. Crystallized intelligence, which consists of the knowledge and experience acquired during the life, shows instead little age-related decline and partially compensates the large decline in fluid intelligence. Most day-to-day tasks rely on a different mix of these two forms of intelligence. Therefore, as people age, their ability to perform a specific task may decline at different rates (or even improve) depending on the tasks considered. For most tasks, the expected age-profile of cognitive function is assumed to be hump shaped, with a peak reached around 50 years of age (for a recent review, see Mazzonna and Peracchi, 2018).

A rich literature, mainly in psychology, investigates how age-related cognitive decline affects individuals' decision-making (see Carpenter and Yoon, 2011 for a review) and shows that older adults are more likely to use biased heuristic strategies because aging increases the cost of engaging in exacting cognitive activities (Hess, 2014). Older adults may in fact choose to limit both the quantity and complexity of the information they use. As in the macroeconomic literature on rational inattention (see, e.g., Sims, 2003), this may be perfectly rational given their increasingly limited capacity for information processing (Kim et al., 2016). Consistent with this view, Abaluck and Gruber (2011) find that elderly patients under Medicare Part D tend to focus on a narrow range of characteristics of the choice set, which is inconsistent with a fully informed rational decision process with no limit on information-processing capacity. Financial decision making also relies on both types of intelligence, but while most basic financial tasks require mainly crystallized intelligence, good financial decisions strongly rely on fluid intelligence (Marson et al., 2009).

Given the fundamental role of preferences in financial decision making, economists have recently focused their attention on the relationship between cognition and risk aversion (see Dohmen et al., 2018 for a review) and the effects of aging on this relationship. For instance, Bonsang and Dohmen (2015) find that the positive association between aging and risk aversion is mediated by numerical ability. Recent experimental evidence in psychology (e.g., Koscielniak et al., 2016) also confirms the positive correlation between aging and risk aversion and the mediating effect of the age-related decline in processing speed and memory. More generally, Christelis et al. (2010) show that cognitive ability is strongly related to portfolio choices. They find that the propensity to invest in stocks is strongly associated with cognitive ability. Further, this relationship persists after controlling for differences in health conditions, which are also related to the likelihood of investing in risky assets (Rosen and Wu, 2004). On the other hand, Hersch Nicholas et al. (2021) find that AD/ADRD are associated with bad financial outcomes not only after clinical diagnosis, but also well before.

Lusardi et al. (2017) present a life-cycle model that provides a conceptual framework for understanding the effect of awareness of cognitive decline on financial decision making. In the simplest version of their model, consumers maximize life-time utility – defined over consumption in two periods, with no bequest – by deciding how to allocate income between initial consumption, savings, and cognitive investment aimed at raising the return on savings. This cognitive investment consists of time, effort, and costly information, and requires both computational and memory skills to produce its effects. The key assumption in their model is that consumption in the second period is equal to the product of savings and the return on savings, which in turn is an increasing function of the level of cognitive investment. This allows one to distinguish between passive investors who make no cognitive investment and are happy with the basic return on their savings, and active investors who make a positive but costly cognitive investment seeking to raise their returns. Their model implies that below some income threshold it is optimal to be a passive investor, while above it the optimal levels of savings and cognitive investment both increase with income. In their setting, cognitive decline may be modeled as an exogenous random shock that hits a consumer before she chooses the amount of savings and cognitive investment, and turns the productivity of cognitive investment from positive to negative. If the consumer is aware of own cognitive decline, her best choice is to make no cognitive investment and just earn the basic return. If she is unaware, she makes positive investments and obtains lower returns than a passive investor – unless she makes no cognitive investment because her income is too low anyway.

3 Data

This section describes our data, in particular our measures of memory and wealth, and presents some descriptive statistics. More detail on the data is provided in Appendix A.

3.1 The HRS

The HRS is a household panel survey that collects rich and detailed information on nationally representative samples of the U.S. population aged 50+. The survey was fielded annually from 1992 to 1996, and has been fielded biennially in even-numbered years since its redesign in 1998. We use the RAND HRS Longitudinal File, a cleaned, easy-to-use, and streamlined version of the data from the original HRS core and exit interviews, with derived variables covering a large range of measures and RAND imputations of missing values. This file has been employed extensively in the economic literature because of consistency and comparability across waves. Some relevant variables which are not included in the RAND HRS Longitudinal File have been directly taken from HRS core modules. We confine attention to the nine survey waves from 1998 to 2014. See Appendix A.1 for more details.

Our main working sample includes all self-respondents aged 50–80 years with non-missing information on our variables of interest – self-rated memory changes, assessed memory performance, and household wealth – and our key covariates (age, sex, race, education, labor force status, marital status, household size and composition, and region of residence). We only keep self-respondents and drop proxy interviews because the latter do not contain direct assessments of memory performance. We further drop people older than 80 years to limit potential selection issues arising from institutionalization and mortality. Since wealth is measured at the household level, for each household we only consider the financial respondent, namely the member designated to answer all household-level financial questions. Smith et al. (2010) argue that the financial respondent is the most knowledgeable person about the financial assets of the household and the chief financial decision maker. The sample is subject to further restrictions when we estimate a DiD model around the first severe memory loss event (Section 4.2).

The robustness checks in Section 5.4 also employ data from the HRS Consumption and Activities Mail Survey (HRS CAMS), a paper-and-pencil survey fielded biennially in odd-numbered years from 2001 (see Appendix A.2 for more details).

3.2 Self-rated and assessed memory

The HRS asks respondents to self-rate their memory at the time of the interview and the changes in their memory relative to the previous interview. It also assesses memory performance directly using two word recall tests. These tests measure the episodic memory domain, which is one of the most important dimensions of fluid intelligence (McArdle et al., 2007). The order of the tasks remains the same across waves: first respondents self-rate their memory and memory changes, then they take the word recall tests. This eliminates the risk that self-ratings are biased by test outcomes.

HRS respondents are first asked "How would you rate your memory at the present time? Would you say it is excellent, very good, good, fair, or poor?" (with answers recorded in the RAND HRS variable `RwSLFMEM`, where `w` indexes the HRS wave). A key feature of the HRS is that respondents are also asked to compare their current memory level to that in the previous interview (about two years earlier): "Compared with previous wave interview, would you say your memory is better now, about the same, or worse now than it was then?" (with answers recorded in the RAND HRS variable `RwPSTMEM`). The availability in the HRS of self-ratings of memory changes is important because it completely removes the problems that would instead arise if forced to work with differences across waves in self-ratings of memory levels.

The word recall tests in the HRS are designed as follows. The interviewer reads a list of 10 words (e.g., lake, car, army, etc.) and then asks the respondent to recall as many words as possible from the list in any order. The respondents hear the list only once and are asked to recall the words two times, immediately after the encoding phase (immediate word recall test) and after a few minutes (delayed word recall test). Our memory score is the sum of the correct answers in the two tests (recorded in the RAND HRS variables `RwIMRC` and `RwDLRC`), hence it is an integer-valued variable ranging between 0 and 20, and its difference across waves is also integer-valued. Figure 1 shows the estimated density of the memory score, in both levels and differences.[1] The mean of the memory score is equal to 10.16, while the mean difference in the memory score between adjacent waves is only slightly negative (-.27), as many respondents actually improve their score from one wave to the next.[2]

[1] Since 1998 is our first HRS wave, information on differences in memory score is only available from 2000.

[2] This partly reflects retesting effects (Salthouse et al., 2004) arising because repeated exposure to the same test format may induce some learning even when respondents are presented with a different list of words in each wave. If attrition across waves is correlated with cognitive functioning, sample selection may also contribute to the observed distribution of the difference in the memory score.

Of particular importance for our purposes is the relationship between self-rated and assessed memory changes. To make it easier to compare the two measures, we distinguish between respondents who experience a severe memory loss across waves and those who do not. Following the neuropsychological literature (see, e.g., Nasreddine et al., 2005), a memory loss may be regarded as severe if it exceeds one standard deviation, corresponding in our case to a loss of three or more words. Such absolute definition may understate cognitive decline among respondents with a low memory score in the previous wave (floor effect). Thus, we henceforth focus on a relative definition and regard a memory loss as severe if it corresponds to a decline of the memory score by 20% or more.[3] This corresponds to the lowest quartile of the distribution of the difference in the memory score across waves and to an average decline of almost four words, starting from a mean of 11.7 words in the previous wave. More than 60% of the individuals in our sample experience at least one severe memory loss event during the observation window. However, since we exclude proxy responses and people older than 80, these events are generally much milder than those associated with AD/ADRD investigated in Hsu and Willis (2013). In fact, our definition captures cognitive decline that occurs at a relatively early age (at age 67 on average), with the first severe memory loss occurring even earlier (at age 64 on average). Table B.1 in the appendix shows the distribution of respondents by the number of severe memory loss events they experience. About 40% of the sample experiences no severe memory loss event, another 40% experiences only one, about 15% experiences exactly 2, and less than 5% experiences 3 or more. Of course, our indicator of severe memory loss is only a crude proxy for cognitive decline but it has the major advantage of being comparable with the self-rated measure of memory change.

Table 1 cross-tabulates self-rated memory changes against our binary indicator of severe memory loss, considering both the relative and the absolute definition. A large fraction of respondents with a severe memory loss (77% of those with a relative decline of 20% or more and 80.5% of those with an absolute decline of one standard deviation or more) rate their memory as "about the same" or "better now". On the other hand, nearly 20% of those who do not experience a severe memory loss rate their memory as "worse now". Since the fraction of respondents rating their memory as "better now" is only 2.6%, little is lost by replacing the original RAND HRS variable `RwPSTMEM` with a binary indicator for worse self-rated memory. Interacting this indicator with that for a severe memory loss results in four possible change-in-memory states which we label as follows: "no loss" (no severe memory loss and stable or improved self-rated memory), "pessimist" (no severe memory loss but worse self-rated memory), "aware" (severe memory loss and worse self-rated memory), and "unaware" (severe memory loss but stable or improved self-rated memory). Table B.2 in the appendix presents the transition

[3] As argued by Dohmen et al. (2018), word recall tests only capture memory performance if other factors that might affect test performance are held constant. For example, distractions on the day of the test or personality traits that determine task motivation could play an important role. This is even more important when changes in memory scores are considered.

rates between these four states from one survey wave to the next. Among those without a severe memory loss over the past two years (the no loss and the pessimists), about 28% experience a severe memory loss over the next two-year window. This chance falls to about 8.6% for those with a severe memory loss over the past two years (9.5% and 7.8% for the aware and the unaware respectively). Thus, another severe memory loss event after experiencing one is not very likely, which justifies our focus in Section 4.2 on the first such event.

The HRS contains additional tasks aimed at assessing cognitive dimensions other than memory, such as basic skills of reasoning, orientation, calculation, language, and knowledge. Figure B.1 in the appendix shows that our indicator of severe memory loss is a strong predictor of decline in all these measures. We restrict attention to the recall test because the other measures either show little variability, or are only asked in a few waves, or are only asked to people aged 65+. Smith et al. (2010) document a strong and independent association between the recall and numeracy tests, wealth and portfolio holdings using HRS data. Weak or no association was instead found for the other cognitive tests in HRS. While most of these other measures are designed to capture severe cognitive impairment and dementia, our indicator mainly captures early episodes of cognitive decline (Figure 3), often among people with high initial cognitive capital. Further, even when we can construct measures of change based on some of the other available measures, we do not have a self-assessed counterpart, which makes it impossible to explore the role of awareness.

3.3 Household wealth

The HRS collects detailed information on household wealth and on the value of individual wealth components (financial wealth, individual retirement accounts, housing wealth, other real estate, business wealth, and transport wealth). These values are all self-reported by the designated financial respondent. We are primarily interested in the net value of total household wealth (or "total wealth" for short)[4] and total household financial wealth (or "financial wealth" for short),[5] and their changes over time during the period considered.[6]

The self-reported nature of wealth information is of course problematic, especially when used to compute wealth changes across waves, as we do. Note, however, that the HRS interview includes an asset verification procedure, in which respondents are asked to verify or correct the asset values

[4] Total household wealth is computed as the value of all assets owned by the household minus the value of all liabilities and is converted to 2014 U.S. dollars using the consumer price index (CPI) as deflator. See Appendix A for more details.

[5] Total household financial wealth is computed as the value of all financial assets owned by the household (stocks, mutual funds, and investment trusts; checking, savings, and money market accounts; CDs, government savings bonds, and Treasury bills; bonds and bond funds; other savings and assets) minus the value of all debt components, except mortgages and home loans. Individual retirement accounts (IRAs) are considered separately and are not included. See Appendix A for more details.

[6] Since 1998 is our first HRS wave, information on wealth changes is only available from 2000.

reported in the previous and the current waves when there is a large discrepancy between them (more than \$50 thousands for single assets or \$150 thousands for total net worth). Using data from an experiment included in the 2001 HRS, Hill (2006) shows that incorporating the corrections from the asset verification procedure leads to a drop in the variance of the change in total wealth across waves by about 50%.

Missing or incomplete information on some wealth components (e.g., bracketed amounts in an unfolding bracket sequence) represents another problem. The RAND HRS file provides imputed values for these cases. To limit the impact of the imputation procedures on our results, we drop observations for which 20% or more of the value of all asset and debt categories is imputed. To limit the impact of outliers, we also trim all observations with total wealth below the 1st or above the 99th percentile. Our final working sample consists of 16,270 financial respondents (7,252 males and 9,018 females), observed on average for 3.5 waves and representing 88% of all financial respondents aged 50–80 in the original HRS sample. As expected, the wealth distribution is heavily skewed to the right and, in the case of financial wealth, a large fraction of respondents (about 25%) reports zero or negative values.

For each HRS respondent, we combine the HRS information on the composition of financial wealth by asset category in each wave with monthly information on average market returns by asset category (see Appendix A.3 and Figure A.1) to predict financial wealth in the following wave. Specifically, consider respondent i who is interviewed in month t and re-interviewed m months later. Given the respondent's wealth W_{ijt} in asset category j in month t, we predict her wealth in that category at the time of the next interview as

$$W^*_{ij,t+m} = W_{ijt} \prod_{s=t+1}^{m} (1 + r_{js}),$$

where r_{js} is the average market return on asset category j between month $s-1$ and month s. The difference between $W^*_{ij,t+m}$ and $W_{ij,t+m}$ reflects both changes in asset holdings and deviations of actual returns for respondent i from market returns. The predicted value of financial wealth at the time of the next interview is then computed by summing the predicted wealth in all asset categories.

3.4 Descriptive statistics

This section presents simple descriptive statistics for our sample. All statistics are computed using the HRS household-level weights, which adjust for differences in the composition of the sample and the population in terms of age, marital status, race, and birth cohort. Since our working sample consists of the financial respondents, one for each household, household- and individual-level weights coincide.

Figure 2 compares the age-profiles of three memory indices: the average assessed memory score, the average of self-ratings of own memory, and the share of respondents who self-rate their memory as "excellent", "very good" or "good" ("good self-rated memory"). We standardize each index using its mean and standard deviation over the entire period 1998–2014 and compute age-specific averages of the standardized index using the HRS respondent-level weights. We then smooth each profile using a 3-year moving average. Interestingly, the profile of the memory score is much steeper than the profile of the two self-rated indices. This result is not due to cohort effects and also holds if we take time-invariant individual-specific effects into account.

Figure 3 shows the distribution of the age when the first severe memory loss occurs, separately for aware and unaware respondents. The two distributions have a mean slightly below 65 years and are bimodal, with the larger peak around age 58 and a smaller peak around age 75. Interestingly, the larger peak is higher and occurs one year earlier for the unaware, while the smaller peak occurs at the same age for both groups but is higher for the aware. Figure B.2 in the appendix compares the distribution of the memory score in the previous wave for those with a severe memory loss (aware and unaware) and those without, and shows that the distribution for the former is a right-shifted version of that for the latter. The shift to the right is bigger for the unaware, though differences with respect to the aware are relatively small.

Table 2 examines whether we can predict a severe memory loss event and unawareness of it. The table shows the estimated marginal effects from probit models for the probability of experiencing a severe relative memory loss (Columns 1–3) and for the probability of being unaware conditional on a severe memory loss (Columns 4–6). For both outcomes, we initially control only for basic socio-demographic characteristics (age, sex, education, labor force status, marital status, and presence of own children), the loss of the partner, plus wealth quartiles and the memory score in the previous wave (Columns 1 and 4). We then add controls for self-rated health in the previous wave, the number of limitations in the activities of daily living (ADL) also in the previous wave, and the number of serious health conditions (cancer, heart problems, stroke, or diabetes) the respondent ever had (Columns 2 and 5). Finally, we also include the last available numeracy score (Columns 3 and 6). Age is positively associated with the probability of a severe memory loss but negatively associated with the probability of being unaware of it, though the latter association is weaker. As expected, education, wealth and health are all negatively associated with the probability of a severe memory loss. However, most of these "protective" factors are only weakly associated with the probability of being unaware, or even increase that probability. In particular, respondents with a higher memory score or in better health conditions (as measured by self-reported health, ADL, or the number of serious health condition) in the previous wave are more likely to be unaware of their memory decline. In other words, the unaware appear to have better initial health and memory, and this may explain why they remain confident about their skills. It is worth noting that the loss of the partner or the presence of own children do not appear to affect the probability of a severe memory loss, though the presence of own children is negatively associated with the probability of being unaware. Females have lower probabilities of a severe memory loss and of being unaware of it, a result in line with the overconfidence literature (Barber and Odean, 2001). Finally, numeracy is negatively associated with the probability of experiencing a severe memory loss but does not help predict awareness.

4 Empirical modeling

The regression models in this section are meant to capture the association between wealth changes and severe memory declines, and the role played by one's awareness. We present two models: a basic model for expected wealth changes across adjacent survey waves as a function of our four change-in-memory states (Section 4.1) and a difference-in-differences (DiD) model that compares expected wealth changes before and after the first severe memory loss event for aware and unaware respondents to expected wealth changes for those who never experience a severe memory loss (Section 4.2).

4.1 The basic model

Our basic model for individual wealth changes is the following first-difference model:

$$\Delta W_{it} = \beta_0 + \beta_1 Aware_{it} + \beta_2 Unaware_{it} + \beta_3 Pessimist_{it} + \boldsymbol{\beta}_4^\top \boldsymbol{X}_i + \boldsymbol{\beta}_5^\top \boldsymbol{Z}_{it} + \psi_t + U_{it}, \tag{1}$$

where $\Delta W_{it} = W_{it} - W_{i,t-1}$ is the change in real wealth (total, financial, or subcomponents, in thousands U.S. dollars at 2014 prices) of individual i from wave $t-1$ to wave t of the survey,[7] $Aware_{it}$, $Unaware_{it}$ and $Pessimist_{it}$ are binary indicators for being aware, unaware or pessimist in wave t (as defined in Section 3.2), $\boldsymbol{X}_i$ is a vector of time-invariant regressors that includes binary indicators for sex, race, years of education, $\boldsymbol{Z}_{it}$ is a vector of time-varying regressors that includes a quadratic age term, lagged wealth and memory score, and a set of binary indicators for labor force status, marital status, and geographical region (census division), ψ_t is a survey-wave effect common across individuals, U_{it} is an unobservable error term assumed to be mean independent of all included regressors, and $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2, \beta_3, \boldsymbol{\beta}_4, \boldsymbol{\beta}_5)$ is a vector of parameters to be estimated. The intercept β_0 may be interpreted as the expected wealth change for an individual in the baseline state ("no loss"). We include lagged wealth and memory score because wealthier respondents may be expected to show larger wealth changes, be less likely to experience a severe memory loss, and more likely to be unaware of it.

Model (1) may be interpreted as the first-difference transformation of a model for expected wealth levels that includes time-invariant unobservable individual-specific effects. This has two important

[7] We model differences in wealth rather than differences in the logarithm of wealth because of the nonnegligible fraction of observations (about 14%) with zero or negative wealth. Section 5.4 shows that results do not change much when we instead use differences in logs for respondents with positive wealth levels.

implications. First, the contrast $\beta_2 - \beta_1$ measures the difference in expected wealth changes after a severe memory loss event between two individuals with the same values of $\boldsymbol{X}_i$ and $\boldsymbol{Z}_{it}$ – one unaware of own memory loss and the other aware. Whether $\beta_2 - \beta_1$ may also be given a causal interpretation depends on whether one is willing to regard $Aware_{it}$ and $Unaware_{it}$ "as if" randomly assigned after conditioning on $\boldsymbol{X}_i$, $\boldsymbol{Z}_{it}$, and ψ_t. Second, since wealth is self-reported, wealth changes across waves may be subject to a substantial amount of measurement error, which is likely to significantly increase the variability of the error term in (1) relative to a model for wealth levels. When we consider separate wealth components, these self-reports may also be subject to classification error.

As a robustness check, in Section 5.4 we consider two other model specifications. One replaces the binary indicator for severe memory loss with linear and nonlinear terms in the memory score difference across waves. The other adds to model (1) a set of time-invariant individual-specific effects to account for unobserved heterogeneity in wealth changes, not only in wealth levels.

4.2 The DiD model

To investigate the differential profiles of wealth changes for aware and unaware respondents, and possibly provide a more convincing causal interpretation of our findings, we also estimate a DiD model that compares the differences in expected wealth changes before and after the first severe memory loss event for three "treatment groups": the aware, the unaware, and those who never experience a severe memory loss during their observation period (the "never treated").[8] The "pre" and "post" periods are individual-specific and, in order to have a direct mapping with model (1), the "never treated" are only included in the "pre" period.

Specifically, we estimate the following model:

$$\Delta W_{it} = \gamma_0 + \gamma_1 Aware_i + \gamma_2 Unaware_i + \gamma_3 Post_{it} + \gamma_4 Post_{it} \times Unaware_i + \boldsymbol{\gamma}_5^\top \boldsymbol{X}_i + \boldsymbol{\gamma}_6^\top \boldsymbol{Z}_{it} + \psi_t + V_{it}, \quad (2)$$

where ΔW_{it} is again the change in real wealth, $Aware_i$ ($Unaware_i$) is now a binary indicator equal to one if individual i has at least one severe memory loss during her observation period and is aware (unaware) of the first such event, $Post_{it}$ is a binary indicator equal to one if wave t follows the first severe memory loss event for individual i, all other regressors are as in equation (1), V_{it} is an unobservable error term assumed to be mean independent of all included regressors, and $\boldsymbol{\gamma} = (\gamma_0, \gamma_1, \gamma_2, \gamma_3, \gamma_4, \boldsymbol{\gamma}_5, \boldsymbol{\gamma}_6)$ is a vector of parameters to be estimated. The coefficient of primary interest is γ_4 (the "DiD coefficient"), which measures the expected wealth change after the first severe memory loss event for two individual with the same values of $\boldsymbol{X}_i$ and $\boldsymbol{Z}_{it}$ – one unaware of own memory loss and the other aware. Model (2) becomes the conventional DiD model when we drop the "never treated" from the sample and exclude from the model the binary indicator for being aware.

[8] We no longer distinguish between "no loss" and "pessimists" because, as shown in Section 5.1, the two categories are indistinguishable from each other.

We further extend our analysis to an event-study (or multi-period DiD) model that interacts the unawareness indicator with indicators for each "event time", defined as the difference between a given survey year and the survey year in which we observe the first memory loss event. Notice that, in our data, respondents are followed on average for only 3.5 waves (about 7 years), so not many of them are observed for a long enough interval around their first memory loss event (event time 0). Figure B.3 in the appendix shows that the sample size shrinks fast when moving further away from the first memory loss event, especially backwards. This problem affects both the aware and the unaware, but is exacerbated for the aware because of their already small number at event time 0. To avoid potential bias due to sample selection, and to maintain precision and the ability to estimate a pre-trend, we choose a time window of 5 waves (from -4 to 4 years) around the first memory loss event. This results in an unbalanced sample of 14,872 respondents observed on average for 2.7 waves, which is further reduced to 10,498 respondents observed on average for 2.8 waves when we ignore the "never treated". Because of the small sample size and the consequent loss in precision, we estimate model (2) and its extensions only for changes in total and financial wealth.

5 Results

In Section 5.1 we examine the relationship between changes in total wealth and the occurrence of a severe memory loss event using various versions of the first-difference model (1) and the multi-period DiD model (2). We then discuss alternative interpretations of our empirical findings (Sections 5.2 and 5.3) and present a number of robustness checks (Section 5.4).

5.1 Memory loss awareness and wealth changes

Table 3 presents the results from the first-difference model (1). Column (1) is for a restricted version of the model that only includes the binary indicator for experiencing a severe memory loss. The negative coefficient on this indicator is statistically significant at the 1% level and quantitatively large – corresponding to the expected loss of 6.7% of mean wealth over a 2-year period. Column (2) is for the full version of model (1). It shows that wealth losses are on average much larger for respondents who are unaware of their memory decline. The estimate of the contrast $\beta_2 - \beta_1$ is statistically significant at the 5% level and quantitatively large, corresponding to the expected loss of 6.8% of mean wealth over a 2-year period. The coefficient on pessimist respondents is small and statistically indistinguishable from zero. Thus, to save space, we henceforth stop reporting it.

The last two columns of Table 3 focus on those who experience a severe memory loss and compare financial respondents (Column 3) with non-financial respondents (Column 4). They show that wealth losses for the unaware are statistically different from zero and quantitatively large (over $20 thousands) only for financial respondents, which indicates that unawareness of own cognitive decline has more serious consequences when affecting those who actually make financial decisions in a household.

Table 4 presents the results for the DiD model (2), for total and financial wealth separately and two samples, one including all financial respondents and one including only those with a severe memory loss. Starting with total wealth (Columns 1 and 2), the estimated DiD coefficient (Unaware×Post) is large and statistically significant. Point estimates are similar in the two samples and amount to more than \$50 thousand. Although not directly comparable, the size of the drop is much larger than the estimated effect from model (1) (the difference $\beta_2 - \beta_1$ in Table 3), but standard errors are also very large. This mainly reflects the relatively small number of aware respondents, whose estimated wealth change in the post period (the coefficient on "Post") is both very large and very noisy. On the contrary, the estimated wealth change in the post period for the unaware respondents (the sum of the coefficient on Post and the DiD coefficient) is more precisely estimated and is about the same as the estimate of β_2 in Table 3. Qualitatively, the results for financial wealth are similar but smaller in absolute terms (though larger relative to the mean value of financial wealth).

Figure 4 presents the results of the event-study model. The figure shows the estimated dynamics of wealth changes (total or financial) for the unaware (left panels) and for the unaware relative to the aware (right panels). To visually inspect the profile of the estimated effects over event time, we use as reference the survey year immediately before the first severe memory loss event. Further, as standard in the literature, we place the control group at event time -1. If we focus on the unaware, the estimated wealth loss is concentrated in the period immediately after the first memory loss event, its size (about -\$23 thousand) is comparable to the estimates in Table 3, and there is no evidence of anticipation effect. When we compare the unaware to the aware, the estimated wealth loss is larger and continues after the first severe memory loss event. We do not want to draw strong conclusions from this last finding, as estimates are very noisy partly because of the reduced sample size as we move away from the memory loss event. Due to the loss of precision when estimating the DiD model, we henceforth focus on extensions of our basic specification (1).

Table 5 presents the results of fitting the model separately by quartile of the distribution of wealth in the previous wave to account for heterogeneous effects at different points in the wealth distribution. The table shows that the wealth losses observed for the unaware are concentrated among those in the top half (third and fourth quartiles) of the wealth distribution. Furthermore, the mean difference $\beta_2 - \beta_1$ between the aware and the unaware is statistically significant and economically meaningful (roughly 9% of mean wealth) only for wealthier respondents. Table B.3 in the appendix shows that wealth losses mainly involve respondents who are still employed or below age 70, and therefore likely to be still saving for retirement. Table B.4 in the appendix shows that average wealth losses of the unaware relative to the aware are much bigger for males than for females. These estimated gender differences are consistent with Barber and Odean (2001), who find that overconfidence is prevalent among men, and reflect the larger fraction of female financial respondents at the bottom of the wealth distribution, and of male financial respondent at the top, along with the higher probability of being unaware among males (Table 2). Finally, Figure B.4 in the appendix shows little evidence of time heterogeneity except for year 2010, the survey year immediately after the Global Financial Crisis, when the predicted wealth loss for the aware is much higher than for the unaware.

5.2 Potential mechanisms

In the previous section we provided evidence of a strong association between memory losses (self-rated or assessed) and wealth losses. To explore potential mechanisms behind the observed relationship, Table 6 compares the results obtained by fitting model (1) to total wealth changes (Column 1, just the same as Column 2 in Table 3) to those obtained by fitting the model separately to changes in the net value of six broad wealth categories (Columns 2–7), namely financial wealth, individual retirement accounts (IRAs),[9] housing wealth, other real estate, business/farm, and transport wealth. The table shows that the wealth losses among unaware respondents are mainly due to a decrease in the value of their financial wealth and, to a lesser extent, of their IRAs. Changes in the net value of the other wealth categories are much smaller or not statistically significant. The estimated financial wealth loss accounts for about 64% of the total wealth loss reported in Column (1) of the table. If we also include IRAs, we account for about 82%. It is worth noting, however, that the mean difference between aware and unaware respondents, measured by $\beta_2 - \beta_1$, is statistically different from zero and large in economic sense (more than \$15 thousands) only for financial wealth.

Table 7 presents the results of fitting model (1) to financial wealth changes separately for people with and without positive financial wealth in the previous wave (Columns 1 and 2 respectively), and for respondents in the third and fourth quartiles of the distribution of financial wealth (Columns 3 and 4). The table shows that our previous findings are largely due to respondents with positive financial wealth in the previous wave, in particular those in the top quartile of financial wealth. More specifically, people in the fourth quartile who are unaware of their memory decline suffer substantial losses across waves, the magnitude of which corresponds to about 9% of their mean financial wealth.

Since financial losses for the unaware are observed only among those with positive financial wealth in the previous wave, Table 8 focuses on this group. Column (1) shows that about 55% of the mean loss in financial wealth for the unaware respondents (which, from Column 2 of Table 7, is equal to about 25 thousand U.S. dollars at 2014 prices) reflects a decrease in the net value of stocks, mutual funds, and investment trusts. The remaining 45% reflects a decrease in the net value of CDs, checking and savings accounts, and other assets or savings (Columns 2, 3 and 5). We instead observe hardly any changes in the value of private bonds and bond funds (Column 4) and in the value of financial

[9] We use the RAND HRS definition of financial wealth which excludes IRAs.

debt different from mortgages and home loans (Column 6).

These results reveal that wealth losses are concentrated among financial respondents who are wealthier but unaware of their cognitive decline, and the losses mainly involve financial assets. We have already seen that respondents who experience a severe memory loss show better cognitive performance at the baseline (Table 2) and are therefore likely to be more confident about their ability. Hence, one possible interpretation of our results is that they made bad financial investments because unaware of their falling cognitive performance. This "bad investment" interpretation is supported by our investigation of the information from Section R (Asset Change) of the HRS. This module asks financial respondents who report owning (or having previously owned) stocks or shares in mutual funds about their stock market activity in the last two years (namely whether they sold or bought stocks or mutual funds shares including automatic reinvestments).[10] Table 9 shows that negative changes in financial wealth are mainly observed among unaware respondents who report that they have been active on the stock market in the last two years (Column 1).[11] Losses are also observed among unaware respondents who were inactive (Columns 2) or did not own stocks (Columns 3) but these losses are much smaller, in both absolute and relative terms, than for unaware respondents who were active. Moreover, the difference between aware and unaware is large and statically significant only for those active in the stock market.

The HRS data do not allow us to distinguish between wealth losses due to bad financial investments and those due to financial frauds or scams. We only observe the results of financial decisions, not how these decisions are made. However, the nonnegligible losses in the value of CDs, checking/savings, and other assets (jewelry, collections, etc.), reported in Table 8 for the unaware, suggest that the second possibility cannot be ruled out. In fact, the two interpretations – bad financial investments and financial frauds or scams – are not mutually exclusive and may both play a role although, in the light of our results, the former is likely to be quantitatively more important.

5.3 Alternative interpretations

The evidence reported so far is consistent with an interpretation in terms of bad financial decisions. However, we cannot a priori exclude alternative interpretations that stress differences between aware and unaware respondents in terms of observable or unobservable characteristics.

[10] The high frequency of bracket responses, and of item nonresponse to questions on the amount of stocks sold or bought in the last period, does not allow to calculate meaningful monetary amounts for these financial transactions.

[11] Moreover, it can be shown that 80% of the average loss in financial wealth estimated in Column (1) reflects a decrease in the value of stocks.

Reverse causality

Financial losses may put individuals under stress and lead them to perform poorly in the word recall tests. This would be consistent with the evidence in Schwandt (2018) showing that exogenous wealth shocks driven by stock market fluctuations may negatively affect health via increasing stress. Although we find no evidence of pre-trends in wealth changes in the multi-period DiD model, the 2-year window between survey waves does not allow us to rule out this possibility. It is worth stressing that this alternative interpretation should also explain the observed differences between aware and unaware respondents. We perform two different tests that lead us to exclude this possibility.

First, as in Schwandt (2018), we employ an arguably exogenous measure of wealth shock, based on the predicted difference in financial wealth, constructed by capitalizing the value of each asset category owned in the previous wave by its average market return across waves, as described in Section 3.3. Reassuringly, Columns (1) and (2) of Table 10 show that this measure is unrelated with the probabilities of experiencing a memory loss or of being aware of it. Further, although this measure strongly predicts wealth changes – a dollar increase in predicted wealth is associated with an increase of 60 cents in actual wealth between waves – the last three columns of Table 10 show that it does not substantially alter our estimates when included in equation (1) as an additional regressor.

Second, in the appendix (Table B.5) we evaluate the stress channel by testing whether there are differences between aware and unaware respondents in depression symptoms, optimism, life satisfaction, having control over their financial situation, the probability of declaring themselves in financial strain, and having difficulties managing money.[12] Not surprisingly, we find that the aware respondents are more likely to be depressed, are less satisfied with their life, and have more difficulties managing their money than the unaware.

Rational disinvestment

Another possibility is that the negative wealth changes observed for unaware respondents reflect rational disinvestment arising for a variety of reasons, such as a shorter life horizon, higher health expenditures, etc.

To investigate whether memory losses induce changes in subjective life expectancy, the first two columns of Table 11 regress changes in subjective life expectancy[13] on the occurrence of a severe memory loss using a specification similar to model (1) for wealth changes. We find a negative association between severe memory losses and changes in subjective life expectancy only for aware respondents, which is consistent with both standard theory and the evidence in Table 2 that the aware are less

[12] Hsu and Willis (2013) use difficulties managing money as a measure of self-awareness of financial capacity, correlated with severe cognitive decline and dementia.

[13] The HRS asks respondents what is the percentage chance that they will reach a certain target age, varying from 75 to 95 years depending on the age of the respondent at the time of the interview.

healthy than the unaware.

As for health expenditures, the last two columns of Table 11 show no evidence that a severe memory loss is associated with statistically significant changes in out-of-pocket medical expenditure, neither for the aware nor for the unaware. Moreover, we show in Table B.6 that our results hardly change if we exclude respondents who experience a new severe health issue, including hospitalization in the last 12 months. This allows us to reject another possible interpretation, namely that people unaware of their cognitive decline face higher medical expenses which negatively affect their wealth profile. Table B.7 in the appendix, based on the HRS CAMS data, shows that severe memory losses are associated neither with increases in total consumption nor with increases in particular consumption categories (durables, nondurables, household spending, and transport spending), and this is true for both aware and unaware respondents. All these findings provide no evidence for the rational disinvestment explanation.

We also find no evidence of an association between severe memory losses and increased financial transfers to children, neither in their probability nor in the expected total amount when they occur (Table B.8 in the appendix). These findings allow us to reject yet another interpretation, namely that the respondent's children, noting her severe memory decline, anticipate bequests.

Differences in portfolios

If cognitive decline is correctly perceived, we should expect a shift away from risky assets. Table 12 investigates whether respondents with a severe memory loss change the composition of their financial portfolio between risky assets (stocks, mutual funds and investment trusts) and safer assets (all other financial assets), distinguishing between changes in the probability of holding risky assets (the extensive margin) and changes in the expected share of risky assets (the intensive margin). Our results show no statistically significant difference between aware and unaware respondents, neither at the extensive or the intensive margin, nor by position in the wealth distribution.

We also investigate whether the observed differences in wealth changes reflect differences in the initial portfolio composition leading to lower returns. Table B.9 in the appendix presents estimates of model (1) where the outcome on the left-hand side is the difference between one's financial wealth in a given wave and the financial wealth predicted, as described in Section 3.3, by capitalizing the value of each asset category owned in the previous wave by its average market return. The table presents separate estimates for the sample of all respondents with positive financial wealth (Columns 1–2) and the subsample with a severe memory loss (Columns 3–4). The results show that, even taking into account the composition of financial portfolios, unaware respondents do worse than the other respondents. Again, the largest difference is found among the wealthier respondents.

Misreporting and measurement error

After a severe memory loss, people may find it hard to remember the value of their assets and therefore make large errors which would result in large wealth changes. The key issue is whether this problem affects aware and unaware respondents differently. For example, a survey participant who is aware of her memory loss may ask a family member or a caregiver for help in providing the necessary information. Unfortunately, no evidence on the patterns of misreporting is possible without a linkage of HRS to administrative data. Nonetheless, the results in Table B.10 provide no evidence of differential misreporting. In particular, we find no indication that the unaware are characterized by higher levels of financial wealth imputation or, when restricting attention to stockholders, by a higher frequency of missing or incomplete values. Furthermore, by exploiting the HRS asset verification procedure, we find no evidence of differential asset misreporting between aware and unaware respondents. Since a large level of misreporting would be needed to explain the observed difference in expected wealth changes between aware and unaware respondents, it is hard to believe that it would not show up in our tests, especially that based on the HRS asset verification procedure which has been proved to be very effective in reducing the measurement error in wealth changes (see, e.g., Hill, 2006).

Finally, the last two columns of Table B.6 show that our results hardly change when we exclude respondents with a higher risk of cognitive impairment (as in Herzog and Wallace 1997) and therefore more likely to forget their assets.

5.4 Robustness checks

Several tables in Appendix B examine the robustness of the results from model (1) to alternative specifications.

To account for right-skeweness of the wealth distribution and for the presence of a few large outliers, Table B.11 shows the estimates of the log-linear version of model (1), with $\Delta \ln W_{it}$ replacing ΔW_{it}.[14] Above the median of the wealth distribution results are similar to those reported in Section 5.1, while below the median they differ because of the substantial fraction of respondents with zero or negative wealth that are dropped when taking log differences.

Table B.12 shows estimates of model (1) with the binary indicator of a severe memory loss replaced by the (absolute or relative) change in the memory score. Wealth changes remain strongly positively associated with changes in the memory score but now they show no statistically significant association with the binary indicator of self-rated memory loss or its interaction with the changes in the memory score. Things are different when we consider a nonlinear specification that includes the quintiles of the changes in the memory score as regressors. The coefficients on these variables are all positive and statistically significant, but the negative coefficients on their interaction with self-rated memory

[14] This is essentially equivalent to modeling relative wealth changes, $\Delta W_{it}/W_{i,t-1}$, rather than wealth changes.

loss are statistically significant only for the lower quintiles, hence confirming the results from model (1).[15] Overall, we think that our basic model (1) with three indicators for being aware, unaware or pessimist captures in a more parsimonious way this nonlinear relation.

Another concern is that people with a severe memory loss may experience further losses, of which they need not to be aware. This implies that they may switch between different change-in-memory states from one wave to the next (e.g., from aware to unaware, and then back). It turns out that 80% of the respondents have at most one severe memory loss and, when they experience more than one, only a quarter of them switches between states. Further, it is reassuring that, if we exclude those who were unaware, aware, or pessimist in the previous wave (Table B.13), results from Model 1 are very similar to those reported in Table 3. This issue is less of a concern for Model 2, since we focus on the first memory loss event and we do not estimate many lagged effects.

Finally, Tables B.14 and B.15 confirm the robustness of our results to the inclusion of time-invariant individual-specific effects. Point estimates are qualitatively similar to the OLS estimates – a little smaller for model (1) and a little larger for the DiD model – but less precise. This is unsurprising, as the estimates are obtained by taking differences of noisy wealth differences.

6 Conclusions

Using data from the HRS, a large representative panel of Americans aged 50+, we show that people tend to substantially underestimate their cognitive decline and we document the financial consequences of misperception. We find that those who experience a severe memory decline and are unaware of it are likely to experience large financial wealth losses compared to those who are aware or do not experience a severe decline. We investigate alternative explanations for our results that stress differences in observable or unobservable characteristics between aware and unaware respondents. We find no differences in health conditions, subjective life expectancy, financial transfers to children, or consumption expenditures between the two types of respondents. This rules out explanations based on rational disinvestment and leaves our proposed explanation, namely that unaware respondents are more likely to make bad financial decisions or to be the victims of financial frauds.

After the Global Financial Crisis, much attention has been devoted to financial literacy and how to raise it, especially among younger people. Our paper implies that preparing for cognitive decline is also important. One may therefore think of designing programs that are explicitly targeted to older investor and cover topics which are relevant for making good financial decisions later in the life cycle.

Our results do not imply that older people should be prevented from making independent finan-

[15] Compared to Table 3, results do not change qualitatively when we take a lower (higher) threshold of 15% (25%) for the relative definition of severe memory loss. Unsurprisingly, the difference between aware and unaware respondents is smaller (larger) when using this lower (higher) threshold.

cial decisions but represent a warning that unrestricted freedom of choice – coupled with the rising complexity of financial products – can have very negative consequences for those unable to promptly recognize their cognitive decline and take appropriate actions. Financial delegation may help address this problem but requires an early commitment by the wealth owner and, after a certain age, frequent assessments of her decision-making skills by others. Designing these assessments, which amounts to a sequence of financial "driving licence" test, may be challenging. Further, the presence of asymmetric information gives rise to a serious principal-agent problem that requires close monitoring. Policy interventions aimed at promoting the annuity market may also help but they would require a stricter regulation and, given the currently high price of annuities, more competition.

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Table 1: Self-rated vs. assessed memory

Self-rated memory change	Severe relat. memory loss No	Yes	Total
Better now	.020	.006	.026
About the same	.590	.181	.771
Worse now	.148	.056	.204
Total	.757	.243	1.00

Self-rated memory change	Severe abs. memory loss No	Yes	Total
Better now	.021	.006	.026
About the same	.600	.171	.771
Worse now	.153	.050	.204
Total	.773	.227	1.00

Notes: This table compares self-rated memory changes across waves with two different measures of memory loss: severe "relative" memory loss, defined as a decline of 20% or more in the memory score, and severe "absolute" memory loss, defined as a memory score change of one standard deviation or more.

Table 2: Probit estimates of the probability of a severe memory loss and of being unaware conditional on having a severe memory loss

	Having a severe memory loss			Unaware conditional on having a severe memory loss		
	(1)	(2)	(3)	(4)	(5)	(6)
Age	.005 ***	.005 ***	.005 ***	-.002 ***	-.001 **	-.002 ***
	(.000)	(.000)	(.000)	(.001)	(.001)	(.001)
Single$_{t-1}$	-.004	-.003	-.005	-.013	-.016 *	-.021 *
	(.004)	(.004)	(.005)	(.010)	(.010)	(.011)
Female	-.077 ***	-.076 ***	-.090 ***	-.045 ***	-.048 ***	-.062 ***
	(.004)	(.004)	(.005)	(.008)	(.008)	(.010)
Children	-.001	-.001	-.002	-.004 **	-.004 **	-.004 *
	(.001)	(.001)	(.001)	(.002)	(.002)	(.002)
Partner death	-.008	-.008	-.003	-.033	-.035 *	-.033
	(.010)	(.010)	(.013)	(.021)	(.021)	(.025)
Years of education	-.017 ***	-.016 ***	-.012 ***	-.004 **	-.006 ***	-.006 ***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.002)
Working$_{t-1}$	-.036 ***	-.028 ***	-.022 ***	.047 ***	.014	.023 **
	(.004)	(.004)	(.005)	(.009)	(.009)	(.011)
Q2 wealth$_{t-1}$	-.033 ***	-.028 ***	-.026 ***	.016	.000	.001
	(.006)	(.006)	(.006)	(.011)	(.011)	(.013)
Q3 wealth$_{t-1}$	-.051 ***	-.043 ***	-.036 ***	.008	-.020 *	-.018
	(.006)	(.006)	(.007)	(.012)	(.012)	(.014)
Q4 wealth$_{t-1}$	-.066 ***	-.055 ***	-.044 ***	.001	-.041 ***	-.038 **
	(.006)	(.006)	(.007)	(.014)	(.014)	(.016)
Recall$_{t-1}$	.095 ***	.097 ***	.103 ***	.023 ***	.018 ***	.021 ***
	(.002)	(.002)	(.002)	(.003)	(.003)	(.004)
Very good health$_{t-1}$		-.021 ***	-.022 ***		.084 ***	.083 ***
		(.004)	(.005)		(.008)	(.010)
ADL limitations$_{t-1}$		.020 ***	.017 ***		-.074 ***	-.085 ***
		(.006)	(.007)		(.011)	(.013)
# serious health conditions		.011 ***	.012 ***		-.037 ***	-.038 ***
		(.002)	(.003)		(.005)	(.005)
Numeracy score			-.045 ***			-.010
			(.003)			(.006)
Obs	81818	81818	57922	19737	19737	13976
N	22573	22573	19132	13699	13699	10808
Mean	.241	.241	.241	.773	.773	.763

Notes: This table shows marginal effects from probit models for the probability of experiencing a severe memory loss (Columns 1–3) and the probability of being unaware conditional on experiencing a severe relative memory loss (Columns 4–6). The models in Columns (1) and (4) include as regressors socio-demographic controls, binary indicators for the survey year (not reported), and the memory score in the previous wave. The models in Columns (2) and (5) also include binary indicators for having some ADL limitations and for self-rating own health as very good or excellent and the number of serious health conditions the respondent ever had (cancer, heart problems, stroke, or diabetes). The models in Columns (3) and (6) also include the most recent numeracy score available before survey year t. Due to missing data problems, the inclusion of this regressor causes a substantial reduction in the sample size. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 3: Changes in total wealth

	Financial respondents (FRs)		Resp. w/severe mem. loss	
			FRs	Non FRs
	(1)	(2)	(3)	(4)
Severe memory loss	-25.431 ***			
	(5.683)			
Aware		-5.378		
		(9.910)		
Unaware		-31.069 ***	-22.764 **	-7.900
		(6.290)	(9.900)	(14.037)
Pessimist		.417		
		(6.672)		
$\beta_2 - \beta_1$		-25.691 **		
		(10.666)		
Obs.	57148	57148	13882	6302
N	16270	16270	9694	4558
Mean W	378.85	378.85	343.58	478.57
Mean ΔW	-11.826	-11.826	-18.677	-15.442

Notes: The table shows OLS estimates of various versions of model (1) for the changes in total wealth (in thousands U.S. dollars at 2014 prices). Columns (1) and (2) estimate the model on the full sample of financial respondents. Columns (3) and (4) focus on respondents experiencing a severe memory loss event between adjacent waves and compare the results for financial respondents (Column 3) and non-financial respondents (Column 4). All models include as regressors a quadratic age term, binary indicators for the survey years, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 4: Changes in total and financial wealth: DiD model

	Total wealth		Financial wealth	
	(1)	(2)	(3)	(4)
Aware	-44.348		-19.158	
	(29.659)		(12.254)	
Unaware	-14.671	26.736	-7.492	5.887
	(11.698)	(23.784)	(6.612)	(9.091)
Post	20.265	17.446	6.058	-.125
	(31.123)	(27.806)	(13.009)	(10.890)
Unaware×Post	-54.874 *	-53.059 **	-29.121 **	-24.211 **
	(29.380)	(26.163)	(12.261)	(10.223)
Obs.	40284	29606	40284	29606
N	14872	10498	14872	10498
Mean W	391.212	386.775	101.163	100.656
Mean ΔW	-10.596	-14.421	-7.643	-10.701

Notes: The table shows OLS estimates of various versions of model (2) for the changes in total and financial wealth (in thousands U.S. dollars at 2014 prices) around the first severe memory loss event (from event time -2 to 2). Columns (1) and (3) show the results for the full sample (including those without any severe memory loss), while Columns (2) and (4) show the results for the restricted sample that only includes those who experienced a severe memory loss events. All models include as regressors a quadratic age term, binary indicators for the survey years, a linear control in event time, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 5: Changes in total wealth by wealth quartile in the previous wave

	1st quartile	2nd quartile	3rd quartile	4th quartile
	(1)	(2)	(3)	(4)
Aware	-3.390	-2.582	-9.482	40.942
	(3.640)	(5.496)	(8.413)	(32.111)
Unaware	-2.737	-4.308	-12.882 **	-52.041 ***
	(2.373)	(2.716)	(5.582)	(17.797)
$\beta_2 - \beta_1$	.653	-1.726	-3.400	-92.983 ***
	(3.993)	(5.843)	(9.288)	(34.359)
Obs.	14133	14292	14313	14410
N	5923	6229	6127	4911
Mean W	20.302	104.52	306.37	1074.6
Mean ΔW	22.214	17.506	30.243	-103.16

Notes: All models include as regressors a quadratic age term, binary indicators for the survey years, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 6: Changes in the value of wealth components

	Total	Financial	IRAs	Housing	Real estate	Business	Transport
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ware	-5.378	-2.155	-2.330	-3.064	2.410	5.135	-.345
	(9.910)	(5.709)	(3.007)	(2.571)	(3.447)	(3.754)	(.439)
Unaware	-31.069 ***	-19.696 ***	-5.554 ***	-3.452 *	-2.415	2.094	.154
	(6.290)	(3.363)	(1.730)	(1.934)	(1.550)	(2.123)	(.622)
$\beta_2 - \beta_1$	-25.691 **	-17.541 ***	-3.225	-.387	-4.825	-3.041	.499
	(10.666)	(5.928)	(3.140)	(2.866)	(3.598)	(4.021)	(.637)
Obs.	57148	57148	57148	57148	57148	57148	57148
N	16270	16270	16270	16270	16270	16270	16270
Mean W	378.85	96.201	58.53	149.43	32.435	26.593	15.67
Mean ΔW	-11.826	-6.388	.684	3.752	-4.8078	-4.5244	-.5418

Notes: All models include as regressors a quadratic age term, binary indicators for the survey years, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 7: Changes in financial wealth by financial wealth ownership and quartile of financial wealth in the previous wave

	No financial wealth	Positive fin. wealth	3rd quartile of fin. wealth	4th quartile of fin. wealth
	(1)	(2)	(3)	(4)
Aware	-4.036 ***	2.379	-8.558 **	21.102
	(1.558)	(7.942)	(4.313)	(19.118)
Unaware	1.075	-25.022 ***	-10.160 ***	-33.832 ***
	(1.672)	(4.346)	(2.552)	(10.366)
$\beta_2 - \beta_1$	5.111 ***	-27.401 ***	-1.602	-54.934 ***
	(1.752)	(8.311)	(4.429)	(19.671)
Obs.	17385	39763	14279	14410
N	8028	12989	6871	5498
Mean W	2.484	137.180	50.607	319.770
Mean ΔW	14.068	-14.292	21.082	-65.952

Notes: All models include as regressors a quadratic age term, binary indicators for the survey years, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 8: Changes in the value of financial wealth components for respondents with positive financial wealth in the previous wave

	Stocks	Checking/ savings	CDs/Gov't bonds	Private bonds	Other assets	Debt
	(1)	(2)	(3)	(4)	(5)	(6)
Aware	-1.661	1.208	-1.225	.003	3.232	-.110
	(5.901)	(1.465)	(2.344)	(1.269)	(2.503)	(.272)
Unaware	-13.364 ***	-1.635 **	-4.670 ***	.297	-5.006 ***	-.119
	(2.763)	(.728)	(1.234)	(.978)	(1.400)	(.239)
$\beta_2 - \beta_1$	-11.704 **	-3.445	-2.843 *	.295	-8.237 ***	-.009
	(5.856)	(2.457)	(1.553)	(1.475)	(2.613)	(.325)
Obs.	39763	39763	39763	39763	39763	39763
N	12989	12989	12989	12989	12989	12989
Mean	65.768	15.763	34.028	8.9568	15.655	2.9949
Mean Δ	-7.6151	-.60191	-.92878	-.68369	-3.2889	1.1739

Notes: All models include as regressors a quadratic age term, binary indicators for the survey years, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 9: Changes in financial wealth by stock market activity

	Active	Inactive	No stocks
	(1)	(2)	(3)
Aware	22.694	6.103	-2.959
	(36.587)	(16.646)	(7.429)
Unaware	-57.559 ***	-10.171	-11.016 **
	(20.726)	(12.586)	(4.875)
$\beta_2 - \beta_1$	-80.253 **	-16.275	-8.057
	(38.538)	(19.110)	(8.536)
Obs.	5504	7433	44211
N	2918	4101	14465
Mean W	342.73	167.39	53.542
Mean ΔW	-11.297	-17.691	-3.5716

Notes: All models include as regressors a quadratic age term, binary indicators for the survey years, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Activity on the stock markets is based on the assets change module of the HRS, in which respondents who hold stocks in the current or the previous wave are asked whether they sold or bought stocks in the last two years. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 10: Actual and predicted wealth changes, cognitive decline and awareness

	Memory loss	Unaware	Actual Δ Wealth		
	(1)	(2)	(3)	(4)	(5)
Predicted Δ Wealth	-.000	-.000 *	.653 ***		.653 ***
	(.000)	(.000)	(.029)		(.029)
Aware				-5.378	-6.119
				(9.910)	(8.774)
Unaware				-31.069 ***	-26.016 ***
				(6.290)	(5.260)
$\beta_2 - \beta_1$				-25.691 **	-19.897 **
				(10.666)	(9.401)
Obs.	57148	13882	57148	57148	57148
N	16270	9694	16270	16270	16270
Mean	.243	.770	378.85	378.85	378.85
Mean Δ			-11.826	-11.826	-11.826

Notes: The dependent variable in Columns (1) is a binary indicator for experiencing a severe memory loss, in Column (2) is the binary indicator for being unaware conditional on experiencing a severe memory loss, while in Columns (3)–(5) is the change in total wealth (in thousands U.S. dollars at 2014 prices). All models include as regressors a quadratic age term, binary indicators for the survey years, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 11: Differences in subjective life expectancy and in out-of-pocket medical expenditure

	Subj. life expectancy		Out-of-pocket exp.	
	(1)	(2)	(3)	(4)
Memory loss	-.250		.029	
	(.402)		(.149)	
Aware		-1.321 *		.062
		(.728)		(.472)
Unaware		.235		.039
		(.438)		(.134)
$\beta_2 - \beta_1$		1.556 **		-.024
		(.789)		(.493)
Obs.	44979	44979	49919	49919
N	13992	13992	15593	15593
Mean	48.533	48.533	3.1952	3.195
Mean	-.944	-.943	-.254	-.254

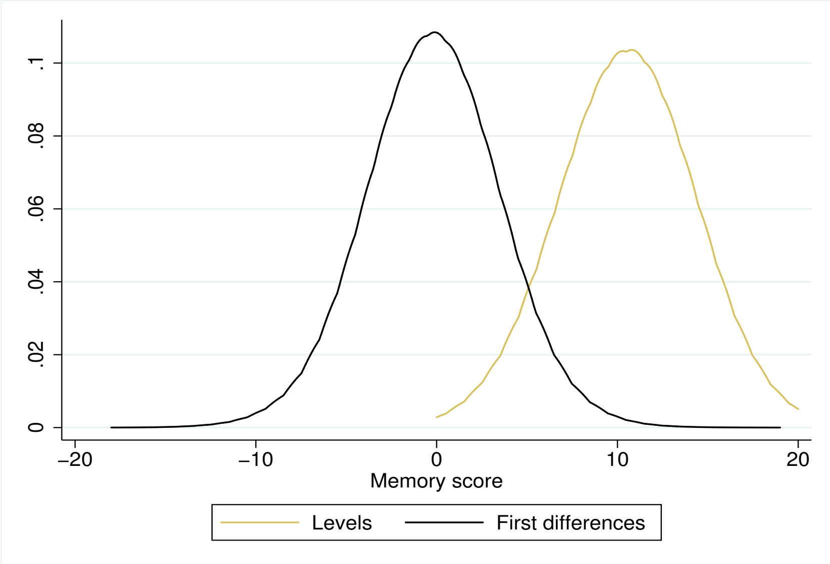
Notes: The dependent variable in Columns (1) and (2) is the self-assessed probability of living for 10 or more years, while in Columns (3) and (4) is out-of-pocket medical expenditure (in thousands U.S. dollars at 2014 prices). All models include as regressors a quadratic age term, binary indicators for the survey years, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table 12: Differences in ownership of risky assets and share of risky assets conditional on ownership

	Risky assets ownership		Risky assets share	
	(1)	(2)	(3)	(4)
Aware	-.009	-.017	.005	-.002
	(.008)	(.013)	(.018)	(.018)
Unaware	-.004	-.008	.016	.006
	(.005)	(.009)	(.011)	(.011)
$\beta_2 - \beta_1$	.005	.008	.011	.007
	(.009)	(.015)	(.020)	(.020)
Obs.	57148	28574	14193	12250
N	16270	8881	5386	4564
Mean	.260	.42871	.439	.561
Mean Δ	-.013	-.024	.123	.098
3rd-4th wealth quartile	No	Yes	No	Yes

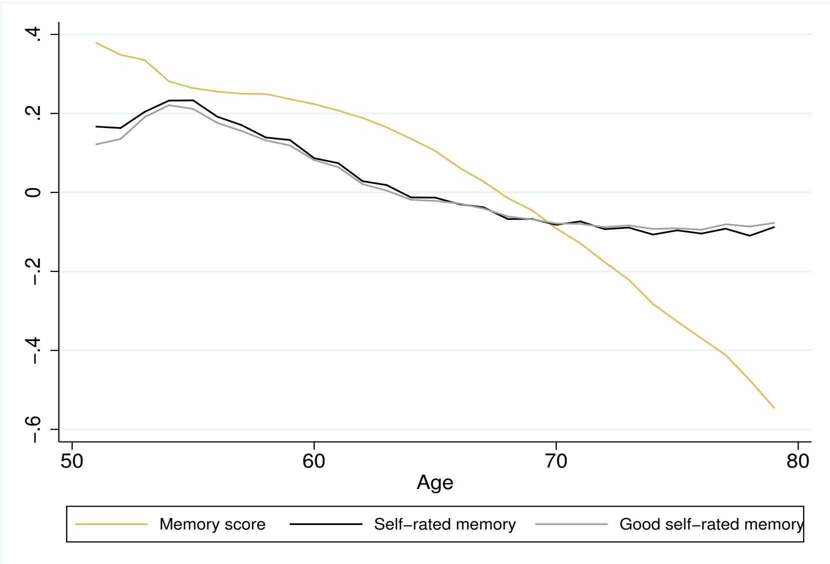
Notes: The dependent variables in Columns (1) and (2) is the binary indicator for owning risky financial asset, while in Columns (3) and (4) is the share of financial wealth invested in risky financial asset conditional on ownership. All models include as regressors a quadratic age term, binary indicators for the survey years, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Figure 1: Density of memory scores in levels and first differences



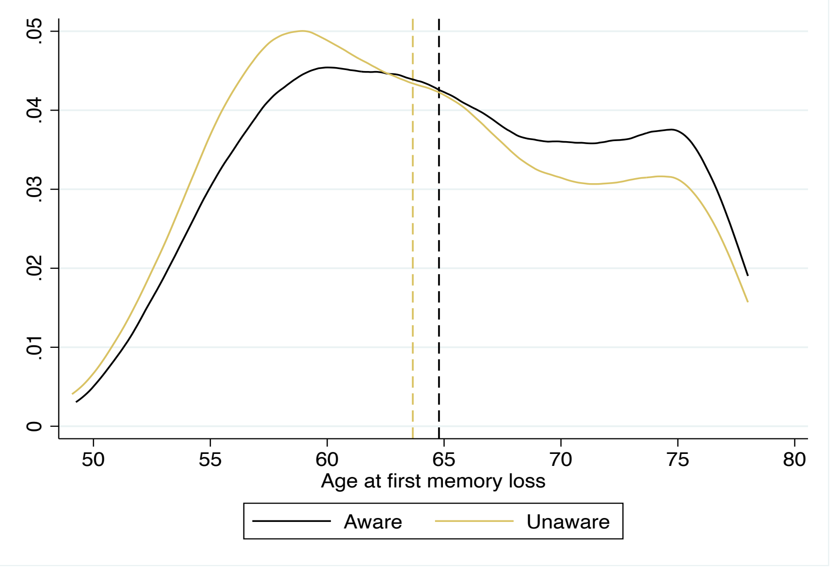
Notes: This figure shows univariate kernel estimates of the density of total memory score in levels and first differences (Epanechnikov kernel with a bandwidth of 2).

Figure 2: Assessed vs. self-rated memory by age



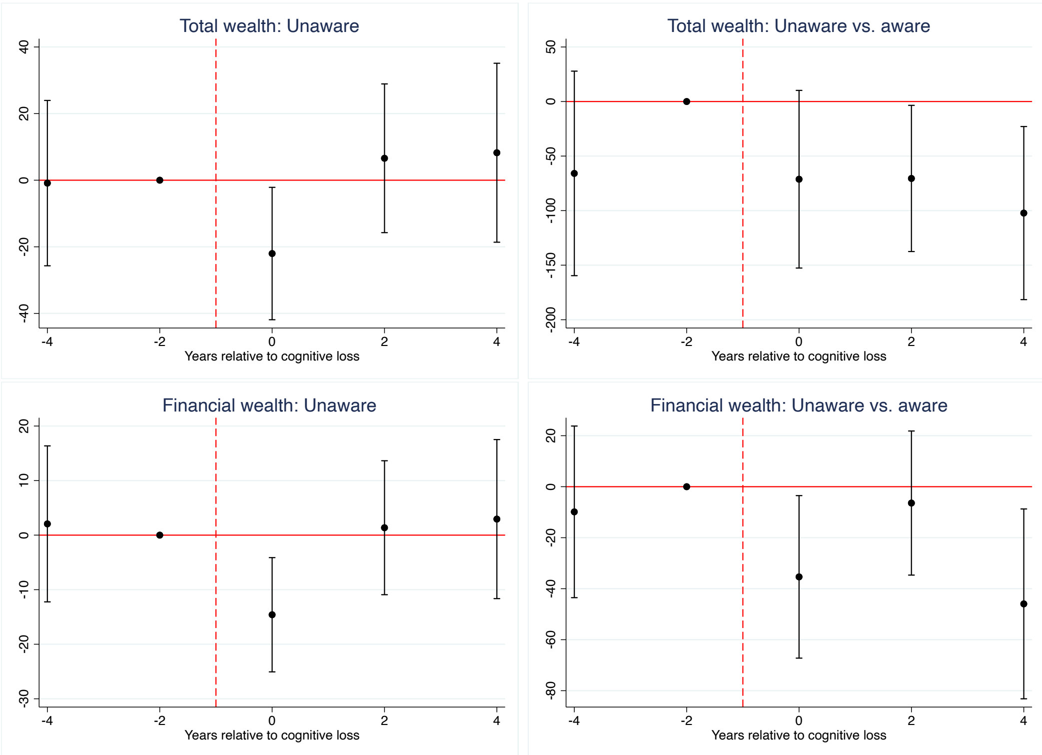
Notes: The figure presents the average age-profile of three indices: the total score in the immediate and delayed recall tasks (in sand), the self-rated memory score (in black), and the share of respondents rating their memory as "excellent", "very good" or "good" (in gray). We standardize each index using its mean and standard deviation over the entire period 1998–2014 and compute age-specific averages of the standardized index using the HRS respondent-level weights. We then smooth each profile using a 3-year moving average.

Figure 3: Age when the first severe memory loss occurs: aware vs. unaware respondents



Notes: This figure compares the density of the age at which individuals experience their first memory loss event for aware and unaware respondents. The dashed vertical lines correspond to the group mean. The age densities are based on Epanechnikov kernel density estimations with a bandwidth of 2.

Figure 4: Event-study coefficients for unaware respondents



Notes: The figure shows the estimated wealth changes (in thousands U.S. dollars at 2014 prices), and the associated 95% confidence intervals, with respect to the period immediately before the first severe memory loss event for unaware respondents. Results for total wealth are shown in the top panels, those for financial wealth in the bottom panels. The panels on the left show the estimated event-study coefficients using only the unaware respondents (and including the "never treated" at event time -1), while those on the right show the the DiD coefficients relative to the aware respondents. All models include as regressors a quadratic age term, binary indicators for the survey years, indicators for the survey year of the first memory loss event, socio-demographic controls (binary indicators for gender, high school degree and college, race, labor force status, marital status, and census division), plus wealth and memory score in the previous wave.

A Data appendix

A.1 HRS

The HRS is a household panel survey conducted by the Institute for Social Research at the University of Michigan and supported by the U.S. National Institute on Aging and the U.S. Social Security Administration. It collects rich and detailed information on nationally representative samples of the U.S. population aged 50+ from seven birth cohorts. Household and individual-level survey weights are provided to correct for oversampling of African Americans, Hispanics, and Floridians. The core survey was fielded annually from 1992 to 1996, and has been fielded biennially in even-numbered years from its redesign in 1998. Core interviews are conducted in-person and by telephone, with supplemental information collected via mail. Each wave of the core survey includes approximately 20,000 people in about 11,000 households. The study initiates contact only with non-institutionalized individuals (not in prisons, jails, nursing homes, or long-term care facilities) but, once in the study, it follows respondents in and out of nursing care.

The HRS cohorts include the original HRS cohort born in 1931–1941, entering the survey in 1992; the Study of Assets and Health Dynamics (AHEAD) cohort born in 1923 or earlier, entering the survey in 1993; the Children of Depression (CODA) cohort born in 1924–1930 and the War Baby (WB) cohort born in 1942–1947, both entering the survey in 1998; the Early Baby Boomers (EBB) cohort born in 1948–1953, entering the survey in 2004; the Mid Baby Boomers (MBB) cohort born in 1954-1959, entering the survey in 2010; and the Late Baby Boomers (LBB) cohort born in 1960–1964, entering the survey in 2016.

We use the RAND HRS Longitudinal File, a cleaned, easy-to-use, and streamlined version of the data from the original HRS core and exit interviews, with derived variables covering a large range of measures and RAND imputations of missing values on income, assets, and medical expenditures. We confine attention to the nine survey waves from 1998 (wave 4) to 2014 (wave 12) because consistent information on total wealth is available only after the HRS redesign in 1998.[16] Thus, we observe the original HRS cohort and the AHEAD, CODA, and WB cohorts for 9 waves from 1998 to 2014 (with wealth changes over the previous wave available for 8 waves, from 2000 to 2014), the EBB cohort for 6 waves from 2004 to 2014 (with wealth changes over the previous wave available for 5 waves, from 2006 to 2014), and the MBB cohort for 3 waves from 2010 to 2014 (with wealth changes over the previous wave available for 2 waves, namely 2012 and 2014).

To minimize the effects of attrition and nonresponse due to aging and aging-related conditions, the HRS makes extensive use of proxy interviews, which are programmed and worded separately.[17] For

[16] Specifically, total wealth cannot be calculated in wave 3 because no questions were asked about second homes in either 1995 or 1996.

[17] Proxy interviews are conducted with someone familiar with the financial, health, and family situation of a sampled

most questions, the proxy interview only involves wording changes (e.g., from "you" to "her"), but cognitive performance tests and some questions that are considered inappropriate to ask proxies are omitted entirely. For this reason, we drop proxy interviews. To limit potential selection issues arising from institutionalization, mortality or proxy interviewing, we restrict the sample to people aged 50–80 years. Since wealth changes are measured at the household level, we only consider the financial respondent, namely the household member designated by each household to answer all household-level financial questions. To avoid potential selection issues arising from a change of the financial respondent after a memory loss, we focus on the designated financial respondent in the previous wave, before the memory loss event. However, just like Hsu and Willis (2013), we find little evidence of switching in financial management shortly after an episode of cognitive decline.

In addition to a rich set of socio-demographic characteristics (age, sex, race, education, labor force status, marital status, household size and composition, and geographical region) and to self-rated and assessed memory (described in Section 3.2), the HRS contains the outcomes of a number of other cognitive tests. These include the serial 7's test, which asks respondents to subtract 7 from 100 and continue subtracting 7 from each subsequent number for a total of five times (RAND HRS variable `RwSER7`); the backwards counting test, which asks respondents to count backwards as quickly as possible for 10 continuous numbers beginning with either the number 20 or 86 (RAND HRS variables `RwBWC20` and `RwBWC86`); a numeracy test, which scores the respondent's numerical ability and includes a financial literacy test (HRS CORE variable `D178 - D179 - D180`); a vocabulary test, which scores the respondent's ability to provide definitions of five given words (RAND HRS variable `RwVOCAB`)), and a measure of mental status based on date naming (RAND HRS variables `RwMO`, `RwDY` and `RwYR`), objects naming (RAND HRS variable `RwSCIS`), and U.S. President and Vice-President naming (RAND HRS variables `RwPRES` and `RwVP` respectively).[18] Figure B.1 shows that our indicator of severe memory loss is a strong predictor of decline in all other available measures and that this decline is larger for aware respondents.

The RAND HRS file contains information on (net) household wealth and the value of its individual components, distinguishing between the following six broad asset categories: (net) financial wealth, IRAs, (net) housing wealth, other real estate, business wealth, and transport wealth. Financial wealth is defined as the total value of stocks, mutual funds, and investment trusts (`HwASTCK`), checking, savings, and money market accounts (`HwACHCK`), CDs, government savings bonds, and Treasury bills (`HwACD`), bonds and bond funds (`HwABOND`), and other savings or assets (`HwAOTHR`),[19] minus the value

individual who is unable to complete the interview because of physical or cognitive limitations, or is unwilling to participate. The proxy respondent is usually some close relative of the sampled individual (most often the partner, a daughter or a son) or a caregiver.

[18] The last two tests are only carried out for people aged more than 65 years. More information on the other cognitive measures in the HRS can be found in Ofstedal et al. (2005).

[19] Other savings or assets contains the net value of jewelry, money owed by others, collections for investment purposes,

of credit card balances, medical debts, life insurance policy loans, loans from relatives, etc. (`HwADEBT`). IRAs (`HwAIRA`) contains the net value of IRA or Keogh plans. Housing wealth (`HwAHOUS`) is defined as the value of the primary and secondary residence minus the value of all mortgages, home equity lines, and other home loans, and is computed as the sum of the value of primary residence (`HwAHOUS`) and second home (`HwAHOUB`) minus the value of mortgages on the primary residence (`HwAMORT`) and second home (`HwAMRTB`) minus other home loans (`HwAHML`). Other real estate (`HwARLES`) contains the net value of all real estate different from primary residence or second home. Business wealth (`HwABSNS`) contains the net value of business or farm wealth. Transport wealth (`HwATRAN`) contains the net value of all vehicles owned by the household. All this information is self-reported by the designated financial respondent (one for each household, namely the member most knowledgeable about household finances) and is converted to 2014 U.S. dollars using the consumer price index for all urban consumers (CPI-U) as deflator.[20]

Figure B.4 shows estimated wealth changes by survey year for aware and unaware respondents relative to respondents without a severe memory loss. For the unaware, differential wealth changes are always negative and are statistically different from zero in all years except 2006, 2010 and 2012. For the aware, instead, we never reject that they are equal to zero except in 2010, the survey year immediately after the Global Financial Crisis, when differential wealth changes are negative, statistically significant, and larger than for the unaware.

The RAND HRS file also provide imputed values for missing or incomplete information (e.g., bracketed amounts in an unfolding bracket sequence) on some wealth components[21] but contain only fragmentary information on 401k, 403(b), and other employer-sponsored retirement plan balances, and no direct measure of Social Security wealth. Including the value of these other wealth components would complicate matters considerably – as they can only be estimated indirectly, for example using the data and the procedure described in Barth et al. (2018).

Table A.1 presents summary statistics on the key variables used in this paper, separately for all financial respondents (the "full sample") and the financial respondents with at least one severe memory loss event (the "loss sample").

A.2 HRS CAMS

The HRS CAMS is a mail survey sent out biennially in odd-numbered years from 2001 to a subsample of about 5,000 HRS core respondents, one randomly chosen per household (thus covering less than half of the households in the core interview). It is inspired by the U.S. Consumer Expenditure Survey, with comparable questions.

rights in a trust or estate, and annuities different from life insurance policies.

[20] The CPI data have been downloaded from the U.S. Bureau of Labor Statistics website: https://www.bls.gov/cpi/.

[21] Detailed information on the imputation procedure can be found in Hurd et al. (2016).

We use the RAND HRS CAMS Data File, which is a user-friendly version of Part B of the HRS CAMS and can easily be merged to the RAND HRS Longitudinal File. It contains annualized, cleaned, and aggregated spending and consumption variables with consistent and intuitive naming conventions across waves. We employ data on total household expenditure and household expenditure on four categories of goods, namely durables, nondurables (including health insurance and health services), housing, and transportation.

A.3 Financial returns

Monthly information on U.S. market returns by asset category have been obtained from the Refinitiv (formerly Thompson Reuters) Datastream database.

Specifically, for stocks we use the percentage differences in the S&P 1500 Super Composite Index with respect to the same month of the previous year (top-left panel of Figure A.1, where it is compared to the returns on the Dow Jones Industrial Average Index); for long-term government bonds we use the yield on 10-year Treasury bonds and for long-term private-sector bonds we use the yield on corporate bonds with 7–10 year maturity (top-right panel of Figure A.1); for T-bills we use the interest rate on 3-month Treasury bills and for CDs the interest rate on 90-day CDs (bottom-left panel of Figure A.1); for checking and savings accounts we use estimates obtained from Statista,[22] and for consumer debt we use the interest rate on 24-month personal loans at commercial banks (bottom-right panel of Figure A.1).

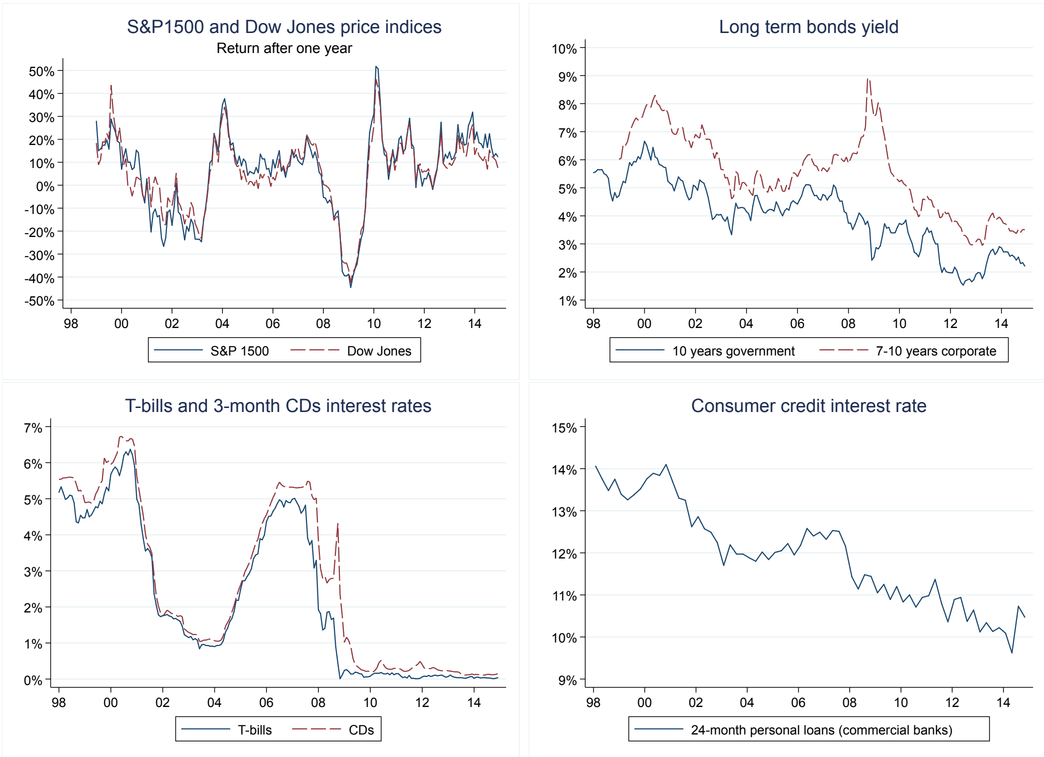
[22] http://www.statista.com/statistics/325600/average-interest-rate-checking-account-usa/.

Table A.1: Mean and standard deviation (SD) of key variables

	All financial respondents			Loss sample		
	N	Mean	SD	N	Mean	SD
ΔWealth$_t$	57148	-14.517	670.301	13882	-18.704	412.776
Wealth$_{t-1}$	57148	393.370	886.495	13882	362.287	687.084
Aware	57148	0.056	0.230	13882	0.230	0.421
Unaware	57148	0.187	0.390	13882	0.770	0.421
Pessimist	57148	0.148	0.355	13882	0.000	0.000
Memory score$_{t-1}$	57148	10.430	3.260	13882	11.654	3.240
Age	57148	66.448	7.359	13882	67.305	7.415
Female	57148	0.553	0.497	13882	0.545	0.498
Single	57148	0.460	0.498	13882	0.482	0.500
High school degree	57148	0.513	0.500	13882	0.514	0.500
College degree	57148	0.269	0.444	13882	0.230	0.421
Working$_{t-1}$	57148	0.362	0.481	13882	0.314	0.464
Black	57148	0.177	0.382	13882	0.201	0.401
Other races	57148	0.057	0.231	13882	0.063	0.243

Notes: The table reports descriptive statistics on the main variables for two samples: the sample of all respondents and the restricted sample of respondents who experience a severe memory loss event between two adjacent waves of the survey. Observations are weighted using the HRS respondent-level weights.

Figure A.1: Financial market returns by asset category, 1998–2014



Notes: The figure shows annualized market returns over the period 1998–2014 for four major asset categories, namely stock returns (using the S&P1500 and the Down Jones price indices), long-term private bonds yields (corporate and government), interest rates on short-term instruments (T-bills and 3-month CDs), and consumer credit interest rates.

B Additional tables and figures

Table B.1: Severe memory loss events and switching states

Total losses	N	N first unaware	Fraction switching	N first aware	Fraction switching
0	6576				
1	6422	4995		1427	
2	2470	1949	0.184	521	0.503
3	696	556	0.315	140	0.629
4	98	72	0.347	26	0.769
5	8	6	0.667	2	0.500
Total	16270	7578	0.074	2116	0.175

Notes: The table reports the distribution of respondents by the number of severe memory loss events and, for respondents who experienced more than one severe memory loss event, the fraction switching from a first episode as unaware (aware) to aware (unaware).

Table B.2: Transition rates between memory loss states

Wave t	Wave $t+1$				
	No loss	Pessimist	Aware	Unaware	Total
No loss	63.9	9.3	4.2	22.6	100.0
Pessimist	35.4	36.1	15.9	12.6	100.0
Aware	46.2	44.2	6.0	3.5	100.0
Unaware	79.5	12.7	1.2	6.6	100.0
Total	61.7	15.4	5.4	17.5	100.0

Notes: The table shows the transition rates between our 4 memory loss states across adjacent waves (t and $t+1$). Observations are weighted using the HRS respondent-level weights.

Table B.3: Changes in total wealth by employment status and age

	Employed (1)	Not employed (2)	Aged<70 (3)	Aged≥70 (4)
Aware	4.394	-11.613	-3.911	-9.620
	(21.901)	(8.926)	(13.632)	(13.341)
Unaware	-38.014 ***	-21.819 ***	-37.616 ***	-13.608 **
	(10.419)	(6.172)	(8.185)	(6.776)
$\beta_2 - \beta_1$	-38.014 ***	-21.819 ***	-33.705 **	-3.988
	(10.419)	(6.172)	(14.368)	(13.973)
Obs.	20697	36451	37125	20023
N	8074	12171	12674	7916
Mean W	383.340	376.310	356.700	419.920
Mean ΔW	1.128	-22.129	-6.105	-27.772

Notes: All models include as regressors a quadratic age term, binary indicators for the survey year, socio-demographic controls (years of education and binary indicators for gender, race, marital and labor force status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.4: Changes in total wealth by gender

	All		1st wealth quartile		4th wealth quartile	
	Male FRs (1)	Female FRs (2)	Male FRs (3)	Female FRs (4)	Male FRs (5)	Female FRs (6)
Aware	1.002	-14.949	7.148	-8.727 ***	19.094	82.119
	(15.126)	(13.779)	(10.069)	(2.250)	(36.514)	(58.671)
Unaware	-36.955 ***	-23.213 ***	-.786	-3.739 *	-62.527 ***	-29.133
	(8.860)	(7.459)	(4.670)	(2.241)	(23.603)	(26.708)
$\beta_2 - \beta_1$	-37.957 **	-8.263	-7.934	4.988 **	-81.621 **	-111.251 *
	(16.381)	(13.287)	(10.771)	(2.324)	(40.307)	(60.530)
Obs.	25533	31615	4686	9601	8387	5900
N	25533.000	31615	4635	9498	8457	5953
Mean W	487.580	291.050	26.947	17.060	1127.900	998.880
Mean ΔW	-16.680	-7.174	28.477	18.451	-107.67	-96.212

Notes: All models include as regressors a quadratic age term, binary indicators for the survey year, socio-demographic controls (years of education and binary indicators for labor force status, marital status, race, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.5: Memory loss, stress, and financial control

	Depression (CESD) (1)	Optimism (2)	Life satisfaction (3)	Financial control (4)	Financial strain (5)	Difficulties managing money (6)
Aware	1.174 ***	-.172 ***	-.550 ***	-.703 ***	.216 ***	.077 ***
	(.061)	(.058)	(.081)	(.123)	(.047)	(.007)
Unaware	.171 ***	.008	-.093 **	-.126 *	.063 **	.016 ***
	(.026)	(.037)	(.047)	(.071)	(.029)	(.003)
$\beta_2 - \beta_1$	-1.002 ***	.179 ***	.457 ***	.577 ***	-.153 ***	-.062 ***
	(.063)	(.063)	(.085)	(.130)	(.050)	(.007)
Obs.	57148	16097	16182	15127	13093	57132
N	16279	9892	9946	9745	8721	16269
Mean	1.452	4.115	4.939	7.223	1.811	.044

Notes: Each column represents the outcome of a different OLS regression. In the last column, we replicate the estimates in Column (3) of Table baseline for the subsample of respondents to the life satisfaction module. All models include as regressors a quadratic age term, binary indicators for the survey year, socio-demographic controls (years of education and binary indicators for gender, race, labor force status, marital status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.6: Changes in total wealth and occurrence of a severe memory loss: Excluding respondents with new major health issues or with a higher risk of cognitive impairment

	All respondents (1)	Excluding severe health shocks (2)	Excluding severe health shocks & hospitalization (3)	Excluding 1st quintile of memory score (4)	Excluding mental status< 8 (5)
Aware	-5.378	-2.146	-4.946	-4.254	-4.946
	(9.910)	(10.761)	(12.604)	(10.236)	(10.873)
Unaware	-31.069 ***	-30.450 ***	-31.352 ***	-31.222 ***	-32.666 ***
	(6.290)	(6.497)	(7.591)	(6.358)	(6.924)
$\beta_2 - \beta_1$	-25.691 **	-28.305 **	-26.406 **	-26.968 **	-27.720 **
	(10.666)	(11.570)	(13.113)	(11.035)	(11.663)
Obs.	57148	53317	41797	55472	46902
N	16270	15940	14374	16061	14671
Mean W	378.85	380.060	397.350	387.300	412.660
Mean ΔW	-11.826	-11.706	-9.947	-11.883	-12.425

Notes: The table investigates the robustness of our main results by excluding people with a major health shock or a hospital stay (Columns 2 and 3) or respondents that are more likely to be cognitive impaired (Columns 4 and 5). Columns (1) corresponds to Column (2) of Table 3; Column (2) excludes respondents who report a new severe health condition (cancer, stroke, heart problem, diabetes) between $t-1$ and t, while Column (3) also excludes respondents with a hospital stay in the last 12 months; Column (4) excludes respondents in the first quintile of the recall test, while Column (5) excludes respondents with a total mental status score below 8 (as in Herzog and Wallace 1997). All regressions include a quadratic age term, indicators for survey years, socio-demographic controls (binary indicators for high school, college, marital status, labor force status, gender, race, and census region), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.7: Changes in consumption expenditures

	Total spending (1)	Durables (2)	Nondurables (3)	Household spending (4)	Transport spending (5)
Aware	-2.051	-.016	-.724	-.025	-1.286
	(1.699)	(.052)	(1.127)	(.535)	(.941)
Unaware	.500	-.067	.008	.171	.387
	(1.111)	(.041)	(.609)	(.424)	(.571)
$\beta_2 - \beta_1$	2.550	-.052	.733	.196	1.673
	(1.891)	(.060)	(1.209)	(.619)	(1.021)
Obs.	10906	10906	10906	10906	10906
N	3487	3487	3487	3487	3487
Mean	43.925	43.925	43.925	43.925	43.925
Mean Δ	.843	-.016	1.027	-.061	-.108

Notes: The data are from the HRS CAMS. Consumption expenditures is in thousands U.S. dollars at 2014 prices. All models include as regressors a quadratic age term, binary indicators for the survey year, socio-demographic controls (years of education and binary indicators for gender, race, marital and labor force status, and census division), a binary indicator for worse self-rated memory but no severe memory loss, and the initial levels of wealth and memory. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.8: Changes in financial transfers to children

	Transfers (Yes/No)		Transferred (amount)	
	(1)	(2)	(3)	(3)
Memory loss	-.006		.946	
	(.006)		(.901)	
Aware		-.014		2.977
		(.011)		(1.875)
Unaware		-.004		.204
		(.007)		(.943)
$\beta_2 - \beta_1$		.009		-2.773
		(.012)		(1.996)
Obs.	57148	57148	6029	6029
N	16270	16270	3234	3234
Mean	.215	.215	11.126	11.126
Mean Δ	-.006	-.006	-1.082	-1.082

Notes: The dependent variable in Columns (1) and (2) is an indicator for the respondent making financial transfers to children, while in Columns (3) and (4) is the amount transferred (in thousands U.S. dollars at 2014 prices) conditional on making financial transfers. All models include as regressors a quadratic age term, binary indicators for the survey year, socio-demographic controls (years of education and binary indicators for gender, race, marital and labor force status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.9: Difference between actual and predicted financial wealth in the next wave for respondents with positive wealth in the previous wave

	All respondents		Resp. w/severe mem. loss	
	(1)	(2)	(3)	(4)
Aware	-3.850	-3.116		
	(7.398)	(11.162)		
Unaware	-16.328 ***	-21.728 ***	-17.411 **	-24.724 **
	(4.342)	(6.125)	(7.352)	(10.837)
$\beta_2 - \beta_1$	-12.478	-18.612		
	(8.071)	(12.042)		
Obs.	39763	26162	9375	5916
N	12989	8352	6966	4392
Mean W	-6.731	-11.304	-11.894	-19.364
Mean ΔW	-6.578	-10.860	-13.787	-21.656
3rd-4th wealth quartiles	No	Yes	No	Yes

Notes: The dependent variable is the absolute difference between observed and expected financial wealth (in thousands U.S. dollars at 2014 prices). The latter is constructed as the financial wealth that a respondent would have if the financial assets she owned in the previous wave had yielded their average market return. Columns (3) and (4) include only respondents who experience a severe memory loss event between two waves. All models include as regressors a quadratic age term, binary indicators for the survey year, socio-demographic controls (years of education and binary indicators for gender, race, marital and labor force status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \le p < .05$, * $.05 \le p < .10$.

Table B.10: Imputation of asset values and assessed misreporting of assets

	Fraction of financial wealth imputed	Incomplete/missing value of stocks	Any asset misreported	Any fin. asset misreported
	(1)	(2)	(3)	(4)
Aware	-.001	.003	-.006	-.004
	(.002)	(.008)	(.009)	(.006)
Unaware	.000	.006	-.008	-.008 *
	(.001)	(.005)	(.006)	(.004)
$\beta_2 - \beta_1$	.001	.005	-.002	-.003
	(.002)	(.009)	(.010)	(.007)
Obs.	57148	13319	57148	57148
N	16270	5056	16270	16270
Mean	.026	.109	.089	.051
Mean Δ	.024	.035	.106	.061

Notes: The dependent variable in Column (1) is the degree of financial wealth imputation (ranging from 0 to 1) for respondents with positive financial wealth, while in Column (2) is an indicator for providing incomplete or missing stock values (conditional on owning stocks). The dependent variable in the last two columns is an indicator for the HRS asset verification procedure detecting discrepancies in the reported value of any asset (Column 3) or only of financial assets (Column 4). All models include as regressors a quadratic age term, binary indicators for the survey year, socio-demographic controls (years of education and binary indicators for gender, race, marital and labor force status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \le p < .05$, * $.05 \le p < .10$.

Table B.11: Changes in the logarithm of total wealth and severe memory losses by quartile of the initial wealth distribution

	All respondents (1)	1st quartile (2)	2nd quartile (3)	3rd quartile (4)	4th quartile (5)
Aware	-.045 **	-.215 **	-.021	-.024	.007
	(.023)	(.104)	(.046)	(.026)	(.024)
Unaware	-.070 ***	-.182 ***	-.038	-.049 ***	-.050 ***
	(.014)	(.063)	(.026)	(.018)	(.016)
$\beta_2 - \beta_1$	-.025	.033	-.016	-.024	-.058 **
	(.025)	(.109)	(.049)	(.029)	(.027)
Obs.	49214	6807	13793	14225	14389
N	14363	3598	5985	6089	4930
Mean W	438.580	31.564	108.64	308.33	1076.2
Mean ΔW	-.021	.405	-.0601	-.053	-.126

Notes: All models include as regressors a quadratic age term, binary indicators for the survey year, socio-demographic controls (years of education and binary indicators for gender, race, marital and labor force status, and census division), a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.12: Changes in total wealth and absolute or relative changes in the memory score: Linear specifications vs. nonlinear specifications using quintiles of the change in the memory score

	Absolute changes		Relative changes	
	Linear	Quintiles	Linear	Quintiles
	(1)	(2)	(3)	(4)
Δ memory score	4.618 ***		24.027 ***	
	(0.856)		(4.711)	
Self-rated memory loss (SML)	6.181	24.282 **	6.461	27.627 **
	(6.047)	(11.664)	(6.021)	(11.218)
Δ memory score×SML	-1.712		-12.963	
	(1.493)		(9.132)	
Quintile2		24.020 ***		26.571 ***
		(7.310)		(7.641)
Quintile3		36.856 ***		34.987 ***
		(8.710)		(7.930)
Quintile4		39.594 ***		40.493 ***
		(8.160)		(7.650)
Quintile5		40.091 ***		42.091 ***
		(7.867)		(8.699)
Quintile2×SML		-32.983 **		-36.370 **
		(15.091)		(16.244)
Quintile3×SML		-22.722		-28.304 *
		(19.078)		(16.444)
Quintile4×SML		-17.057		-21.549
		(14.781)		(14.906)
Quintile5×SML		-17.698		-20.289
		(15.498)		(14.471)
Obs.	57148	57148	57148	57148
N	16270	16270	16270	16270
Mean W	378.854	378.854	378.854	378.854
Mean ΔW	-11.826	-11.826	-11.826	-11.826

Notes: All models include as regressors years of education, binary indicators for gender, race, labor force status, marital status and census division, a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.13: Changes in total wealth: Estimates from the full sample ("baseline") and excluding respondents who are aware, unaware or pessimists at $t-1$

	Baseline (1)	Excluding Aware$_{t-1}$ (2)	Excluding Unaware$_{t-1}$ (3)	Excluding Pessimist$_{t-1}$ (4)	Including only No loss$_{t-1}$ (5)
Aware	-5.378	-4.646	-2.064	-3.317	-3.429
	(9.910)	(10.958)	(11.192)	(13.764)	(15.101)
Unaware	-31.069 ***	-34.338 ***	-32.662 ***	-32.145 ***	-32.711 ***
	(6.290)	(6.701)	(7.413)	(7.012)	(8.267)
$\beta_2 - \beta_1$	-25.691 **	-29.692 ***	-30.597 **	-28.829 *	-29.282 *
	(10.666)	(11.249)	(12.117)	(14.898)	(16.249)
Obs.	57148	46250	40023	41534	30387
N	16270	14635	13839	14153	12391
Mean W	378.85	396.15	403.97	393.33	408.1
Mean ΔW	-11.826	-16.747	-16.974	-16.837	-16.338

Notes: All models include as regressors a quadratic age term, binary indicators for the survey year, socio-demographic controls (years of education and binary indicators for gender, race, labor force status, marital status, and census division), plus wealth and memory in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.14: Changes in total wealth: Model (1) with time-invariant individual-specific effects

	All FRs		Above median wealth	
	OLS (1)	FE (2)	OLS (3)	FE (4)
Aware	.096	6.444	20.921	9.608
	(10.227)	(11.074)	(19.596)	(21.817)
Unaware	-29.562 ***	-14.382 *	-34.684 ***	-27.593 *
	(6.736)	(7.621)	(10.667)	(15.170)
$\beta_2 - \beta_1$	-29.658 ***	-20.827 *	-55.605 ***	-37.202
	(11.335)	(11.920)	(21.367)	(23.579)
Obs.	53807	53807	26157	26157
N	12929	12929	6359	6359
Mean W	381.919	381.919	715.867	715.867
Mean ΔW	-8.082	-8.082	-27.705	-27.705

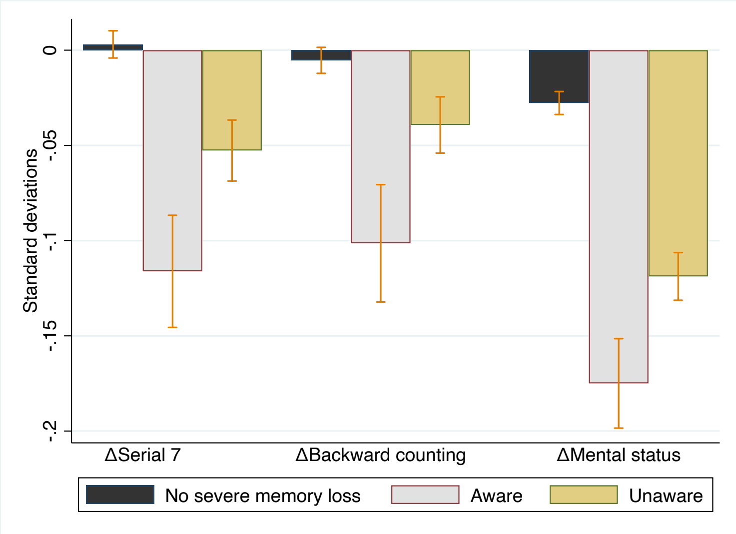
Notes: This table compares the estimates of the baseline model in equation (1) estimated using OLS (columns 1 and 3) and the same model with time invariant individual specific fixed effect (columns 2 and 4). The first two columns show the results for the full sample of financial respondents with at least two observations, while the last two columns restrict this sample to those above median wealth in the previous wave. All models include as regressors a quadratic age term, binary indicators for the survey years, labor force status, marital status and census division, a binary indicator for being "pessimist", plus wealth and memory score in the previous wave. The OLS specification also includes the following time-invariant regressors: binary indicators for high school degree and college, gender and race. Observations are weighted using the HRS respondent-level sample weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Table B.15: Changes in total and financial wealth: DiD model with time-invariant individual-specific fixed effects

	Total wealth		Financial wealth	
	(1)	(2)	(3)	(4)
Post	73.710	73.094	71.719	69.963
	(74.648)	(74.427)	(72.346)	(72.154)
Unaware×Post	-89.904	-92.553	-83.667	-83.962
	(66.735)	(66.408)	(63.399)	(63.102)
Obs.	38283	28510	38283	28510
N	12210	9037	12210	9037
Mean W	392.871	387.623	101.412	100.716
Mean ΔWW	-7.327	-9.780	-5.830	-8.362

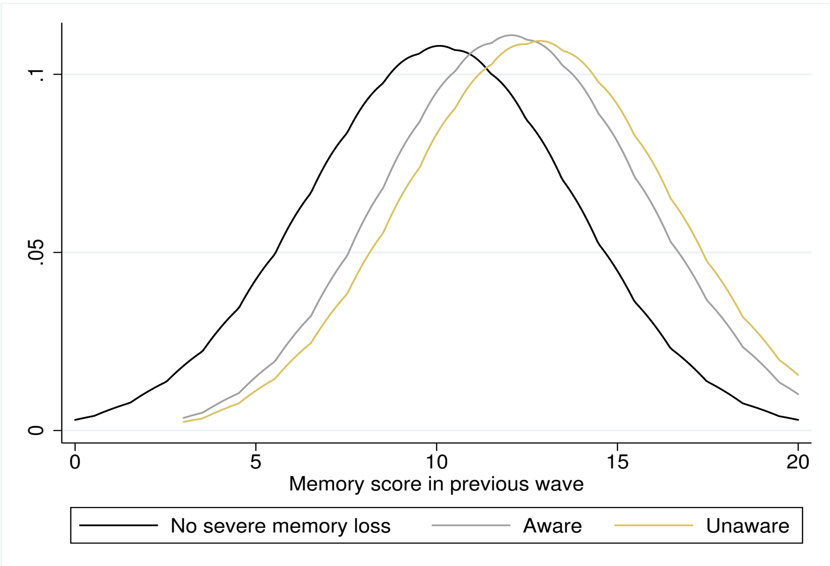
Notes: The table shows fixed effects estimates of various versions of model (2) for the changes in total and financial wealth (in thousands U.S. dollars at 2014 prices) around the first severe memory loss event (from event time -2 to 2). Columns (1) and (3) show the results for the full sample (including those without any severe memory loss), while Columns (2) and (4) show the results for the restricted sample that only includes those who experienced a severe memory loss events. All models include as regressors a quadratic age term, binary indicators for the survey years, a linear control in event time, time-varying socio-demographic controls (labor force status, marital status, and census division), plus wealth and memory score in the previous wave. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level. Significance levels: *** $p < .01$, ** $.01 \leq p < .05$, * $.05 \leq p < .10$.

Figure B.1: Memory loss and other cognitive measures



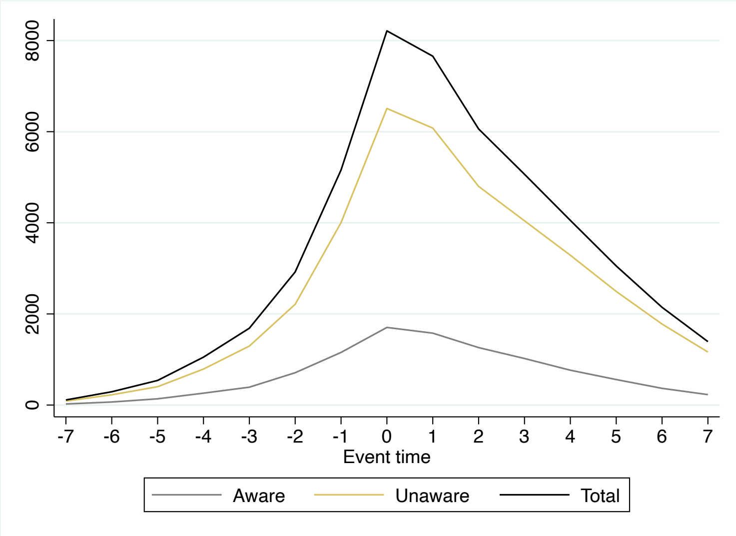
Notes: The figure shows the average standardize changes (from $t-1$ to t) in three HRS cognitive tests (serial 7, backward counting test, and mental status) for respondents who did not experience a severe memory loss (black bar), respondents who had a severe memory loss and were aware (gray bar), or unaware (sand bar) of it. For each type of respondents, we also report the corresponding 95% confidence interval. Observations are weighted using the HRS respondent-level weights.

Figure B.2: Density of the memory score in the previous wave



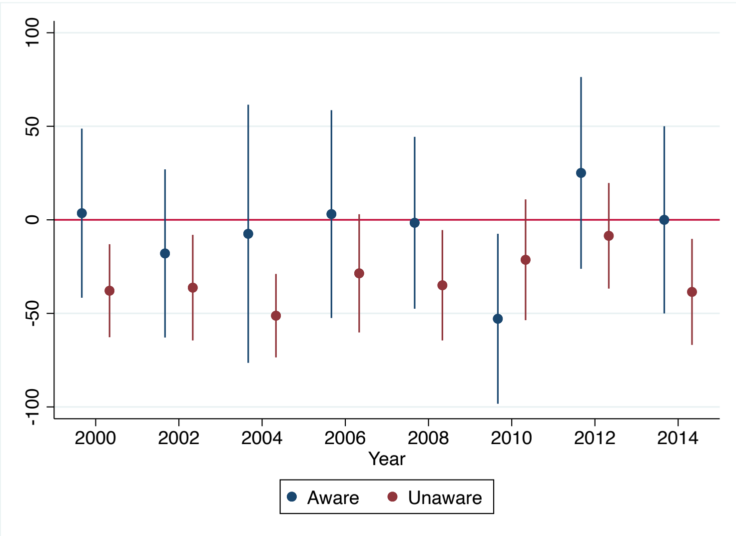
Notes: This figure compares the density of the memory score in the previous waves for respondents who did not experience a severe memory loss (black curve), respondents who had a severe memory loss and were aware (gray curve) or unaware (sand curve) of it. Densities are estimated using the Epanechnikov kernel with a bandwidth of 2. Observations are weighted using the HRS respondent-level weights.

Figure B.3: Number of observations by event time and awareness of severe memory loss



Notes: The figure shows the number of observations by event time for respondents who were aware or unaware of their first severe memory loss event (event time 0).

Figure B.4: Estimated wealth changes by survey year



Notes: The figure reports the estimated heterogeneity across adjacent survey waves in the effect of being aware (blue dots) and unaware (red dots) on wealth changes. The effects are estimated using Model (1) as in Table 3 augmented with a full set of interaction terms between the indicators for being aware and unaware and the survey year indicators. For each coefficient, we report the 95% confidence interval constructed using robust standard errors clustered at the household level. Observations are weighted using the HRS respondent-level weights.