Are Older People Aware of Their Cognitive Decline? Misperception and Financial Decision-Making

Fabrizio Mazzonna

Università della Svizzera Italiana

Franco Peracchi

Einaudi Institute for Economics and Finance and Università di Roma Tor Vergata

We investigate whether older people correctly perceive their cognitive decline and the potential financial consequences of misperception. First, we show that older people tend to underestimate their cognitive decline. We then show that those experiencing a severe decline but unaware of it are more likely to suffer wealth losses. 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.

I. 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

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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 issue is becoming increasingly 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 health care systems—and to rely more on private providers that require much higher decision-making skills. For instance, the pension landscape in the United States and many other countries has changed dramatically in the past three decades, with a major shift away from defined benefit systems toward defined contribution systems (Poterba, Venti, and Wise 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, Clark, and Lusardi 2021), with important 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, Maurer, and Mitchell 2018; Egan, Matvos, and Seru 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, Howe, and Huston 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 because of a high level of self-confidence (von Gaudecker 2015; Kim, Maurer, and Mitchell 2018).

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In this paper, we use data from the Health and Retirement Study (HRS), a representative panel of the US population aged 50 and older, to explore the relationships between self-ratings of memory changes, actual 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 self-respondents aged 50–80. 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), though 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. First, we show that older people are often unaware of their cognitive decline, even when severe. Unawareness has so far been investigated only in particular settings (e.g., retirement communities) focusing on very old people affected by severe cognitive impairment (see, e.g., Gamble et al. 2015). Second, we analyze the financial consequences of this underestimation and show that older people who are unaware of their severe memory loss are more likely to suffer large wealth losses (negative wealth changes between adjacent survey waves) relative to otherwise similar people who either are aware or did 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 in the real value of financial wealth—equal on average to about 10% of initial financial wealth—and are much larger among respondents who were active on the stock market in the previous years.

To provide a more convincing causal interpretation of our findings, we investigate the dynamics around the first severe memory loss event by estimating difference-in-differences (DiD) and event study models of wealth changes that focus on the different wealth profiles of aware and unaware respondents. We show that being unaware of own severe memory loss 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 static baseline 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 depends on only the initial portfolio composition of each household and exogenous stock market fluctuations. Although our measure strongly predicts wealth changes, it does not appear to 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 are either inactive on the stock market or 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, overestimation of own performance in tasks requiring particular abilities. 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 as well as assets such as jewelry, collections, and so on suggests that money or 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 observe only the results of financial decisions, not how they were made.

To explore alternative interpretations of our findings, we ask whether differences in health or other personal characteristics might provide an explanation. For example, if the unaware have lower subjective life expectancy, they might optimally decide to disinvest more, which would explain their different wealth profiles. In fact, their self-reported physical health is on average better, and their self-assessed life expectancy is on average not lower than the aware. For them, the standard life cycle model would predict smaller disinvestment, the opposite of what we observe. We also find no systematic differences between the aware and the unaware 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 systematic differences between the aware and the unaware in portfolio composition or differential misreporting of wealth.

Our paper speaks to a growing literature on the determinants of the large wealth dispersion observed in the United States and other developed economies (for a review, see Campbell 2016), especially around the age of retirement. While earlier works focus on cross-sectional heterogeneity in saving rates (Dynan, Skinner, and Zeldes 2004) or risk aversion (Calvet, Campbell, and Sodini 2009), recently attention has been devoted to heterogeneity in the rates of returns (Fagereng et al. 2016), possibly arising from differences in financial knowledge (Lusardi, Michaud, and Mitchell

2017). We contribute to this line of research by proposing yet another channel that may affect wealth dispersion at older ages, 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 joint relations 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 precommitment to financial delegation in case of failure of some financial "driver's license" test.

The remainder of this paper is organized as follows. Section II reviews the literature on cognitive aging and decision-making. Section III introduces our data and presents some descriptive statistics. Section IV outlines our modeling strategy. Section V presents our empirical results and discusses some alternative interpretations. Section VI concludes. Appendix A (apps. A and B are available online) provides more detail on key features of the HRS and includes summary information on financial returns during the period considered, while the tables and figures in appendix B examine the robustness of our results.

II. Cognitive Aging and Decision-Making

Cognitive ability is the power 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 age, their cognitive ability tends to deteriorate, albeit with large differences across individuals in both the nature and the sources of cognitive decline (see, e.g., 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 functioning 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, and diseases/conditions that affect blood flow in the brain.

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 performance on new tasks and is characterized by a steady decline over one's adult life, starting already from age 20. Crystallized intelligence—which consists of the knowledge and experience acquired during 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 functioning is assumed to be hump shaped, with a peak reached around age 50 (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 (for a review, see Carpenter and Yoon 2011) 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 the 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, Maurer, and Mitchell 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 (for a review, see Dohmen et al. 2018) 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, Rydzewska, and Sedek 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, Jappelli, and Padula (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, Nicholas, Langa, and Bynum (2021) find that AD/ADRD are associated with bad financial outcomes not only after clinical diagnosis but also well before.

Lusardi, Michaud, and Mitchell (2017) present a life cycle model that provides a simple conceptual framework for understanding the effect of awareness of cognitive decline on financial decision-making. In the simplest version of their model, consumers maximize lifetime 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 distinguishing 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.

III. 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.

A. The HRS

The HRS (HRS 2014) is a household panel survey that collects rich and detailed information on nationally representative samples of the US population aged 50 and older.[1] Considered jointly with the Study of Assets and

[1] The HRS is sponsored by the National Institute on Aging (grant NIA U01AG009740) and is conducted by the University of Michigan.

Health Dynamics (AHEAD), the survey was fielded annually from 1992 to 1996 and has been fielded biennially in even-numbered years from its redesign in 1998. We mostly use the RAND HRS Longitudinal File (RAND 2016), 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 imputations of missing values. This file has been employed extensively in the economic literature because of consistency and comparability across waves. Some relevant variables that are not included in the RAND HRS Longitudinal File have been taken directly from the relevant HRS modules. We confine attention to the nine survey waves from 1998 to 2014. For more details, see appendix section A.1.

Our main working sample includes all self-respondents aged 50–80 with nonmissing 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 keep only self-respondents and drop proxy interviews because they do not contain direct assessments of memory performance. We also drop people older than age 80 to limit potential selection issues arising from institutionalization and mortality. Since wealth is measured at the household level, for each household we consider only the financial respondent, namely, the member designated to answer all household-level financial questions. Smith, McArdle, and Willis (2010) argue that the financial respondent is the most knowledgeable person about household finances and the chief financial decision maker. We apply some additional sample selection criteria when we estimate a DiD model around the first severe memory loss event (sec. IV.B).

The robustness checks in section V.D also employ data from the HRS CAMS, a paper-and-pencil survey fielded biennially in odd-numbered years from 2001. For more details, see appendix section A.2.

B. Self-Rated and Assessed Memory

The HRS asks participants to self-rate their memory at the time of the survey 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, one of the most important dimensions of fluid intelligence (McArdle, Fisher, and Kadlec 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 participants 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 participants are also asked to compare their current memory level to that in the previous interview (about 2 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) and then asks the participant to recall as many words as possible from the list in any order. The participants 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.[2] 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 (-0.27), as many respondents actually improve their score from one wave to the next.[3]

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 those 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 1 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 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.[4] This corresponds to the lowest quartile of the

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

[3] This partly reflects retesting effects (Salthouse, Schroeder, and Ferrer 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.

[4] As argued by Dohmen et al. (2018), word recall tests capture memory performance only 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

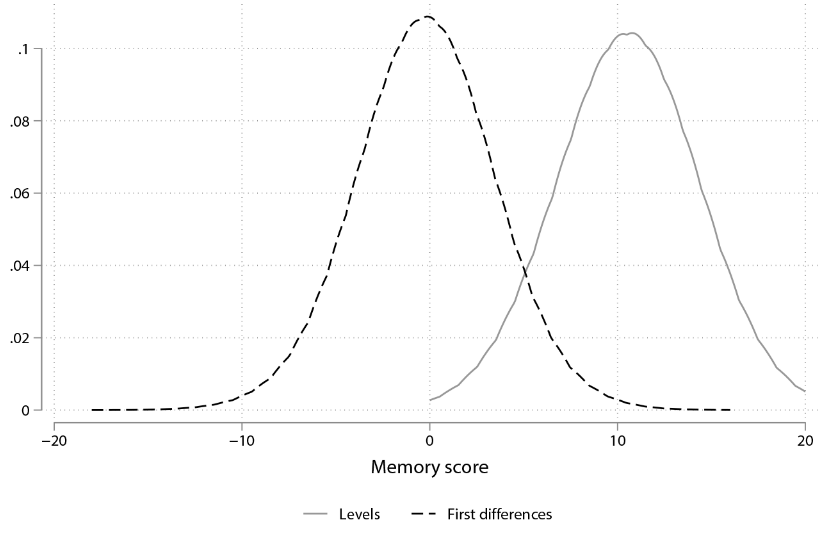

Fig. 1.—Density of memory scores in levels and first differences. The figure shows univariate kernel estimates of the density of total memory score in levels and first differences (Epanechnikov kernel with a bandwidth of 2).

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 our sample units experience at least one severe memory loss event during the observation window. However, since we exclude proxy responses and people older than age 80, these events are generally much milder than those investigated by Hsu and Willis (2013) and associated with AD/ADRD.

In fact, our definition captures cognitive decline that occurs at a relatively early age (age 67 on average), with the first severe memory loss occurring even earlier (at age 64 on average). Table B1 (tables B1–B19 are available online) shows the distribution of respondents by the number of severe memory loss events they experience. About 40% of them experience no severe memory loss event, another 40% experience only one, about 15% experience exactly two, and less than 5% experience three 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

play an important role. This is even more important when changes in memory scores are considered.

TABLE 1
SELF-RATED VERSUS ASSESSED MEMORY

Self-Rated Memory Change	No	Yes	Total
	A. Severe Relative Memory Loss		
Better now	.020	.006	.026
About the same	.590	.181	.771
Worse now	.148	.056	.204
Total	.757	.243	1.00
	B. Severe Absolute Memory Loss		
Better now	.021	.006	.026
About the same	.600	.171	.771
Worse now	.153	.050	.204
Total	.773	.227	1.00

NOTE.—The table compares self-rated memory changes across waves with two different measures of memory loss: severe relative memory loss (panel A), defined as a decline of 20% or more in the memory score, and severe absolute memory loss (panel B), defined as a memory score change of 1 standard deviation or more.

(77% of those with a relative decline of 20% or more and 80.5% of those with an absolute decline of 1 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 B2 presents the transition rates between these four states from one survey wave to the next. Among those without a severe memory loss over the past 2 years (no loss and pessimists), about 28% experience a severe memory loss over the next 2-year window. This chance falls to about 8.6% for those with a severe memory loss over the past 2 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 IV.B 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 B1 (figs. A1 and B1–B4 are available online) 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 show little variability, are asked only in a few waves, or are asked only to people aged 65 and older. Smith, McArdle, and Willis (2010) document a strong association between recall and numeracy tests, wealth levels, and portfolio holdings using HRS data. Weak or no association was instead found for the other cognitive tests in the 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 (fig. 3) often among people with high initial cognitive capital. Further, even when we can construct measures of change on the basis of some of the other available measures, we do not have a self-assessed counterpart, which makes it impossible to explore the role of awareness.

C. *Household Wealth*

The HRS collects detailed information on household wealth and the value of specific wealth components (financial wealth, individual retirement accounts [IRAs], 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 (total wealth) and total household financial wealth (financial wealth) and their changes over time during the period considered.[5]

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 financial respondents are asked to verify or correct the asset values reported in the previous and the current waves when there is a large discrepancy between them (more than $50,000 for single assets or $150,000 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 of about 50% in the variance of the change in total wealth across waves.

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

[5] The net value of 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 US dollars using the consumer price index as deflator. The net value of 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; certificates of deposit (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. IRAs are considered separately and are not included. For more details, see app. sec. A.1.

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

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 are imputed. To limit the impact of outliers, we also trim all observations with total wealth below the first 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%) report zero or negative values.

For each HRS respondent, we predict financial wealth in the following wave by combining the HRS information on the composition of household financial wealth by asset category in each wave with monthly information on average market returns by asset category (see app. sec. A.3 for more details on these data). Specifically, consider respondent i who is interviewed in month t and reinterviewed 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.

D. *Descriptive Statistics*

This section presents simple descriptive statistics for our working 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.

Table 2 presents summary statistics on the key variables used in this paper separately for all financial respondents (full sample) and the financial respondents with at least one severe memory loss event (loss sample).

Figure 2 compares the age profiles of three memory indexes: the average assessed memory score, the average of self-ratings of own memory, and the share of respondents who self-rate their memory as at least good

TABLE 2
Means and Standard Deviations (SDs) of Key Variables

	Full Sample			Loss Sample		
	N	Mean	SD	N	Mean	SD
ΔWealth_t	57,148	−14.517	670.301	13,882	−18.704	412.776
Wealth_{t-1}	57,148	393.370	886.495	13,882	362.287	687.084
Aware	57,148	.056	.230	13,882	.230	.421
Unaware	57,148	.187	.390	13,882	.770	.421
Pessimist	57,148	.148	.355	13,882	.000	.000
Memory score_{t-1}	57,148	10.430	3.260	13,882	11.654	3.240
Age	57,148	66.448	7.359	13,882	67.305	7.415
Female	57,148	.553	.497	13,882	.545	.498
Single	57,148	.460	.498	13,882	.482	.500
High school degree	57,148	.513	.500	13,882	.514	.500
College degree	57,148	.269	.444	13,882	.230	.421
Working_{t-1}	57,148	.362	.481	13,882	.314	.464
Black	57,148	.177	.382	13,882	.201	.401
Other race	57,148	.057	.231	13,882	.063	.243

Note.—The table reports descriptive statistics on the main variables for two samples: all financial respondents (full sample) and the financial respondents with at least one severe memory loss event (loss sample). Observations are weighted using the HRS respondent-level weights.

(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 centered 3-year moving average. All three indexes tend to decline with age, but the profile of the memory score is much steeper than the profiles of the two self-rated indexes. 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 the aware and the unaware. The two distributions have a mean slightly below age 65 and are bimodal, with the larger peak around age 58 and the smaller one around age 75. Interestingly, the larger peak is higher and occurs 1 year earlier for the unaware, while the smaller peak occurs at the same age for both groups but is higher for the aware. Figure B2 compares the distribution of the memory score in the previous wave for those with a severe memory loss (aware or unaware) and those without and shows that the first distribution is a right-shifted version of the second and the shift to the right is slightly bigger for the unaware.

Table 3 examines whether we can predict a severe memory loss event and, conditional on occurrence, unawareness of it. The table shows the estimated marginal effects from probit models for the probability of experiencing a severe relative memory loss (cols. 1–3) and the probability of being unaware conditional on a severe memory loss (cols. 4–6). In both

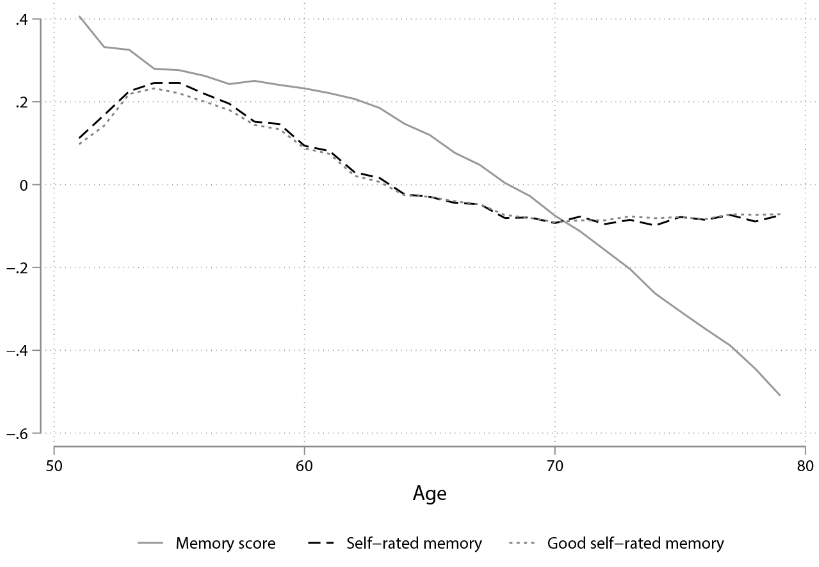

FIG. 2.—Assessed versus self-rated memory by age. The figure presents the average age profile of three indexes: the total score in the immediate and delayed recall tasks (gray line), the self-rated memory score (dashed line), and the share of respondents rating their memory as excellent, very good, or good (dotted line). 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.

cases, we initially control for only basic sociodemographic 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 (cols. 1, 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 (cols. 2, 5). Finally, we also include the last available numeracy score (cols. 3, 6).

We find that 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 conditions) in the previous wave are more

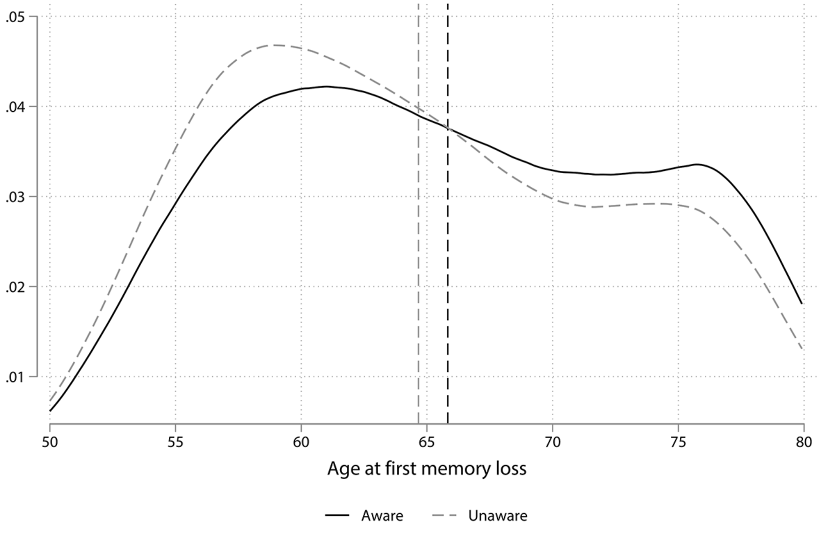

FIG. 3.—Age when first severe memory loss occurs: aware versus unaware respondents. The figure compares the density of the age at which individuals experience their first memory loss event for aware and unaware respondents. The dashed vertical lines correspond to the group mean. The age densities are based on Epanechnikov kernel density estimations with a bandwidth of 2.

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.

IV. 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 awareness. We present two models: a basic model for expected wealth changes across adjacent survey waves as a function of change-in-memory status (sec. IV.A) and a 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 (sec. IV.B).

TABLE 3
Probit Estimates of 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)
Number of serious health conditions		.011***	.012***		−.037***	−.038***
		(.002)	(.003)		(.005)	(.005)
Numeracy score			−.045***			−.010
			(.003)			(.006)
Observations	81,818	81,818	57,922	19,737	19,737	13,976
N	22,573	22,573	19,132	13,699	13,699	10,808
Mean	.241	.241	.241	.773	.773	.763

Note.—The table shows marginal effects from probit models for the probability of experiencing a severe memory loss (cols. 1–3) and the probability of being unaware conditional on experiencing a severe relative memory loss (cols. 4–6). The models in cols. 1 and 4 include as regressors sociodemographic controls, binary indicators for the survey year (not reported), and the memory score in the previous wave. The models in cols. 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 cols. 3 and 6 also include the most recent numeracy score available before survey year t. Because of 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.

* $.05 \leq p < .10$.
** $.01 \leq p < .05$.
*** $p < .01$.

A. The Basic Model

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

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

where $\Delta W_{it} = W_{it} - W_{i,t-1}$ is the change in real wealth (total, financial, or subcomponents; US\$1,000s in 2014 prices) of individual i between survey wave $t - 1$ and t;[6] Aware_{it}, Unaware_{it}, and Pessimist_{it} are binary indicators for being aware, unaware, or pessimist in wave t (as defined in sec. III.B); $\boldsymbol{X}_i$ is a vector of time-invariant regressors that includes binary indicators for sex, race, and 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 the β_j are unknown coefficients to be estimated. 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 be 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 three important implications. First, the intercept β_0 is interpreted as the expected wealth change for a randomly chosen individual in the baseline state (no loss). Second, 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. This difference is our coefficient of primary interest. Whether it may 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. Third, 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 V.D we consider two other model specifications. One replaces the binary indicator for severe memory loss with

[6] 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 V.D shows that results do not change much when we instead use differences in logs for respondents with positive wealth levels.

linear and nonlinear terms in memory score changes 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 just in wealth levels.

B. 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 (never treated).[7] The preperiod and postperiod are individual specific, and in order to have a direct mapping with model (1), the never treated are included only in the preperiod.

Specifically, we estimate the following model:

$$\begin{aligned}\Delta W_{it} = \gamma_0 + \gamma_1 \text{Aware}_i + \gamma_2 \text{Unaware}_i + \gamma_3 \text{Post}_{it} + \gamma_4 \text{Post}_{it} \\ \times \text{Unaware}_i + \gamma_5^\top \boldsymbol{X}_i + \gamma_6^\top \boldsymbol{Z}_{it} + \psi_t + V_{it},\end{aligned} \tag{2}$$

where ΔW_{it} is again the change in real wealth, Aware_i (Unaware_i) is now a binary indicator equal to 1 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 1 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 the γ_j are unknown coefficients to be estimated. Our primary interest is in γ_4 (the DiD coefficient), which measures the expected wealth change after the first severe memory loss event for two individuals 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.

We further extend our analysis to an event study (or multiperiod 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 B3 shows that the sample size shrinks fast when moving further away from the first memory

[7] We no longer distinguish between no loss and pessimists because, as shown in sec. V.A, the two categories are indistinguishable from each other.

loss event, especially backward. This problem affects both the aware and the unaware but is particularly severe 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 pretrend, 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.

V. Results

In section V.A, 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 DiD model (2). We then discuss alternative interpretations of our empirical findings (secs. V.B, V.C) and present a number of robustness checks (sec. V.D).

A. Memory Loss Awareness and Wealth Changes

Table 4 presents the results from the first-difference model (1). Column 1 is for a restricted version of the model that includes only 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 an 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. Columns 3 and 4 of the table focus on those who experience a severe memory loss and compare our financial respondents (col. 3) with the non–financial respondents excluded from our working sample (col. 4). They show that wealth losses for the unaware are statistically different from zero and quantitatively large (over $20,000) 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 5 presents the results for the DiD model (2) separately for total and financial wealth and for two samples, one including all financial

TABLE 4
CHANGES IN TOTAL WEALTH

	FINANCIAL RESPONDENTS		RESPONDENTS WITH SEVERE MEMORY LOSS	
			Financial Respondents	Non–Financial Respondents
	(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)		
Observations	57,148	57,148	13,882	6,302
N	16,270	16,270	9,694	4,558
Mean W	378.85	378.85	343.58	478.57
Mean ΔW	−11.826	−11.826	−18.677	−15.442

NOTE.—The table shows OLS estimates of various versions of model (1) for the changes in total wealth (US$1,000s in 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 (col. 3) and non–financial respondents (col. 4). All models include as regressors a quadratic age term, binary indicators for the survey years, sociodemographic 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.

** $.01 \le p < .05$.

*** $p < .01$.

respondents and the other including only those with a severe memory loss. Starting with total wealth (cols. 1, 2), the estimated DiD coefficient (the coefficient on Unaware × Post) is large and statistically significant. Point estimates are similar in the two samples and amount to more than $50,000. Although not directly comparable, the size of the drop is much larger than the estimated effect from model (1), 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 4. 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

TABLE 5
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)
Observations	40,284	29,606	40,284	29,606
N	14,872	10,498	14,872	10,498
Mean W	391.212	386.775	101.163	100.656
Mean ΔW	−10.596	−14.421	−7.643	−10.701

NOTE.—The table shows OLS estimates of various versions of model (2) for the changes in total and financial wealth (US$1,000s in 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 cols. 2 and 4 show the results for the restricted sample that includes only 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, sociodemographic 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.

* $.05 \leq p < .10$.

** $.01 \leq p < .05$.

(fig. 4*A*, 4*C*) and for the unaware relative to the aware (fig. 4*B*, 4*D*). To represent 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 −$23,000) is comparable to the estimates in table 4, and there is no evidence of anticipation effects. When we compare the unaware with the aware, the estimated wealth loss is larger and continues after the first severe memory loss event. However, estimates are very noisy because of the reduced sample size as we move away from the memory loss event. Because of the loss of precision when estimating the DiD model, we henceforth focus on extensions of our basic specification (1).

Table 6 presents the results of fitting the first-difference model (1) 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

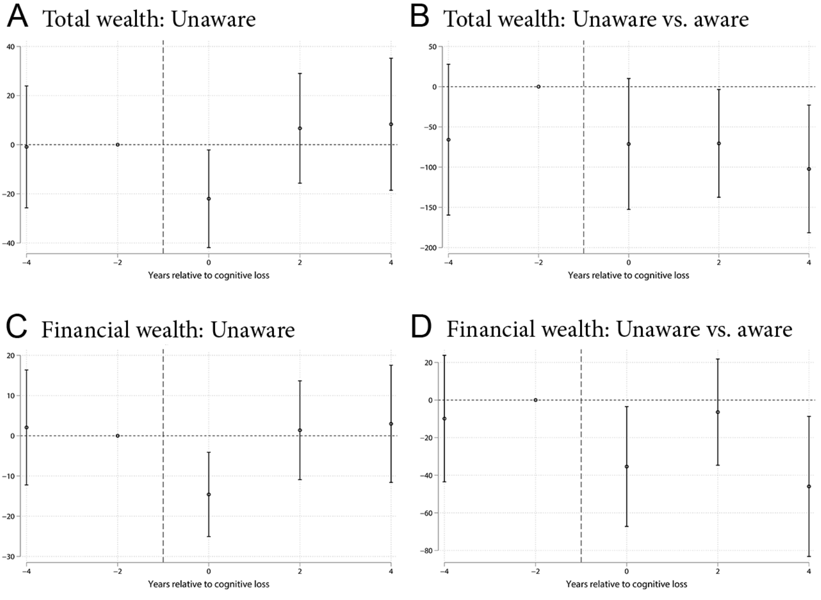

Fig. 4.—Event study coefficients for unaware respondents. The figure shows the estimated wealth changes (US$1,000s in 2014 prices) and the associated 95% confidence intervals with respect to the period immediately before the first severe memory loss event for unaware respondents. *A* and *B* show results for total wealth, and *C* and *D* show results for financial wealth. *A* and *C* show the estimated event study coefficients using only the unaware respondents (and including the never treated at event time −1), while *B* and *D* show the DiD coefficients relative to the aware respondents.

the wealth distribution. Furthermore, the mean difference $\beta_2 - \beta_1$ between the unaware and the aware is statistically significant and economically meaningful only for wealthier respondents (about 9% of mean wealth). Table B3 shows that wealth losses mainly involve respondents who are still employed or below age 70 and therefore likely to still be saving for retirement, while table B4 shows that the average wealth losses of the unaware relative to the aware are much bigger for males than for females. These gender differences match those estimated by Barber and Odean (2001)—who also 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 respondents at the top along with the higher probability of being unaware among males (table 3). Finally, figure B4 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.

TABLE 6
Changes in Total Wealth by Wealth Quartile in Previous Wave

	Quartile			
	First (1)	Second (2)	Third (3)	Fourth (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)
Observations	14,133	14,292	14,313	14,410
N	5,923	6,229	6,127	4,911
Mean W	20.302	104.52	306.37	1,074.6
Mean ΔW	22.214	17.506	30.243	−103.16

Note.—All models include as regressors a quadratic age term, binary indicators for the survey years, sociodemographic 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.

** $.01 \leq p < .05$.

*** $p < .01$.

B. *Potential Mechanisms*

In section V.A, 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, in table 7 we compare the results obtained by fitting model (1) to total wealth changes (col. 1, which repeats col. 2 in table 4) with those obtained by fitting the model separately to changes in the net value of six broad wealth categories (cols. 2–7), namely, financial wealth, IRAs,[8] 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%. Notice, however, that the mean difference $\beta_2 - \beta_1$ between the unaware and the aware is statistically different from zero and large in an economic sense (more than \$15,000) only for financial wealth.

Table 8 presents the results of fitting model (1) to financial wealth changes separately for people with and without positive financial wealth

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

TABLE 7
Changes in Value of Wealth Components

	Total (1)	Financial (2)	IRAs (3)	Housing (4)	Real Estate (5)	Business (6)	Transport (7)
Aware	−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)
Observations	57,148	57,148	57,148	57,148	57,148	57,148	57,148
N	16,270	16,270	16,270	16,270	16,270	16,270	16,270
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

Note.—All models include as regressors a quadratic age term, binary indicators for the survey years, sociodemographic 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.

* $.05 \le p < .10$.
** $.01 \le p < .05$.
*** $p < .01$.

TABLE 8
Changes in Financial Wealth by Financial Wealth Ownership and Quartile of Financial Wealth in Previous Wave

	No Financial Wealth (1)	Positive Financial Wealth (2)	Quartile of Financial Wealth: Third (3)	Quartile of Financial Wealth: Fourth (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)
Observations	17,385	39,763	14,279	14,410
N	8,028	12,989	6,871	5,498
Mean W	2.484	137.180	50.607	319.770
Mean ΔW	14.068	−14.292	21.082	−65.952

Note.—All models include as regressors a quadratic age term, binary indicators for the survey years, sociodemographic 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.

** $.01 \le p < .05$.
*** $p < .01$.

in the previous wave (cols. 1, 2) and for respondents in the third and fourth quartiles of the distribution of financial wealth (cols. 3, 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. 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 9 focuses on this particular group. Column 1 shows that about 55% of the mean loss in financial wealth for the unaware (which, from col. 2 of table 8, is equal to about US$25,000 in 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 (cols. 2, 3, 5). We instead observe hardly any changes in the value of private bonds and bond funds (col. 4) and in the value of financial debt other than mortgages and home loans (col. 6).

Our results reveal two facts: first, wealth losses are concentrated among financial respondents who are wealthier but unaware of their cognitive decline; second, the losses mainly involve financial assets. We have already seen that respondents who experience a severe memory loss show better cognitive performance at baseline (table 3) 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 cognitive decline. 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 past 2 years.[9] Table 10 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 past 2 years (col. 1).[10] Losses are also observed among unaware respondents who were inactive (col. 2) or did not own stocks (col. 3), but these losses are much smaller in both absolute and relative terms than they are for unaware respondents who were active. Moreover, the difference between the aware and the unaware is large and statically significant only for those active in the stock market.

[9] Namely, whether they sold or bought stocks or mutual funds shares, including automatic reinvestment. The high frequency of bracketed responses and of item nonresponse to questions on the amount of stocks sold or bought does not allow us to calculate meaningful monetary amounts for these financial transactions.

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

TABLE 9

Changes in Value of Financial Wealth Components for Respondents with Positive Financial Wealth in Previous Wave

	Stocks (1)	Checking/Savings (2)	CDs/Government Bonds (3)	Private Bonds (4)	Other Assets (5)	Debt (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)
Observations	39,763	39,763	39,763	39,763	39,763	39,763
N	12,989	12,989	12,989	12,989	12,989	12,989
Mean	65.768	15.763	34.028	8.9568	15.655	2.9949
Mean Δ	−7.6151	−.60191	−.92878	−.68369	−3.2889	1.1739

Note.—All models include as regressors a quadratic age term, binary indicators for the survey years, sociodemographic 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.

* $.05 \le p < .10$.

** $.01 \le p < .05$.

*** $p < .01$.

TABLE 10
Changes in Financial Wealth by Stock Market Activity

	Active (1)	Inactive (2)	No Stocks (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)
Observations	5,504	7,433	44,211
N	2,918	4,101	14,465
Mean W	342.73	167.39	53.542
Mean ΔW	−11.297	−17.691	−3.5716

Note.—All models include as regressors a quadratic age term, binary indicators for the survey years, sociodemographic 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 past 2 years. Observations are weighted using the HRS respondent-level weights. We use robust standard errors clustered at the household level.

** $.01 \le p < .05$.

*** $p < .01$.

The HRS data do not allow us to distinguish wealth losses due to bad financial investments from those due to financial frauds or scams. We observe only 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 (e.g., jewelry, collections), reported in table 9 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.

C. *Alternative Interpretations*

The evidence reported so far is consistent with an interpretation in terms of bad financial decisions. However, since we do not observe financial decisions, we cannot a priori exclude alternative interpretations that stress differences between the aware and the unaware in terms of observable or unobservable characteristics. In what follows, we review the available evidence for these alternative interpretations.

1. Reverse Causality

Financial losses may put individuals under severe stress and lead them to perform poorly in the word recall tests. This interpretation would be consistent with the evidence in Schwandt (2018) that exogenous wealth shocks may negatively affect health via increasing stress. We perform two different exercises that lead us to exclude this interpretation.

First, as in Schwandt (2018), we employ an arguably exogenous measure of wealth shock, constructed in the way described in section III.C, by capitalizing the value of each asset category owned in the previous wave by its average market return across waves. Reassuringly, columns 1 and 2 of table 11 show that this measure is unrelated to 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—columns 3–5 of table 11 show that it does not substantially alter our estimates when included in equation (1) as an additional regressor.

Second, in the appendix (table B5), we evaluate the stress channel and the role of socioemotional skills 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

TABLE 11
Actual and Predicted Wealth Changes, Cognitive Decline, and Awareness

	Memory Loss (1)	Unaware (2)	Actual Δ Wealth (3)	Actual Δ Wealth (4)	Actual Δ Wealth (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)
Observations	57,148	13,882	57,148	57,148	57,148
N	16,270	9,694	16,270	16,270	16,270
Mean	.243	.770	378.85	378.85	378.85
Mean Δ			−11.826	−11.826	−11.826

Note.—The dependent variable is a binary indicator for experiencing a severe memory loss (col. 1), a binary indicator for being unaware conditional on experiencing a severe memory loss (col. 2), and the change in total wealth (US$1,000s in 2014 prices; cols. 3–5). All models include as regressors a quadratic age term, binary indicators for the survey years, sociodemographic 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.

* $.05 \le p < .10$.

** $.01 \le p < .05$.

*** $p < .01$.

money.[11] We find no evidence that the aware are better off relative to the unaware. If anything, they are more likely to be depressed, are less satisfied with their life, and have more difficulties managing their money than the unaware.

2. Rational Disinvestment

Another hypothesis is that the negative wealth changes observed for unaware respondents reflect rational disinvestment for reasons such as shorter life horizon and higher health expenditures.

To investigate whether memory losses are associated with changes in subjective life expectancy, columns 1 and 2 of table 12 regress changes in subjective life expectancy on the occurrence of a severe memory loss using a specification similar to model (1) for wealth changes.[12] 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 3 that the aware are less healthy than the unaware.

As for health expenditures, columns 3 and 4 of table 12 show no evidence that a severe memory loss is associated with statistically significant changes in out-of-pocket medical expenditure for the aware or the unaware. Additionally, table B6 shows that the results from model (1) hardly change if we exclude respondents who experience a new severe health issue (including hospitalization) in the past 12 months. This allows us to reject another interpretation, namely, that people unaware of their cognitive decline face higher medical expenses that negatively affect their wealth profile.

Table B7 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 the aware and the unaware. All these findings provide no evidence for the rational disinvestment hypothesis.

We also find no evidence of an association between severe memory losses and increased financial transfers to children in either their probability or the expected total amount when they occur (table B8). These findings allow us to reject yet another interpretation, namely, that the respondent's children—noting her severe memory decline—anticipate bequests.

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

[12] 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.

TABLE 12
CHANGES IN SUBJECTIVE LIFE EXPECTANCY AND OUT-OF-POCKET MEDICAL EXPENDITURE

	SUBJECTIVE LIFE EXPECTANCY		OUT-OF-POCKET EXPENDITURE	
	(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)
Observations	44,979	44,979	49,919	49,919
N	13,992	13,992	15,593	15,593
Mean	48.533	48.533	3.1952	3.195
Mean Δ	−.944	−.943	−.254	−.254

NOTE.—The dependent variable is the change in the self-assessed probability of living for 10 years or more (cols. 1, 2) and the change in out-of-pocket medical expenditure (US$1,000s in 2014 prices; cols. 3, 4). All models include as regressors a quadratic age term, binary indicators for the survey years, sociodemographic 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.
* $.05 \leq p < .10$.
** $.01 \leq p < .05$.

3. Differences in Portfolios

If cognitive decline is correctly perceived, it should induce changes in preferences (risk aversion or time discount) and lead to a reallocation of the portfolio away from risky assets. Although the HRS does not contain information on changes in preferences,[13] it does provide information on portfolio changes. Table 13 uses this information to investigate whether respondents with a severe memory loss alter their portfolio composition 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 on the extensive or the intensive margin or by position in the wealth distribution.

We also investigate whether observed differences in wealth changes reflect differences in the initial portfolio composition leading to lower returns. Table B9 presents estimates of model (1), where the outcome

[13] The HRS asks hypothetical gamble questions to a small random sample of the respondents in each wave, but these questions are about the level of risk aversion or time discount at a point in time, not about their changes over time, possibly in response to cognitive decline.

TABLE 13
CHANGES 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	−.001
	(.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)
Observations	57,148	28,574	14,193	12,250
N	16,270	8,881	5,386	4,564
Mean	.260	.42871	.439	.561
Mean Δ	−.013	−.024	.123	.098
Third to fourth quartile wealth	No	Yes	No	Yes

NOTE.—The dependent variable is the change in the binary indicator for owning risky financial asset (cols. 1, 2) and the change in the share of financial wealth invested in risky financial asset conditional on ownership (cols. 3, 4). All models include as regressors a quadratic age term, binary indicators for the survey years, sociodemographic 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.

on the left-hand side is the difference between one's financial wealth in a given wave and the financial wealth predicted by capitalizing the value of each asset category owned in the previous wave by its average market return, as described in section III.C. The table presents separate estimates for the sample of all respondents with positive financial wealth (cols. 1, 2) and the subsample with a severe memory loss (cols. 3, 4). The results show that even when we take into account the composition of financial portfolios, unaware respondents do worse than the other respondents. Again, the largest difference is found for the wealthier respondents.

4. Misreporting and Measurement Error

After a severe memory loss, people may find it hard to remember the value of their assets, which may cause large measurement errors in wealth changes. A key issue here is whether this problem affects aware and unaware respondents differently. Addressing this issue would require linking the HRS to actual financial statements. Nonetheless, the results in the appendix (table B10) provide no indication that the unaware are characterized by higher levels of financial wealth imputation or, when we restrict 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 the aware and the unaware. Since a high level of misreporting would be needed to explain the observed difference in wealth changes between the two groups, 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 measurement error in wealth changes (see, e.g., Hill 2006). Finally, columns 4 and 5 of table B6 show that our results hardly change when we exclude respondents with a higher risk of cognitive impairment (as in Herzog and Wallace 1997) and who are therefore more likely to forget their assets.

D. Robustness Checks

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

To account for right skewness of the wealth distribution and for the presence of a few large outliers, in table B11 we show 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 V.A, 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 B12 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 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 parsimonious way this nonlinear relation.

Another concern is that people with a severe memory loss may experience further losses of which they need not be aware. This implies that they may switch between different change-in-memory states from one wave

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

[15] Compared with table 4, 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.

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 over the period they are observed, and when they experience more than one, only a quarter of them switch between states. It is reassuring that if we estimate model (1) excluding those who are unaware, aware, or pessimist in the previous wave (table B13), results are very similar to those reported in table 4. 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.

To enhance our causal interpretation, on the basis of the assumption of selection on observables, we further exploit the richness of the HRS and examine how our results change when we control for the additional information on individual genetic endowments available for a subset of the respondents. Following Barth, Papageorge, and Thom (2020) and Papageorge and Thom (2020), we focus on three specific measures of genetic variation, namely, the polygenic scores associated with education, cognition, and Alzheimer disease (more details are provided in app. sec. A.4). Table B14 shows the results from a version of model (1) that includes the three polygenic scores as additional covariates. As common in this literature, we restrict the analysis to individuals of European ancestry. Compared with the baseline (table 4), estimated wealth losses for the unaware are larger, as individuals of European ancestry are more likely to be in the upper tail of the wealth distribution.

Tables B15 and B16 confirm the robustness of our results to the inclusion of time-invariant individual-specific effects. Point estimates are qualitatively similar to the ordinary least squares (OLS) estimates—a little smaller for model (1) and a little larger for the DiD model (2)—but less precise. This is unsurprising, as the estimates are obtained by taking differences of noisy wealth differences.

Finally, we consider a different form of robustness by looking at some important decisions other than financial wealth—namely, doctor visits for preventive health care and vaccinations; health, life, and long-term care insurance coverage; and other health behaviors—using the same specification as model (1). The results are presented in tables B17–B19. They reveal a pattern that is broadly consistent with our main findings in this paper. Consider, for example, table B17. It shows that unaware people are significantly less likely to see doctors for most preventive checks, though the difference with respect to the aware is statistically significant for only cholesterol checks because of the reduced sample size. This behavior is consistent with the unaware self-reporting a better health status (tables 3, 12).

VI. Conclusions

Using data from the HRS, a large representative panel of Americans aged 50 and older, 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 with those who are aware or do not experience a severe decline. We investigate alternative interpretations of our results that stress potential 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 evidence leaves little support for interpretations based on rational disinvestment and is consistent with our proposed explanation, namely, that unaware respondents are more likely to make bad financial decisions or to be the victims of financial frauds. However, because of the lack of experimental evidence, we cannot rule out the presence of unobservable factors correlated with both awareness and wealth changes. Moreover, the fact that we do not observe the actual financial decisions but only their consequences limits our ability to pin down the underlying mechanisms.

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 investors and cover topics that are relevant for making good financial decisions later in life.

Our results do not imply that older people should be prevented from making independent financial 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, preventive measures such as medical tests in yearly medical checkups along with the assessments of decision-making skills. Designing these assessments—which amount to a sequence of financial driver's license tests—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 stricter regulation and, given the currently high price of annuities, more competition. Finally, regulators should consider stepping up measures aimed at preventing fraud against the elderly.

Data Availability

Code replicating the tables and figures in this article as well as information about the proprietary data used can be found in Mazzonna and Peracchi

(2024) in the Harvard Dataverse, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/IBIQU0.

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