Thinking, Fast and Slow:

How Response Times Can Predict Cognitive Decline and (Bad) Financial Decision-Making at Older Ages

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PRELIMINARY VERSION

Abstract

This study investigates the potential of response times (RT) as a predictor of cognitive decline, leveraging previously untapped data from the Survey of Health, Ageing, and Retirement in Europe (SHARE). Recorded automatically during Computer-Assisted Personal Interviews (CAPI), RTs offer a unique opportunity to study cognitive and decision-making processes without added respondent burden. Building on Sanders et al. (2017), we show that slower RTs are associated with lower cognitive scores, higher rates of cognitive decline, and increased mortality. Our analysis extends these findings by showing that RT predicts health decline in several dimensions, including functional health, chronic disease, mental health, and mobility limitations.

Furthermore, we show that the predictive power of RTs goes beyond the health domain as they also predict future wealth decline, particularly in individuals unaware of their cognitive deterioration, a category shown to be at risk of "bad" financial decision-making in Mazzonna and Peracchi (2024).

Our study highlights how the ability to extract meaningful insights from existing survey infrastructure at no additional cost makes RTs a powerful and practical tool for understanding cognitive and financial trajectories in aging populations.

JEL codes:.

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1 Introduction

Traditional cognitive assessments focus on accuracy or the number of correct responses, but an increasingly important dimension of cognitive performance is the speed of decision-making. Neuroscience research has demonstrated the value of the time needed to solve cognitive challenges, i.e. response times (RT), in assessing cognitive functioning. Seminal work in Psychology and Neuroscience have introduced (Ratcliff, 1978; Smith, 2000) a framework for modeling how individuals accumulate information over time when making binary choices, such as yes/no decisions. This model captures the cognitive process by which individuals gather and evaluate evidence until they reach a decision threshold, with the time taken to make the decision (response time) providing insights into the complexity and difficulty of the task. This literature highlights how response times can be predictive of cognitive performance (in levels) and the potential for RT to act as an early marker of pathological cognitive changes, offering a simple yet powerful measure of cognitive health.

Moreover, a key strength of using RT lies in its ability to detect subtle cognitive changes that may not be immediately evident in traditional cognitive tests, which typically focus on accuracy. Declines in processing speed are often the earliest signs of cognitive impairment, preceding noticeable deficits in memory, reasoning, or verbal fluency. Ratcliff et al. (2010) analyzed the effects of aging on decision-making using response times: older adults tend to have slower response times but that these changes can be explained by strategic shifts in how information is accumulated, rather than just a decline in cognitive function. This paper is crucial in showing how RT can help distinguish between normal cognitive aging and pathological decline.

Neuroscientific studies have thus paved the way for applying RT in population surveys, offering a bridge between lab-based cognitive neuroscience and real-world applications.

Following Sanders et al. (2017), we build on these insights from neuroscience and investigate the potential of RT data as a predictor of cognitive *decline* in a large, longitudinal population survey, i.e., SHARE (Survey of Health, Ageing, and Retirement in Europe). Unlike many prior studies, which are limited by small sample sizes or rely on controlled laboratory environments, we utilize response time data gathered as a natural (and free) by-product of Computer-Assisted Personal Interviewing (CAPI) systems, which is automatically generated during the data collection process, recording time stamps for each question asked during the survey, without imposing additional burdens on respondents or researchers. This allows us to examine whether the speed at which participants answer cognitive tasks is predictive of their cognitive performance both at the time of the survey and in future waves. This approach - pioneered by Sanders et al. (2017) using the National Social, Health and Aging Project (NSHAP)-represents a significant methodological advance, as it leverages large-scale, population-representative data rather than controlled, laboratory-based tasks that often do not reflect real-world cognitive functioning.

We first replicate Sanders et al. (2017) using the eighth and ninth waves of the SHARE data, which feature an

extended "Cognitive Functioning" module with respect to the first seven waves. Our findings confirm theirs, i.e. we find a robust correlation between slower RTs and both lower cognitive scores and higher rates of cognitive decline, and a higher likelihood of mortality between survey waves. These results persist even after accounting for potential confounding factors through the inclusion of interviewer fixed effects, ensuring that the observed relationships are robust to variations in survey administration. Importantly, we also control for participants' current cognitive scores, demonstrating that RT provides additional predictive power beyond what can be explained by baseline cognitive ability alone. This strengthens the case for using RT as a complementary measure in large-scale surveys aimed at tracking cognitive decline over time. It also demonstrates that RT data can serve as a valuable tool for predicting cognitive decline in older adults, even when collected outside a controlled laboratory environment.

In addition to supporting the findings of Sanders et al. (2017), our study extends their analysis by exploring the predictive capacity of RT for a broader range of health outcomes. Specifically, we show that response times from the cognitive module are predictive not only of future cognitive scores but also of various dimensions of future health, including functional health (as measured by activities of daily living, or ADLs), chronic disease incidence, mental health, and mobility limitations. This suggests that RT may serve as a general marker of physiological aging, with slower RTs indicating a decline not only in cognitive function but also in overall physical health. By demonstrating that RT is associated with multiple health domains, our findings highlight the versatility of RT as a predictive tool, with potential applications in identifying individuals at risk for a range of adverse health outcomes.

Moreover, we extend the scope of the analysis beyond health outcomes to explore the relationship between cognitive RTs and financial well-being. Banks et al. (2010) and Smith et al. (2010) find wealth trajectories to differ between high and low-cognition older individuals. One of the novel contributions of our study is to answer the question of whether slower RTs are predictive of future wealth trajectories. We find that individuals with slower response times in the cognitive module are more likely to experience a decline in wealth in subsequent survey waves. Notably, this relationship is particularly pronounced among individuals whose cognitive health deteriorates without their awareness, echoing the novel findings from Mazzonna and Peracchi (2024) regarding the financial vulnerability of cognitively impaired individuals who are not aware of their cognitive decline. This suggests that RT data may help identify older adults who are at heightened risk of making poor financial decisions, potentially due to undiagnosed cognitive decline. In sum, our study adds to the growing body of evidence that response time data, when properly contextualized and analyzed, can provide valuable insights into both cognitive and financial health trajectories in aging populations. As cognitive aging becomes a critical issue in public health, leveraging RT as a predictive tool for cognitive decline holds significant promise, especially in the context of population-based studies that may not have the resources for more elaborate neuropsychological testing.

2 The informational content of Response Times

Seminal work in Psychology and Neuroscience has introduced the Drift Diffusion Model (DDM) (Ratcliff, 1978) as a framework for modeling how individuals accumulate information over time when making binary choices, such as yes/no decisions. This model captures the cognitive process by which individuals gather and evaluate evidence until they reach a decision threshold, with the time taken to make the decision (response time) providing insights into the complexity and difficulty of the task. Smith (2000) extended this work by refining the mathematical foundations of the DDM and applying it to a broader range of cognitive tasks. Both papers highlight how response times can be predictive of cognitive performance and decision-making efficiency, offering a tool for examining the underlying neural mechanisms of cognition.

Ratcliff and Rouder (1998) further developed the DDM, applying it to recognition memory tasks. They demonstrated that response times, alongside accuracy, provide a more complete understanding of cognitive performance. Their work helped validate the DDM across different cognitive domains, highlighting the model's broad applicability. Ratcliff et al. (2010) analyzed the effects of aging on decision-making and showed that older adults tend to have slower response times, but these changes reflect strategic adjustments in information accumulation rather than just a decline in cognitive function. This distinction is crucial in differentiating normal cognitive aging from pathological decline.

More recently, as put forward in Clithero (2018), there has been a growing interest in exploring the usefulness of response time data for economic analysis. Liu and Netzer (2023) demonstrate that response times in survey data can be used to address identification issues in ordered response models, leveraging the chronometric effect, i.e. the idea that response speed reflects the strength of an underlying latent variable. Their findings show that response times contain valuable information about latent traits, reinforcing their utility in measuring cognitive processes more precisely.

Closer to our study, Mazzonna and Peracchi (2012) used response times by leveraging keystroke files from the first two waves of SHARE to measure processing speed, which they already considered as a potential additional dimension of cognitive ability. They argued that aging is associated with a decrease in the speed at which cognitive operations are executed and used response times to capture this aspect of cognitive deterioration. Specifically, they incorporated the time taken to answer cognitive test questions, such as orientation in time and word recall, to construct adjusted cognitive scores that combine accuracy with response speed.

This approach aligns well with our study, which further explores response times as an informative signal in cognitive assessments. By integrating response times into models predicting cognitive decline and related outcomes, we build on this framework and extend the analysis beyond cognitive performance levels to examine their predictive power for longer-term outcomes.

Given the increasing interest in using response times for cognitive evaluations, this study contributes to a growing literature that views response times as a valuable source of information, complementing traditional cognitive measures,

with the potential to enhance existing cognitive metrics and offer additional predictive power for aging and economic outcomes.

3 The Predictive Power of Cognition

Most of the literature in Economics using measures of cognition, cognitive functioning, and cognitive decline has looked at cognition as an outcome variable, for instance when investigating the causal effect of retirement on cognitive functioning (see Rohwedder and Willis (2010); Bonsang et al. (2012); Mazzonna and Peracchi (2017); Celidoni et al. (2017)), or the impact of early life conditions on later-life cognition (Case and Paxson (2009)). Here we shift our focus to cognition as a predictor, exploring its role in anticipating significant life outcomes such as health, mortality, and financial decision-making.

Measures of recall memory, which capture the ability to learn and retrieve information, have been shown to be particularly powerful in this regard. Recall memory tests, such as the immediate and delayed recall tasks used in the SHARE survey, ask respondents to learn a list of ten common words and then reproduce them immediately (immediate recall) and again after a short delay (delayed recall). These measures are strongly associated with the onset of dementia, as highlighted by Celidoni et al. (2017), who demonstrate that a decline of more than 20% in recall scores between survey waves is a robust indicator of pathological cognitive impairments. This finding is further supported by validation efforts using clinical assessments of dementia in the HRS (Health and Retirement Study), which confirm the predictive accuracy of this measure. Beyond dementia, key domains of cognitive functioning (memory, executive function, and processing speed) have been shown to correlate strongly with broader health-related outcomes, including increased risks of mortality from cancer, cardiovascular and respiratory diseases (Batty et al. (2016)), suggesting that cognitive test scores can provide relatively simple indicators of the risk of death from a variety of chronic diseases, independently of other commonly assessed risk factors.

The predictive power of cognition extends beyond health, influencing financial and economic outcomes. Smith et al. (2010) demonstrate the role of numeracy, i.e. numerical ability, measured as the number of correct answers out of three mathematical computations, in predicting household wealth. They show that higher numeracy levels—especially among the financial decision-makers (embodied by the survey's "financial respondent") in households—are strongly correlated with greater wealth holdings. Banks et al. (2010) build on this by showing that cognitive abilities impact not only current wealth levels but also trajectories over time. Their findings underscore the role of cognition in enabling better financial decisions and wealth accumulation, even among those with modest initial wealth levels.

Adding complexity to this narrative, Mazzonna and Peracchi (2024) explore the role of respondents'level of awareness regarding their cognitive decline. They find that individuals who are unaware of their cognitive deterioration are significantly more likely to experience wealth losses, primarily due to suboptimal financial decisions. These losses are

particularly pronounced among wealthier individuals who actively manage their finances. Their findings suggest that cognitive decline—and the lack of awareness thereof—can undermine financial stability, even among those who were previously effective decision-makers.

An emerging frontier in this research is the use of response times (RTs) as a complementary measure of cognitive functioning. Using NSHAP, (Sanders et al., 2017) have shown that slower RTs, indicative of a decreased cognitive processing speed, are predictive of a higher rate of cognitive decline and even of a higher mortality.

Our study seeks to enrich this nascent literature by incorporating response time along with cognitive scores in predictive models of health and financial outcomes.

4 Data and Descriptive Analysis

4.1 SHARE

This study relies on data from the Survey of Health, Ageing and Retirement in Europe (SHARE), a large-scale, multi-country survey conducted across 28 European countries. SHARE collects detailed information on respondents' demographic characteristics, health, labor force status, household composition, and financial status. The survey targets individuals aged 50 and older who reside in participating countries and speak the respective country's language. Each wave includes both a longitudinal sample and new respondents, allowing for comprehensive tracking of aging populations. In cases where a respondent has passed away, SHARE also conducts end-of-life interviews with a close relative or partner.

For our analysis, we utilize data from SHARE's eighth and ninth waves, fielded between 2019 and 2022, and in which an extended cognitive module was introduced for the first time. We were also granted access to the time stamp data, recorded automatically during computer-aided personal interviews (CAPI), for these two waves. This time stamp data captures the time that respondents take to answer individual questions, providing a rich source of information for studying cognitive and decision-making processes, for the first time in SHARE.

4.2 Sample selection

Our sample is made of individuals aged 60 and over whose baseline interview occurred before Wave 8 since this is the subsample that was targeted by the extended cognition module. On top of that we add the restriction that these individuals must be re-interviewed in Wave 9, since our models use information at Wave 8 to predict changes between Waves 8 and 9.

In order to minimize biases stemming from hospitalizations and mortality, we also limit the sample to self-respondents under the age of 80 (see Mazzonna and Peracchi (2024)). We exclude proxy interviews because although

a cognitive module aimed at proxies about the cognitive health of the respondent was implemented at wave 8, this does not include the tests needed to compute our cognitive measures. The same goes for respondents with missing values in any of those tests scores at wave 8 (and in the recall test score at wave 9 when investigating memory loss across waves).

For the wealth analysis, since wealth variables are asked to only one respondent of a household, we keep only one observation per household, the one corresponding to the individual chosen by the household as "the one most able to answer questions about [their] finances?', labeled as "financial respondent", and whose numeracy skills seem to matter more for wealth accumulation as shown in Smith et al. (2010).

4.3 Cognitive measures and their Time Stamps

Most of the literature on cognitive functioning using SHARE or its sister studies, such as HRS or ELSA, has focused on episodic memory measures (mainly recall tests) when examining cognitive aging (see Celidoni et al. (2017)), or on numeracy (e.g., percentage computation tasks, as in Banks et al. (2010); Smith et al. (2010)) when investigating cognitive skills in later life, without necessarily addressing cognitive decline.

Discussions by Mazzonna and Peracchi (2012) and Mazzonna and Peracchi (2018) emphasize the dual role of episodic memory and numeracy in capturing fluid and crystallized intelligence. Fluid intelligence, representing basic information-processing mechanisms, begins to decline early in life and is closely tied to biological and physical factors, including processing speed (Horn and Cattell, 1967; Salthouse, 1985). Crystallized intelligence, on the other hand, reflects accumulated knowledge from education and life experiences. It continues to develop until midlife, typically around age 50, before stabilizing and gradually declining. According to Salthouse (1985), cognitive functions such as orientation, memory, fluency, and numeracy represent varying combinations of these two dimensions of intelligence, underscoring the importance of incorporating multiple cognitive domains in understanding cognitive aging.

Building on this framework, we adapt the Langa-Weir classification, originally developed for the HRS, to the newly extended cognitive module introduced in SHARE Wave 8. Two versions of the Langa-Weir classification exist: the Langa-Weir 36, which includes a broader range of cognitive tests, and the Langa-Weir 27, which excludes orientation and object naming items to maintain comparability across different age groups. We adopt the Langa-Weir 27 approach, which relies on memory (word recall), working memory (serial 7s substraction), and attention-processing speed (backwards counting), as these core domains have been validated against clinical diagnoses from the Aging, Demographics, and Memory Study (ADAMS). ADAMS, a sub-study of the HRS, provides a "gold standard" for assessing cognitive impairment and dementia through detailed neuropsychological evaluations. The Langa-Weir classification was developed to align with ADAMS using equipercentile equating methods, ensuring that cognitive classifications drawn from large-scale surveys reflect clinically meaningful classifications (see Crimmins et al. (2011)

for more details).

Thus, following Langa et al. (2020), we construct a 26-point cognitive functioning scale based on three tests:

A ten-word-list recall test: The respondent is asked to learn a list of ten common words (e.g., hotel, river, tree) and recall them in any order, first immediately and then after an interference period (delayed recall), approximately five minutes later. This component is computed as the sum of words remembered in both recalls (score range: 0 to 20), following prior studies (Rohwedder and Willis, 2010; Bonsang et al., 2012; Celidoni et al., 2017; Mazzonna and Peracchi, 2024). A serial subtraction test ("serial 7s"): The respondent subtracts 7 from 100 repeatedly for a total of five trials (score range: 0–5). A backwards counting test: The respondent is asked to count backwards from 20 to 10 as quickly as possible (1 point). This is where the 1-point different with the 27-point Langa-Weir comes from, as this task is only asked once in SHARE, starting from number 20 (it starts from numbers 20 and 86 in HRS).

Although the extended cognitive module in SHARE includes additional elements such as clock drawing, object naming, and orientation tasks, we exclude these measures in line with prior applications of the Langa-Weir 27 approach. As noted by Crimmins et al. (2011), these additional items were omitted in HRS for individuals under 65 years old to maintain consistency across age groups and to ensure that cognitive scores reflect core memory and processing abilities rather than broader knowledge-based assessments.

The Langa-Weir classification then maps onto the 26-point scale in the following way, as shown in Table 3: individuals are classified as "Normal" for scores between 12 and 26 (75% of our sample), "Cognitively Impaired but not Demented (CIND)" (19%) for scores between 7 and 11, and Demented (6%) for scores between 0 and 6.

We compute the total response time corresponding to the 26-point cognitive score by aggregating the time taken for the three cognitive tests, measured in seconds. If a respondent paused and resumed the backward counting task, we combine both time segments to obtain a complete measure. We expect this aggregated response time to provide an additional layer of information about cognitive function, beyond and above the final cognitive score itself.

While the relationship is not entirely monotonic, there is a significant gap between those with normal cognition, who exhibit the shortest response times, averaging 119.6 seconds, and both those in the Cognitively Impaired but Not Demented (CIND) category (128.0 seconds) and individuals classified as Demented (126.9 seconds). Furthermore, the standard deviation of response times increases as cognition worsens, suggesting greater heterogeneity in processing speed among individuals with cognitive impairment. This growing variability may reflect a broader range of cognitive deficits in impaired individuals, difficulties in task engagement or less willingness to put effort in the task. The combination of longer response times and increasing dispersion reinforces the idea that response time metrics can provide valuable complementary information to standard cognitive assessments. Figure 1 explores the relationship between response times and scores across different cognitive measures. The pattern is particularly clear for numeracy (serial 7s) and the counting backwards task, where shorter response times are strongly associated with higher scores. However, the relationship for recall scores is more complex, displaying an inverse U-shape: very short response times

can indicate either strong performance (many words remembered) or poor performance (few words recalled).

A similar pattern was observed by Sanders et al. (2017) in their analysis of MoCA-SA components within NSHAP. They found that response times decline monotonically for simpler tasks, such as recalling the date. However, for more demanding tasks like serial 7s, the pattern holds only for individuals scoring high on the MoCA-SA. Respondents with severe memory issues or limited numeracy often abandon the task quickly, leading to very short response times. In these cases, lower cognitive ability can be linked to faster response times, as individuals do not engage with the task at all.

Last, we follow Mazzonna and Peracchi (2024) in their definition of a cognitive decline awareness classification in the HRS. To do so, we first define whether an individual goes through a memory loss event between the two waves, i.e. if his/her recall measure (the total numbers of words recalled in both the immediate and delay recall) goes down by at least 20% from wave 8 to wave 9, a threshold that has been validated by important studies. Indeed, while there is no universally established threshold in the literature to define cognitive decline based on word recall, a 20% drop in recall performance has been shown to capture changes in cognition that fall within the bottom quarter of the distribution of memory score variations across survey waves (see Celidoni et al. (2017); Mazzonna and Peracchi (2024)). By discarding small changes, a 20% threshold helps mitigate measurement error, as small declines may not necessarily reflect true cognitive deterioration but rather random variation in test performance. Other studies in the neuropsychological literature have favored an alternative approach, e.g. defining severe memory loss as a decline exceeding one standard deviation (Nasreddine et al., 2005), which corresponds in our case to a drop of approximately three words. However, as noted in Mazzonna and Peracchi (2024), relying solely on an absolute threshold may understate cognitive decline for individuals who started with lower memory scores in the previous wave (floor effect). By using a relative definition—considering a 20% decline—we account for individual baseline differences, ensuring that cognitive deterioration is consistently captured across the distribution. Additionally, validation using data from the HRS-ADAMS sample, where clinical dementia assessments are available, indicates that a high decline in cognition aligns with a clinical dementia diagnosis in 70% of cases (see Celidoni et al. (2017) for the validation exercise). Figure 5 displays the estimated density of the word recall memory score in both levels and differences. Extremely similar to what Mazzonna and Peracchi (2024) shows with data from the HRS, the mean of the memory score is equal to 10, and the mean difference in the memory score between waves 8 and 9 is only slightly negative, suggesting many respondents actually improve their score from one wave to the next, which should happen in presence of "re-testing" effects, if respondents remember some words from one wave to the next, or simply get better at the test after learning how to take it.

The memory loss event is then interacted with respondents' self-reported perceptions of memory decline, i.e. a binary variable equal to 1 if the respondent reports worsening memory and 0 otherwise. This has only become possible in SHARE in the newly extended cognitive module introduced in Wave 8. The goal of the self-assessed

memory change item is to detect potential memory problems before clinical tests can detect them (see Bergmann and Börsch-Supan (2021) for more details about this new item in SHARE Wave 8). As put forward in Reid and MacLullich (2006), subjective memory complaints, if only inconsistently related to current cognition, seem to be more strongly related to future cognitive decline. This is especially true for people with high levels of cognitive abilities since these people would still score high on cognitive tests despite an onset of cognitive decline. They also correlate significantly with personality traits (neuroticism) and depression, which is why a special attention should be given to these two potential confounders, luckily also measured in SHARE. Table 11 shows how respondents rate their memory change since last wave, and how this translated into actual memory loss as measured by our 20% drop in memory score versus as measured by a 1-standard deviation drop in memory score. Amongst those who went through a severe memory loss episode since last wave, i.e. 26% according to the 20% drop threshold, (Panel A), and 12.6% according to the absolute threshold (Panel B), less than a third (roughly 30%) self-rate their memory as worse. This is not so far from the share of those who self-report their memory as worse while experiencing no severe memory loss episode (25%). [1]

We finally combine these two variables to define the following four categories of people: "No loss" individuals are those who suffered no cognitive decline and correctly assess the absence of memory loss; the "Pessimistic" are those who suffered no memory loss event but still assess their memory has worsened since the last wave; the remaining two categories went through memory loss, but one group of people is aware of it (the "Aware"), the other mistakenly believes their memory has not worsened (the "Unaware").

Figure 6 presents the distribution of the age at which individuals experience a severe memory loss, distinguishing between those who are aware and those who are unaware of their decline. While we could go back in time for panel respondents in order to identify the first occurrence of a severe memory loss episode, the awareness classification does not exist prior to Wave 8. We therefore show the distribution of age for those who experienced a severe loss between waves 8 and 9. The aware and unaware seem to differ in one aspect: the probability of going through a memory loss episode increases with age for the aware, but the same does not seem to apply to the unaware, amongst whom memory loss seems to strike at a younger age (between 60 and 70), and less so at older ages (past 75).

This classification will be at the core of the second part of the analysis on financial outcomes, the first part being centered on Cognitive and other Health outcomes.

4.4 Health and Wealth Outcomes

To explore the relationship between response times and health outcomes, we examine variables related to mental health, physical mobility, and chronic disease burden. Physical mobility is assessed through two measures: an indicator

[1] Same as in Mazzonna and Peracchi (2024), very little information is lost when collapsing the 3-item scale of this variable into a binary one, as only 1.17% declare their memory has become better since last wave.

variable for at least one activity of daily living (ADL) limitation and a continuous mobility scale ranging from 0 to 10, where 0 denotes no limitations. Chronic disease burden is measured as an indicator variable for having at least two chronic conditions, while mental health is proxied by the EURO-D depression scale, on a scale from 0 to 12, where 0 indicates no symptoms of depression. A comprehensive list of the items comprising these multi-item health indicators is provided in Table 1.

Our wealth variable, "net worth" is defined as the sum of net financial assets and real assets, i.e. $Net\ Worth = (hgfass–liab) + (home * perho/100 + vbus * sbus/100 + car + ores–mort)$, i.e. household gross financial assets $hgfass$ (sum of bank accounts, bond, stock and mutual funds, and savings for long-term investments), minus financial liabilities ($liab$), plus the value of residence (depending on the percentage of the house owned), the value of businesses (depending on the share of business owned), value of cars, and of other residences minus mortgages. To account for non-negligible rates of item non-response (higher for monetary variables than for the others), we use the imputations module for the wealth variable, which we then adjust for purchasing power parity (Germany 2015=1) to account for cross-country differences.[2]

5 Empirical strategy

5.1 Response Times, Cognitive Decline, and Health

To estimate the relationship between cognitive score and response times, we follow Sanders et al. (2017) and start with the following equation:

$$CogScore_i = \beta_0 + \beta_1 Time_i + \beta_2 X_i + \delta_k + \epsilon_i \tag{1}$$

where $CogScore_i$ denotes the 26-point cognitive score of respondent i at Wave 8, $Time_i$ stands for the respondent's standardized time response, and X_i is a set of individual control variables that include the standardized respondent's age (i.e. respondent's age deviated from the sample mean age), and a measure of being above or below the average time for every score item, referred to as "steady". The concept of "steady" in Sanders et al., 2017 refers to the consistency of response times across different cognitive test items. A respondent is considered "steady" if they answer all items in a relatively uniform amount of time, meaning that their response times for individual tasks do not deviate significantly from their own average response time.

This measure is constructed by checking whether a respondent's response time for each item remains within one standard deviation of their own mean response time across all tasks. If they consistently stay within this range, they

[2]See the SHARE Release Guide 9.0.0. for an explanation of the fully conditional specification (FCS) method used to compute imputed values.

are categorized as "steady." Sanders et al. (2017) finds that being "steady" is associated with higher cognitive test scores, suggesting that individuals who maintain a stable pace across cognitive tasks tend to perform better overall. In contrast, greater variability in response times may indicate cognitive difficulties or fluctuations in attention.

To account for the fact that interviewers with more experience may be assigned to participants with lower cognitive abilities, we also enrich the model with interviewer-fixed effects δ_k (*this equation is used to estimate Table 5*).

Since "steady" subjects tend to have lower response times and non-steady subjects are disproportionately found at the upper tail of the response time distribution (see Figures 2-4), we apply a reweighting procedure to balance the two groups. Specifically, we estimate a logistic regression where the dependent variable indicates whether an individual is in the steady group, and the independent variable is a cubic in response time. The predicted probability p_i from this model is then used to construct a weight: it equals 1 for steady individuals and $p_i(1 - p_i)$ for non-steady individuals. This adjustment ensures that the response time distribution of non-steady individuals aligns more closely with that of steady individuals, allowing for a fairer comparison. Table 6 presents results using this balanced sample, showing how they compare to the unweighted estimates in Table 5.

Next, to study how time response at Wave 8 predicts either the Cognitive Score, or an alternative health dimension, at Wave 9, we estimate the following equation:

$$Y_{i,t+1} = \alpha_0 + \alpha_1 Time_{it} + \alpha_2 X_{it} + \alpha_3 Y_{it} + \gamma_{kt} + \epsilon_{i,t+1} \tag{2}$$

where $Y_{i,t+1}$ is an outcome variable in wave 9 (e.g., cognitive score or health outcome), $Time_{it}$ is the response time in wave 8, X_{it} is a set of individual controls in wave 8 (same as described above), γ_{kt} denote interviewer fixed effects in wave 8. All controls are set at baseline i.e. at wave 8. Importantly, we control for the lagged outcome Y_{it}, i.e. either the cognitive score or another health variable, in wave 8, which is crucial for ensuring that the estimated effect of response time Z_{it} on future outcomes $Y_{i,t+1}$ is not confounded by pre-existing differences in cognitive ability or health status. Without this control, the coefficient α_1 on response time could capture the simple persistence of cognitive or health trajectories rather than the specific role of response time in predicting changes. Furthermore,if response time is correlated with past cognition or health (which is highly likely), failing to condition on Y_{it} would result in an over- or underestimation of α_1.

All Tables between 7-9 are based on this specification.

5.2 Response Times and Wealth Accumulation

Building on Banks et al. (2010) and Smith et al. (2010), in which wealth trajectories are shown to differ between low and high-cognition individuals, we turn to estimating how response times impact future wealth trajectories, using the

following equation:

$$\Delta W_{i,t} = \beta_0 + \beta_1 Time_{i,t} + \beta_2 X_i + \beta_3 Z_{it} + \psi_c + \epsilon_{i,t} \tag{3}$$

where the outcome $\Delta W_{i,t}$ is the difference in wealth from wave t to $t+1$. i.e. from 8 to wave 9, $Time_{i,t}$ is the response time corresponding to the 26-point cognitive score questions in wave 8, X_i is a set of time-invariant characteristics, such as sex and age, $Z_i t$ is a set of time-varying control variables such as age squared, labor force status, educational attainment, lagged wealth and the lagged 26-point score. ψ_c denote country fixed effects.

Finally, we introduce the degree of awareness of cognitive decline in the last specification, following Mazzonna and Peracchi (2024):

$$\Delta W_{i,t} = \beta_0 + \beta_1 Time_{i,t} + \beta_2 Aware_{it} + \beta_3 Unaware_{it} + \beta_4 Pessimist_{it} + \beta_5 X_i + \beta_6 Z_{it} + \psi_c + \epsilon_{i,t}$$

$Aware_{it}, Unaware_{it}, Pessimist_{it}$ are indicators for the corresponding perception of cognitive decline, the omitted category being "No cognitive decline". X_i is the same as before, and $Z_i t$ is the same as before, with the exception of the lagged numeracy score instead of the 26-point score. Table 13 presents the summary statistics of response times based on awareness classification. Notably, the largest difference in response times emerges between the Aware and Unaware groups, both of whom experienced severe memory loss, rather than between any other two categories. In contrast, individuals classified as "pessimistic" or "normal", neither of whom experienced severe memory loss, exhibit very similar response times across all tasks. This pattern raises an important question: To what extent do differences in response times between the Aware and Unaware groups reflect varying levels of cognitive decline rather than awareness itself?

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6 Results

6.1 Response Times, Cognitive Decline, and Health

Tables 5 and 6 estimate Equation 1. In both our analysis and that of Sanders et al. (2017), the key coefficient of interest is the effect of response time on cognitive performance. Across specifications, we find that longer response times are associated with significantly lower cognitive scores, confirming prior findings that processing speed is a strong predictor of cognitive ability.

To benchmark this effect, we compare it to the estimated impact of age on cognitive scores. Using the estimated coefficient of age (β_{age}) from Table 5 (column (2)) and the standard deviation of age (around 7.8 years) from Table

2, we calculate the predicted cognitive decline corresponding to one additional year of age as $\beta_{age} \times \text{sd}_{Age}$. We then compare this to the estimated effect of one standard deviation (i.e. around 38 seconds in the overall sample) response time on cognition (β_{RT}). The equivalent number of years of aging is then computed as follows:

$$\text{Equivalent years of aging} = \frac{\beta_{rt} \times \text{std}rt}{\beta age} \tag{4}$$

i.e. 2.3 additional years of age for a one standard deviation increase in response time.

In Sanders et al. (2017), a one standard deviation increase in response time was associated with a cognitive score reduction comparable to aging by approximately 6-7 years. Our results indicate a slightly weaker but still substantial effect, suggesting that response time is an equally powerful predictor of cognition as age, even when accounting for baseline cognitive ability.

One of the key differences between our results and those of Sanders et al. (2017) is the sign of the "steady" coefficient. While Sanders et al. (2017) found a positive relationship between being "steady" and cognitive scores, we find a negative relationship. This suggests that, in our data, individuals classified as steady actually perform worse in cognitive assessments, contrary to Sanders et al. (2017)'s findings.

A likely explanation for this discrepancy lies in differences between the cognitive tasks used in SHARE and NSHAP. Although both studies include recall and numeracy components, the cognitive module of NSHAP is broader and incorporates tasks that assess executive function and visuospatial abilities (drawing a clock or identifying a rhinoceros), which are used to construct the MoCA-SA score. In contrast, SHARE relies more heavily on episodic memory and numerical reasoning, including a longer 10-word recall test and arithmetic-based tasks like serial 7s. This difference in test structure and length may affect the way response times relate to cognitive ability across the two datasets.

Our results indicate that adding interviewer fixed effects (FE) does not substantially change the estimated relationship between response times and cognitive scores, suggesting that interviewer-specific pacing does not drive the observed correlation. However, including interviewer FEs reduces the absolute magnitude of the steady coefficient, aligning somewhat more with Sanders et al. (2017), who found that interviewer pacing influenced their steadiness measure, and our results suggest a similar but weaker effect.

Our Table 6, like Sanders et al. (2017)'s equivalent table, addresses the issue that non-steady respondents have a different response time distribution than steady ones. After restricting the sample to the common support and reweighting non-steady individuals, Sanders et al. (2017) found that the effect of steadiness weakened but remained positive. In contrast, our results still show a negative effect of steadiness even after reweighting, suggesting that it is not purely driven by response time distribution differences, but rather something deeper about how response consistency relates to cognition in SHARE.

We then estimate Equation 2, first predicting cognitive score at Wave 9 based on cognitive score at Wave 8 and response times at Wave 8. Again, response times seem to incorporate information about the cognitive status of the respondent that goes beyond that contained in the items producing the cognitive score at Wave 8: the estimates in 7 indicate that a 1 standard deviation increase in response time in Wave 8 (Z-time) is associated with a 0.19 to 0.20 point decline in cognitive functioning by Wave 9, consistently across specifications (Columns 1, 2, 4, and 5). This effect is comparable in magnitude to the cognitive decline associated with aging nearly two years (1.5 years based on column (5) estimates), highlighting the strong predictive power of response speed as an early marker of cognitive deterioration.

Furthermore, Column (3) estimates how the relationship between response time and cognitive decline varies by initial cognitive status. The interaction terms suggest that longer response times are particularly correlated with cognitive decline among individuals with Mild Cognitive Impairment (MCI) and Dementia in Wave 8. A one standard deviation increase in response time is associated with a 0.98-point drop for those with MCI and a 1.74-point decline for individuals classified as demented (column (6)). The effect, though significant, is smaller for those classified as cognitively normal, at approximately -0.36 points.

Additionally, the role of steadiness (i.e., variability in response time across items) appears to be a significant factor in cognitive decline. While greater steadiness is associated with better cognitive scores among normal individuals (Columns 3 and 6), lack of steadiness is especially predictive of cognitive decline among those with MCI, where it is associated with a 2.76 to 3.51-point drop in cognitive score. The effect is even stronger for demented individuals, where lower steadiness predicts an additional 6.41 to 8.00-point decline in cognitive functioning.

The next question we ask is whether response time in cognitive tests can serve as a meaningful predictor of future health outcomes, beyond standard cognitive measures. Cognitive impairment is widely recognized as a marker of physical decline and mortality, particularly when dementia is present (Nguyen et al., 2003; Sachs, 2009). Several studies have documented strong associations between cognitive decline and frailty, linking cognitive impairment to weight loss, weakness, exhaustion, slow walking speed, and reduced physical activity. Importantly, research suggests that cognition and frailty interact within a cycle of decline, where cognitive impairment increases the risk of frailty, and frailty, in turn, accelerates cognitive deterioration (Robertson et al., 2013). While frailty may mediate part of this relationship, Cano et al. (2012) find that cognitive impairment itself exerts an independent effect on mortality risk.

Given this evidence, we regress future health outcomes—including ADLs, IADLs, chronic disease burden, depression (EURO-D), and mobility limitations—on both cognitive functioning (Langa-Weir 26 score) and response time at the previous wave. If response times contain additional predictive information about cognitive function and its decline, they may serve as an early marker of physical deterioration, even before standard cognitive assessments detect impairment. By incorporating response time into our models, we aim to assess whether processing speed declines are an early signal of broader health deterioration, particularly within the frailty-cognition cycle in older adults. Table 9 estimates Equation 2 for those health outcomes. A comprehensive list of the items comprising these multi-item health

indicators is provided in Table 1.

Tables 10 and 11 examine the relationship between cognitive functioning, response time, and future health outcomes, controlling for age, interviewer fixed effects, and baseline cognitive function (Langa-Weir 26 score). This specification ensures that results reflect how cognitive ability and processing speed—beyond a person's baseline level—predict subsequent health deterioration.

Table 9 shows that slower response time is significantly associated with worsening health, particularly for IADLs, chronic diseases, depression, and mobility limitations. The strongest association is with mobility, suggesting that cognitive slowing may be an early indicator of frailty. However, response time is not significantly linked to ADLs, indicating that its effects may be more relevant for more complex functional tasks. Higher cognitive function is consistently protective across all health dimensions, with particularly strong effects on IADLs, depression, and mobility. The fact that these effects hold even after adjusting for baseline cognitive ability underscores the role of cognitive changes in shaping future health trajectories. As expected, age is a strong predictor of worse outcomes, especially for mobility.

Table 10 introduces an even more demanding specification by controlling for prior health outcomes, making it akin to a first-difference approach. Despite this stricter control, response time remains significantly associated with future IADL limitations, chronic disease burden, and depression, highlighting its role as an early warning sign of deteriorating health. However, the effect on mobility disappears, suggesting that the previous association was largely driven by individuals already experiencing mobility limitations. Cognitive function remains a robust predictor of future health, reinforcing the protective role of higher cognitive ability even after accounting for prior health. The effects of age are somewhat attenuated but still significant, particularly for IADLs, depression, and mobility decline.

The persistence of some associations in Table 11 is notable, as it suggests that cognitive processing speed and function have predictive power for future health beyond past health conditions. These findings reinforce the idea that response time in cognitive assessments may serve as an early biomarker of frailty and functional decline in aging populations.

6.2 Response Times and Wealth Accumulation

Examining the broader implications of cognitive decline beyond health, we begin by estimating Equation 3 to assess how severe memory loss between Waves 8 and 9 relates to changes in wealth (net worth accumulation or depletion), which is very similar to what Banks et al. (2010) and Smith et al. (2010) do, although we here focus on memory loss (instead of numeracy). Table 15 indicates that a higher baseline cognitive score is associated with greater wealth accumulation over this period. More notably, even after controlling for this initial cognitive score, slower response times at Wave 8 appear to be linked to a decline in wealth. While not consistently significant across all specifications, the neg-

ative association between response times and wealth accumulation—independent of cognitive scores—is particularly striking.

6.3 Do older people know about their cognitive decline? And how response times might help

In line with the findings from Mazzonna and Peracchi (2024) using the HRS, we find that both the aware and the unaware lose wealth from one wave to another, when compared to those who do not go through severe memory loss, but those who are unaware of their cognitive decline lose much more wealth than those who are aware of it (see Tables 16-18).

Since response times are also positively correlated with unawareness of cognitive decline, this metric—readily extractable from any survey incorporating cognitive functioning data—could serve as a valuable tool for identifying older individuals at heightened risk of wealth loss due to a cognitive decline they are unaware has already compromised their decision-making.

Table 14 replicates the main findings of Mazzonna and Peracchi (2024) using SHARE data. In columns 1 and 3, severe memory loss and awareness of it are measured through immediate and delayed recall tests, while columns 2 and 4 rely on the total 26-point cognitive score described in Langa et al. (2020). Consistent with Mazzonna and Peracchi (2024), we find that severe memory loss, as measured by immediate and delayed recall tests, is negatively associated with changes in net worth. Notably, financial respondents who are unaware of their cognitive decline experience even greater losses. Similar patterns emerge when severe memory loss and awareness are assessed using the total cognitive score.

Table 15 extends the previous specifications by incorporating lagged standardized time stamps. In this table, columns 1 and 2 measure severe memory loss and awareness based on recall scores, while column 3 relies on the total cognitive score. Column 1 considers the time stamp of recall tests, whereas columns 2 and 3 use the time stamp from all tests contributing to the 26-point score. The results indicate that recall time stamps alone do not predict changes in wealth. However, total time stamps exhibit a negative association with net worth changes, suggesting that broader cognitive processing speed, rather than recall-specific speed, plays a role in financial outcomes.

Tables 19-21 examine if lagged time stamps can predict awareness of cognitive decline. It seems that this is only the case when the cognitive loss is defined using all the items that are used in the 26-point score instead of the memory loss based on the recall test. In Table 21, response times at Wave 8 positively correlate with going through a severe cognitive decline and being unaware of it.

7 Conclusion

This study uncovers the significant yet previously overlooked potential of response times (RTs) as an indicator of cognitive decline and its broader socioeconomic consequences. Using large-scale survey data from SHARE, we demonstrate that response times, beyond capturing cognitive processing speed, provide valuable predictive insights into wealth accumulation and financial vulnerability among older individuals. Crucially, these effects persist even after controlling for cognitive test scores, suggesting that response times contain additional information that traditional cognitive measures fail to capture.

Our findings indicate three key patterns. First, slower response times at baseline are associated with a greater likelihood of experiencing severe cognitive decline in subsequent survey waves. Second, beyond their predictive power for cognitive deterioration, response times also correlate with negative wealth trajectories—individuals with slower RTs tend to de-accumulate wealth at a faster rate. Third, and most strikingly, response times are particularly relevant for identifying unaware cognitive decline: individuals whose financial decision-making is likely already impaired but who do not perceive themselves as experiencing cognitive difficulties. This suggests that RTs could serve as an early warning signal for financial vulnerability, particularly among older adults at risk of making suboptimal economic choices due to undetected cognitive impairment.

The implications of these results extend well beyond our specific empirical context. Because response times are automatically recorded in most large-scale surveys incorporating cognitive tests, they represent a cost-free, scalable, and non-intrusive tool for enhancing the predictive power of existing datasets. Their inclusion in empirical models can significantly improve our understanding of aging-related economic behaviors without requiring additional data collection efforts.

By transforming response times from a mere technical byproduct into a meaningful cognitive indicator, our study provides a valuable contribution to the fields of aging economics, cognitive health, and financial decision-making. It highlights the untapped potential of survey-based time stamps to identify at-risk individuals, inform policy interventions, and ultimately, improve economic well-being in aging populations.

Figure 1. Time Response and Performance at each Test

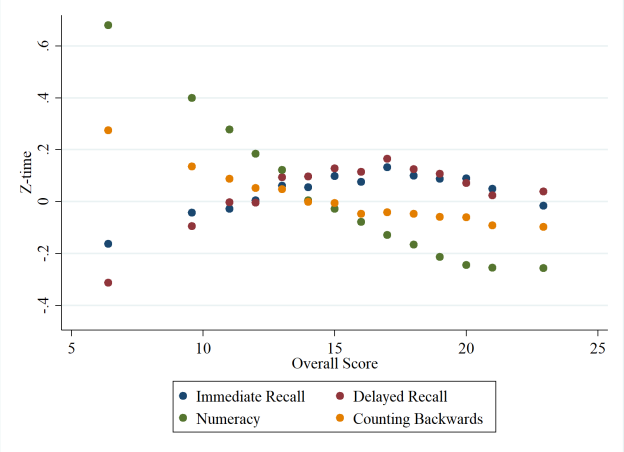


Figure 2. Wave 8 Response Time, Seconds

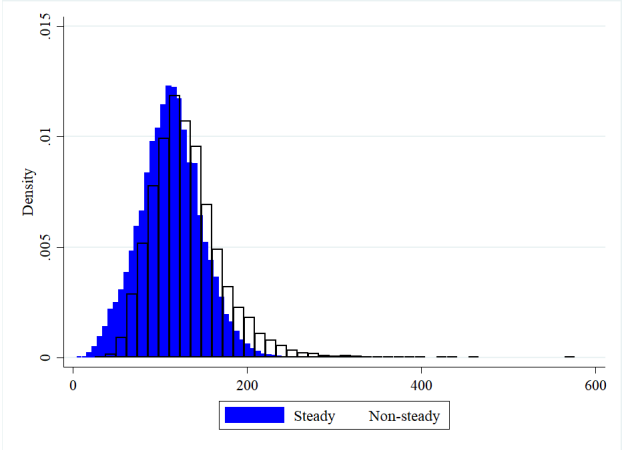


Figure 3. Wave 8 Response Time with Common Support, Seconds

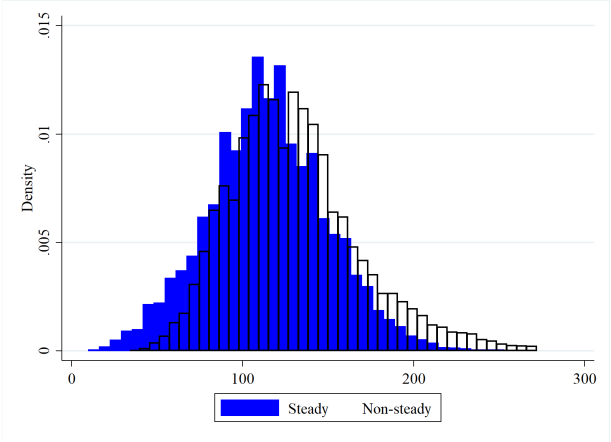


Figure 4. Wave 8 Weighted Response Time, Seconds

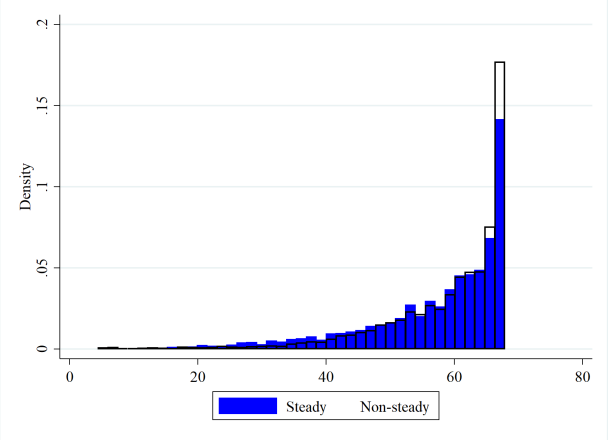


Table 1. Health Indicators Definitions

Indicator	Definition
ADLs (Activities of Daily Living)	Number of difficulties in: 1. Dressing, including putting on shoes and socks 2. Walking across a room 3. Bathing or showering 4. Eating, such as cutting up food 5. Getting in or out of bed 6. Using the toilet, including getting up or down
IADLs (Instrumental Activities of Daily Living)	Number of difficulties in: 1. Using a map to figure out how to get around in a strange place 2. Preparing a hot meal 3. Shopping for groceries 4. Making telephone calls 5. Taking medications 6. Doing work around the house or garden 7. Managing money (paying bills, tracking expenses) 8. Leaving the house independently and accessing transportation
Multimorbidity (2+ Chronic Diseases)	Indicator for having at least two of the following: 1. Heart attack, including myocardial infarction or coronary thrombosis 2. High blood pressure or hypertension 3. High blood cholesterol 4. Stroke or cerebral vascular disease 5. Diabetes or high blood sugar 6. Chronic lung disease (bronchitis, emphysema) 7. Cancer or malignant tumor (excluding minor skin cancers) 8. Stomach or duodenal ulcer, peptic ulcer 9. Parkinson's disease 10. Cataracts 11. Hip fracture 12. Other fractures 13. Alzheimer's disease, dementia, or other serious memory impairment 14. Other emotional disorders (e.g., anxiety, psychiatric issues) 15. Rheumatoid arthritis 16. Osteoarthritis or other rheumatic conditions
EURO-D Depression Scale (0-12)	Count of depressive symptoms: 1. Feelings of depression or sadness 2. Any hopes for the future 3. Would rather be dead 4. Feelings of guilt 5. Trouble sleeping 6. Less interest in things 7. Irritability 8. Loss of appetite 9. Fatigue 10. Trouble concentrating 11. No enjoyment 12. Tearfulness
Mobility Score (0-10)	Score based on number of limitations (10 = no limitations) in: 1. Walking 100 meters 2. Sitting for about two hours 3. Getting up from a chair after sitting for long periods 4. Climbing several flights of stairs without resting 5. Climbing one flight of stairs without resting 6. Stooping, kneeling, or crouching 7. Reaching or extending arms above shoulder level 8. Pulling or pushing large objects (e.g., living room chair) 9. Lifting or carrying weights over 5 kg (e.g., heavy grocery bag) 10. Picking up a small coin from a table

Table 2. Summary Statistics

	(1) Wave 8	(2) Wave 9	(3) Both
Female	0.561	0.565	0.563
	(0.496)	(0.496)	(0.496)
Age	72.151	72.067	72.101
	(7.810)	(7.784)	(7.794)
Observations	28,242	41,075	69,317

Notes: The data come from SHARE. The dependent variable is cognitive score and the variable of interest is the standardized time needed to answer the questions. The regression controls for the respondent's age.

Table 3. Descriptive Statistics for the Score, Langa-Weir Classification

	Mean	St. Dev.
Cognitive score	14.08662	4.509767
Fraction with normal Cognition	.747489	.4344556
Fraction with CIND	.1890278	.3915332
Fraction with Dementia	.0634832	.2438317
Observations	77,359	77,359

Notes: The data come from SHARE. The scale and classification is based on Langa et al. (2020)

Table 4. Descriptive Statistics for Response Times, Langa-Weir classification

	Mean	St.dev.	Min	Max	N
Overall	121.1852	38.68556	4	577	69,413
With normal Cognition	119.5983	36.78539	4	577	55,689
With CIND	127.982	43.53064	15	432	11,786
With Dementia	126.8692	53.14981	8	418	1,842

Notes: The data come from SHARE. The scale and classification is based on Langa et al. (2020)

Table 5. Cognitive Health and Time Stamps, Wave 8

	(1) Score	(2) Score	(3) Score	(4) Score
Z-time	-0.4542***	-0.5317***	-0.4940***	-0.5540***
	(0.0216)	(0.0221)	(0.0225)	(0.0228)
Z-age	-1.7916***	-1.7823***	-1.8596***	-1.8537***
	(0.0262)	(0.0261)	(0.0248)	(0.0247)
Steady		-0.7176***		-0.5959***
		(0.0438)		(0.0418)
Interviewer FE	No	No	Yes	Yes
Observations	28,242	28,242	28,171	28,171
R^2	0.163	0.171	0.362	0.367

Notes: The data come from SHARE. The dependent variable is cognitive score and the variable of interest is the standardized time needed to answer the questions. The regression controls for the respondent's age.

Table 6. Cognitive Health and Time Stamps with Common Support

	Unweighted		Propensity Weighted	
	(1)	(2)	(3)	(4)
	Score	Score	Score	Score
Z-time	-0.5320***	-0.5624***	-0.3092***	-0.4188***
	(0.0229)	(0.0236)	(0.0237)	(0.0253)
Z-age	-1.7815***	-1.8517***	-1.7034***	-1.7836***
	(0.0262)	(0.0247)	(0.0259)	(0.0246)
Steady	-0.7182***	-0.5976***	-0.6795***	-0.5513***
	(0.0438)	(0.0418)	(0.0545)	(0.0509)
Observations	28,158	28,087	28,158	28,087
R^2	0.169	0.367	0.147	0.354
Interviewer FE	No	Yes	No	Yes

Notes: The data come from SHARE. The dependent variable is cognitive score and the variable of interest is the standardized time needed to answer the questions. The regression controls for the respondent's age.

Table 7. Wave 9 cognitive Health and Wave 8 Time Stamps, Langa Classification

	(1) Score	(2) Score	(3) Score	(4) Score	(5) Score	(6) Score
Z-time	-0.1868***	-0.1870***		-0.1987***	-0.1997***	
	(0.0212)	(0.0217)		(0.0235)	(0.0239)	
Z-age	-0.9220***	-0.9220***	-1.6732***	-1.0393***	-1.0393***	-1.7991***
	(0.0283)	(0.0283)	(0.0325)	(0.0290)	(0.0290)	(0.0314)
Steady		-0.0016			-0.0095	
		(0.0425)			(0.0430)	
Z-time*Normal			-0.3702***			-0.3609***
			(0.0291)			(0.0301)
Z-time*MCI			-1.0460***			-0.9793***
			(0.0574)			(0.0566)
Z-time*Dementia			-1.6922***			-1.7437***
			(0.1348)			(0.1287)
Steady*Normal			0.1689***			0.1139**
			(0.0531)			(0.0514)
Steady*MCI			-3.5136***			-2.7652***
			(0.0959)			(0.0925)
Steady*Dementia			-8.0015***			-6.4107***
			(0.3033)			(0.2866)
Observations	21,674	21,674	21,674	21,589	21,589	21,589
R^2	0.464	0.464	0.235	0.554	0.554	0.414
Interviewer FE	No	No	No	Yes	Yes	Yes

Notes: The data come from SHARE. The dependent variable is cognitive score and the variable of interest is the standardized time needed to answer the questions. The regression controls for the respondent's age.

Table 8. Wave 9 cognitive Health and Wave 8 Time Stamps, with Common Support

	Unweighted		Propensity Weighted	
	(1) Score	(2) Score	(3) Score	(4) Score
Z-time	-0.1923***	-0.2090***	-0.1788***	-0.2421***
	(0.0226)	(0.0247)	(0.0234)	(0.0265)
Z-age	-0.9199***	-1.0382***	-0.8711***	-1.0016***
	(0.0283)	(0.0290)	(0.0281)	(0.0288)
Steady	-0.0021	-0.0114	-0.0065	-0.0244
	(0.0425)	(0.0431)	(0.0532)	(0.0524)
Observations	21608	21522	21608	21522
R^2	0.464	0.554	0.447	0.548
Interviewer FE	No	Yes	No	Yes

Notes: The data come from SHARE. The dependent variable is cognitive score in wave 9 and the variable of interest is the standardized time needed to answer the questions in wave 8. The regression controls for the respondent's age.

Table 9. Health Outcomes and Time Stamps

	(1) ADL	(2) IADL	(3) Chronic diseases	(4) Depression scale	(5) Mobility
Z-time	0.0027	0.0576***	0.0266**	0.0695***	0.0926***
	(0.0024)	(0.0107)	(0.0120)	(0.0163)	(0.0167)
Z-scale	-0.0459***	-0.3339***	-0.1664***	-0.2793***	-0.4001***
	(0.0030)	(0.0131)	(0.0146)	(0.0200)	(0.0204)
Z-age	0.0701***	0.4931***	0.3475***	0.3087***	0.7633***
	(0.0030)	(0.0132)	(0.0147)	(0.0201)	(0.0206)
Observations	21,996	21,996	22,039	21,543	22,004
R^2	0.157	0.241	0.207	0.222	0.275

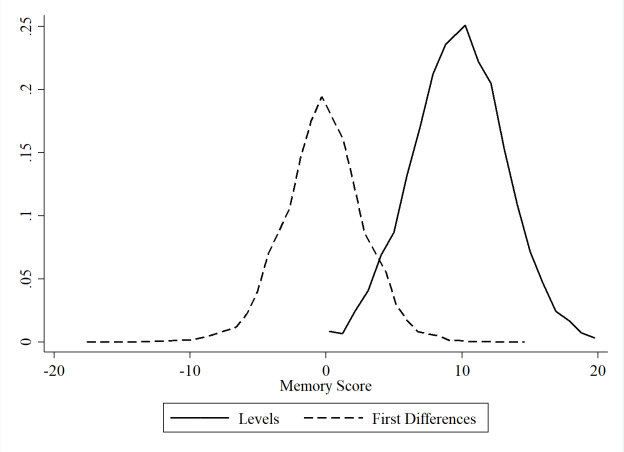
Notes: The data come from SHARE. The dependent variable in column one is an indicator variable that takes value one if a respondent has at least one ADL; in column two - limitations with instrumental activities of daily living (iadl); in column three 0 number of chronic diseases; in columns four and five are the scales of depression (from 0 to 12, 0 denotes no depression) and mobility limitations (0 to 10, 0 denotes no limitations). All the regressions control for interviewer fixed effects

Table 10. Health Outcomes and Time Stamps Controlling for Wave 8 Health Outcomes

	(1) ADL	(2) IADL	(3) Chronic diseases	(4) Depression scale	(5) Mobility
Z-time	-0.0027	0.0232***	0.0178*	0.0249*	0.0179
	(0.0022)	(0.0088)	(0.0093)	(0.0141)	(0.0129)
Z-scale	-0.0281***	-0.1787***	-0.0446***	-0.1103***	-0.1574***
	(0.0027)	(0.0109)	(0.0115)	(0.0174)	(0.0159)
Z-age	0.0503***	0.2884***	0.1254***	0.2172***	0.3810***
	(0.0027)	(0.0111)	(0.0117)	(0.0174)	(0.0162)
Observations	21,992	21,992	22,039	21,374	22,004
R^2	0.310	0.483	0.518	0.424	0.568

Notes: The data come from SHARE. The dependent variable in column one is an indicator variable that takes value one if a respondent has at least one ADL; in column two - limitations with instrumental activities of daily living (iadl); in column three 0 number of chronic diseases; in columns four and five are the scales of depression (from 0 to 12, 0 denotes no depression) and mobility limitations (0 to 10, 0 denotes no limitations). All the regressions control for interviewer fixed effects

Figure 5. Memory Score



Notes: Based on SHARE. Density of memory scores in levels and first differences.

Table 11. Self-Rated versus Assessed Memory

Self-Rated Memory Change	No	Yes	Total
	A. Severe Relative Memory Loss		
Better now	0.86	0.31	1.17
About the same	54.23	18.16	72.39
Worse now	18.42	8.02	26.44
Total	73.51	26.49	100.00
	B. Severe Absolute Memory Loss		
Better now	1.01	0.16	1.17
About the same	63.79	8.60	72.39
Worse now	22.62	3.82	26.44
Total	87.42	12.58	100.00

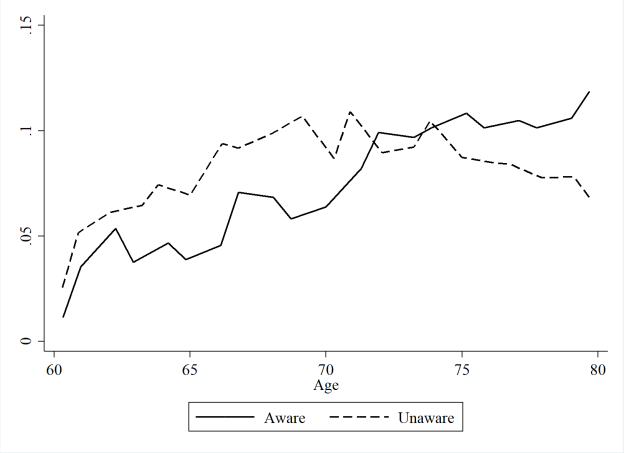
Notes: Based on SHARE. The table compares self-rated memory changes across waves with two different measures of memory loss: severe relative memory loss (panel A), defined as a decline of 20% or more in the memory score, and severe absolute memory loss (panel B), defined as a memory score change of 1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

Table 12. Means and Standard Deviations (SDs) of Key Variables

	(1) Full Sample	(2) Loss Sample
D.Wealth	25.865	33.690
	(1667.891)	(399.861)
L.Wealth	303.067	253.185
	(1701.668)	(528.365)
Aware	0.080	0.303
	(0.272)	(0.460)
Unaware	0.185	0.697
	(0.388)	(0.460)
Pessimist	0.184	0.000
	(0.388)	(0.000)
L.Memory Score	9.989	10.712
	(3.323)	(3.397)
Age	69.983	70.691
	(5.561)	(5.524)
Female	0.601	0.589
	(0.490)	(0.492)
Married	0.566	0.550
	(0.496)	(0.498)
Widowed	0.210	0.232
	(0.407)	(0.422)
High School	0.319	0.288
	(0.466)	(0.453)
College	0.263	0.234
	(0.440)	(0.424)
L.Employed	0.175	0.141
	(0.380)	(0.348)
N	16,956	4,492

Notes: Based on SHARE. The table presents the mean and standard deviations (in parentheses) of key variables for the full sample and the sample of respondents who experienced a memory loss of at least 20%.

Figure 6. Age at Memory Loss



Notes: Based on SHARE. The figure shows the distribution of age among respondents who experienced a memory loss of at least 20%.

Table 13. Time Response and Awareness Classification, Awareness is based on Recall

	(1) Total	(2) Aware	(3) Unaware	(4) Pessimistic	(5) Normal
Overall Time	120.8738	121.7903	117.8513	120.0535	120.3377
Recall Time	64.6515	62.0156	62.1657	65.5423	65.35634
Numeracy Time	39.1140	40.9749	38.3501	38.9686	38.4387
Backwards Time	8.1528	8.3831	8.2848	7.5038	8.1834
N	32,550	1,159	2,911	2,896	8,893

Table 14. Changes in Net Worth

	(1) D.NW	(2) D.NW	(3) D.NW	(4) D.NW
Severe memory loss	-154.1584***	-88.8020		
	(58.0591)	(59.3321)		
Pessimistic			93.4949	5.6619
			(81.2036)	(76.6403)
Unaware			-154.4454**	-123.1001*
			(63.2588)	(64.8770)
Aware			-77.1279	-17.7814
			(82.7677)	(108.8403)
Observations	16,956	12,543	16,956	12,543
R^2	0.468	0.107	0.468	0.107

Notes: Based on SHARE. The dependent variable is the change in net worth. Columns 1 and 3 measure severe memory loss based on recall score, and columns 2 and 4 measure severe memory loss based on total score. All regressions include age squared, sex, educational attainment, labor force status, marital status, country identifiers, and lagged wealth and corresponding lagged score.

Table 15. Relationship between Changes in Net Worth and Time Stamps

	(1) D.NW	(2) D.NW	(3) D.NW
L.Z-time	-21.9966	-73.9553**	-72.2749**
	(28.9763)	(33.1552)	(33.4000)
Severe memory loss	-65.1494	-62.3916	-65.1902
	(56.5992)	(56.7481)	(61.3452)
Observations	11,914	11,914	11,914
R^2	0.103	0.103	0.103

Notes: Based on SHARE. The dependent variable is the change in net worth. Columns 1 and 2 measure severe memory loss based on recall score, and columns 3 measure severe memory loss based on total score. Column 1 measures standardized time based on the recall time stamp variable, and columns 2 and 3 measure standardized time based on the total timestamp variable. All regressions include age squared, sex, educational attainment, labor force status, marital status, country identifiers, and lagged wealth and corresponding lagged score.

Table 16. Changes in Net Worth

	(1) D.NW	(2) D.NW	(3) D.NW	(4) D.NW Flag	(5) D.NW Flag	(6) D.NW Flag
Pessimistic	12.2828	14.2489	79.9622	-78.7084	-79.8909	11.3271
	(97.1614)	(97.3250)	(87.1710)	(86.8929)	(86.5637)	(85.8632)
Unaware	-449.3393***	-433.6629***	-160.4114**	-143.5975**	-136.9051**	-59.3462
	(130.9007)	(127.2835)	(69.2810)	(61.1003)	(60.8813)	(57.0591)
Aware	-279.9165**	-253.5611**	-42.2932	-82.6903	-79.3452	43.8306
	(129.2038)	(125.1312)	(92.0795)	(131.9891)	(132.0446)	(111.9384)
Marital Status	No	Yes	Yes	No	Yes	Yes
Country FE	No	No	Yes	No	No	Yes
Mean of D.V.	412.7736	412.8308	412.8308	276.3043	276.3043	276.3043
Observations	14,840	14,837	14,837	3,731	3,731	3,731

Notes: The data come from SHARE. The dependent variable is the change in net worth (using all imputations in columns 1-3 and imputations with the flag "regular observations" in columns 4-6). All regressions control for age, age squared, sex, educational attainment, labor force status, lagged numeracy score, and lagged wealth.

Table 17. Changes in Net Assets

	(1) D.NA	(2) D.NA	(3) D.NA	(4) D.NA Flag	(5) D.NA Flag	(6) D.NA Flag
Pessimistic	13.1868	13.5363	13.7924	7.4888	8.5153	13.4529
	(35.2766)	(35.2274)	(32.9261)	(17.9080)	(17.8745)	(17.1952)
Unaware	-19.9616	-18.3622	-1.5733	-27.1694	-27.5437	-22.0553
	(30.7321)	(30.3998)	(30.7764)	(19.2004)	(18.8994)	(21.7004)
Aware	-47.4568	-43.3692	-20.3648	-43.9075	-40.8908	-36.1028
	(42.2662)	(42.2119)	(41.2960)	(32.9442)	(32.6769)	(35.6181)
Marital Status	No	Yes	Yes	No	Yes	Yes
Country FE	No	No	Yes	No	No	Yes
Mean of D.V.	113.8638	113.7103	113.7103	31.3246	30.8782	30.8782
Observations	14,840	14,837	14,837	5,654	5,653	5,653

Notes: The data come from SHARE. The dependent variable is the change in net assets (using all imputations in columns 1-3 and imputations with the flag "regular observations" in columns 4-6). All regressions control for age, age squared, sex, educational attainment, labor force status, lagged numeracy score, and lagged wealth.

Table 18. Changes in Real Assets

	(1) D.RA	(2) D.RA	(3) D.RA	(4) D.RA Flag	(5) D.RA Flag	(6) D.RA Flag
Pessimistic	-4.8874	-3.2692	70.2731	-58.8911	-60.0413	-8.9204
	(79.8101)	(79.8735)	(70.5138)	(55.1293)	(55.1107)	(53.3113)
Unaware	-423.1301***	-408.3371***	-134.3270**	-85.7509**	-82.2508*	-10.2810
	(87.8402)	(85.8368)	(52.7498)	(43.0501)	(42.9040)	(38.7865)
Aware	-268.4598**	-245.4987**	-39.1604	36.5400	38.2047	89.8123
	(106.8151)	(104.2641)	(74.4897)	(92.8223)	(92.9470)	(87.4461)
Marital Status	No	Yes	Yes	No	Yes	Yes
Country FE	No	No	Yes	No	No	Yes
Mean of D.V. 298.9098	299.1206	299.1206	270.2027	270.2415	270.2415	
Observations	14,840	14,837	14,837	6,892	6,891	6,891

Notes: The data come from SHARE. The dependent variable is the change in real assets (using all imputations in columns 1-3 and imputations with the flag "regular observations" in columns 4-6). All regressions control for age, age squared, sex, educational attainment, labor force status, lagged numeracy score, and lagged wealth.

Table 19. Predicting Awareness, Multinomial logit

	(1) Pessimistic	(2) Aware	(3) Unaware
Z-time	0.0033	-0.0249	-0.0137
	(0.0221)	(0.0303)	(0.0216)
Observation	16,735	16,735	16,735

Notes: Based on SHARE. Awareness classification is measured by memory loss based on recall. Z-time measures standardized recall time stamps. All regressions include age squared, sex, educational attainment, labor force status, marital status, country identifiers, and lagged wealth and corresponding lagged score.

Table 20. Predicting Awareness, Multinomial logit

	(1) Pessimistic	(2) Aware	(3) Unaware
Z-time	0.0097	0.0212	0.0268
	(0.0275)	(0.0382)	(0.0275)
Observation	11,922	11,922	11,922

Notes: Based on SHARE. Awareness classification is measured by memory loss based on recall. Z-time measures standardized total time stamps. All regressions include age squared, sex, educational attainment, labor force status, marital status, country identifiers, and lagged wealth and corresponding lagged score.

Table 21. Predicting Awareness, Multinomial logit

	(1) Pessimistic	(2) Aware	(3) Unaware
Z-time	0.0129	0.0307	0.0723**
	(0.0258)	(0.0455)	(0.0321)
Observation	11,922	11,922	11,922

Notes: Based on SHARE. Awareness classification is measured by memory loss based on the total score. Z-time measures standardized total time stamps. All regressions include age squared, sex, educational attainment, labor force status, marital status, country identifiers, and lagged wealth and corresponding lagged score.

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