Using Response Times to Predict Cognitive Decline and Bad Financial Decision-Making

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January 7, 2025

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:.

Keywords: Time Stamps, Cognitive decline, longitudinal studies, Financial wealth.

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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 What is known of the response times-cognitive abilities nexus

Seminal work in Psychology and Neuroscience have introduced the Drift Diffusion Model (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 (in levels) and decision-making efficiency, offering a tool for examining the underlying neural mechanisms of cognition.

Ratcliff and Rouder (1998): This paper further developed the Drift Diffusion Model (DDM), applying it to recognition memory tasks. The authors showed that response times, along with accuracy, can provide a more complete understanding of cognitive performance. Their work helped validate the DDM across different types of cognitive tasks, highlighting the model's broad applicability.

Ratcliff et al. (2010): This study analyzed the effects of aging on decision-making using response times. Ratcliff and colleagues showed that 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.

Voss et al. (2004): They proposed the "diffusion model for conflict tasks" and used response times to explore how individuals make decisions when faced with conflicting information, like in the Stroop task. Their research connected response times to the brain's decision-making processes, particularly in situations requiring inhibitory control.

Forstmann et al. (2011): This paper combined neuroimaging (fMRI) with response time modeling to explore the neural correlates of decision-making. It advanced the understanding of how response times relate to brain activity, showing that both cognitive and neural processes underlying decision-making can be mapped through RTs and drift-diffusion models.

These studies, along with Ratcliff (1978) and Smith (2000), are foundational in the field of cognitive neuroscience and decision-making, illustrating how response times can reveal not only cognitive abilities but also the underlying mechanisms of decision-making across various contexts.

3 Data Description

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, conducted between 2019 and 2022. These waves uniquely include timestamp information, recorded automatically during Computer-Assisted Personal Interviews (CAPI). This timestamp data captures the time respondents take to answer individual questions, providing a rich source of information for studying cognitive and decision-making processes.

To minimize biases stemming from hospitalizations and mortality, we limit the sample to self-respondents under the age of 80. We also impute educational attainment values using information from previous waves to maximize the sample size.

Following the approach in Langa et al. (2020), we construct a 26-point cognitive functioning scale based on three components. These include immediate and delayed recall tests of 10 nouns each, accounting for up to 20 points; a serial subtraction test using the number 7, worth up to 5 points; and a counting-backward test, contributing a single point. If respondents paused and resumed the backward counting task, we aggregated their time responses. Based on this scale, we categorize cognitive functioning as normal for scores between 12 and 26, mild cognitive impairment for scores between 7 and 11, and dementia for scores below 7. The time (in seconds) taken to complete these tests serves as a key variable in our analysis.

Descriptive statistics on cognitive health are presented in Table 1, with additional comparisons to HCAP classifications shown in Table 2 and Figure 1. The average cognitive score in our sample is approximately 14 points, with 6.3

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 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 represented on a scale from 0 to 12, where 0 indicates no symptoms of depression.

For the financial analysis, we restrict the sample to respondents who provided detailed financial information. The key financial variables are real assets, which include the value of properties, vehicles, and businesses, adjusted for ownership and debt; net assets, comprising liquid and long-term investments minus liabilities; and net worth, defined as the sum of real and net assets. Due to missing data, these variables are calculated using imputed values and adjusted for purchasing power parity (Germany 2015=1) to account for cross-country differences.

To measure cognitive decline perception, we adopt a multi-step approach. First, we calculate the percentage change in recall test performance between waves 8 and 9, defining a "worsened score" as a decline of at least 20%. We then interact this measure with respondents' self-reported perceptions of memory decline, generating a "decline" indicator variable, which equals 1 if the respondent reported worsening memory and 0 otherwise. Combining these two variables allows us to define four categories, as in Mazzonna and Peracchi (2024):

- No loss: no objective decline and no perceived decline.
- Pessimist: no objective decline but perceived decline.
- Aware: both objective and perceived decline.
- Unaware: objective decline but no perceived decline.

This classification is central to our analysis of how cognitive decline, both perceived and unperceived, relates to response times and financial outcomes.

4 Empirical strategy and Results

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

$$Score_i = \beta_0 + \beta_1 Z_i + \beta_2 X_i + \delta_k + \epsilon_i$$

where $Score_i$ denotes the 26-point score of respondent i, Z_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 and measure of being above or below the average time for every score item, referred to as "steady" (Sanders et al., 2017). 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 the interviewer-fixed effects δ_k (*this equation is used to estimate Table 5*).

Since "steady" subjects have lower response time and are disproportionately at the upper tail of response time distribution (see figures 2-4 for the unweighted and weighted distributions), we weigh the individuals who are not classified as "steady" to balance their distribution. The weight is equal to one if an individual is classified as steady and it is equal to $p_i(1 - p_i)$ otherwise. The probability p_i is a predicted probability in the common support from the logistic regression, where the dependent variable is equal to one if an individual is in a steady group and the control a cubic of response time (hence, table 6 is the same as table 5 but with the common support and weighted columns 3 and 4).

Next, to study how time response predicts the score, we estimate the following equation:

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

where $Y_{i,t+1}$ is an outcome variable in wave 9 (e.g., cognitive score or health outcome), Z_{it} is a response time in wave 8, X_{it} is a set of individual controls in wave 8 as described above, Y_{it} is a score in wave 8 and γ_{kt} denote interviewer fixed effects in wave 8. Importantly, all controls are set at baseline i.e. at wave 8.

All Tables between 7-11 are based on this specification.

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:

$$\Delta W_{i,t} = \beta_0 + \beta_1 Time_{i,t-1} + \beta_2 X_i + \beta_3 Z_{it} + \psi_c + \epsilon_{i,t}$$

where the outcome $\Delta W_{i,t}$ is the difference in wealth from wave 8 to wave 9, $Time_{i,t-1}$ 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.

Tables 12-14 suggest that a higher cognitive score at baseline is associated with an increase in wealth between waves 8 and 9. More interestingly, even controlling for that score, slower response times at wave 8 seem to correlate with a decrease in wealth. Although not significant in all specifications, there seems to be a negative relationship between RTs and wealth accumulation, even though the cognitive score itself is controlled for, which is remarkable.

Finally, we introduce the degree of awareness of cognitive decline in the last specification order to replicate the findings from Mazzonna and Peracchi (2024). To estimate the relationship between perceiving cognitive decline and financial wealth, the following equation is used:

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

$Aware_{it}, Unaware_{it}, Pessimist_{it}$ 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.

The summary statistics of time response by awareness classification are shown in tables 15-16. Table 15 shows the total time response by awareness classification based on the recall test. At first sight, it seems that those who are unaware of their cognitive decline have the lowest response time, i.e. are the quickest. As shown in table 16, this

result is actually driven by the response time of the recall test. This is due to the time response in the recall test being positively correlated with the total cognitive score, unlike numeracy or counting backward (see figure 5). Indeed, in the recall test, respondents are asked to recall as many words as they can out of a list of ten words, so dedicating more time to answering this item is likely a "good" sign for the respondent's memory. Respondents who cannot remember any word or have severe memory issues will probably give up on the task before those who do recall a few words.

When we define awareness classification based on the total cognitive score instead of the recall test alone, a more expected gradient shows up (Table 17): those going through cognitive decline, whether aware or unaware, exhibit a faster time response than those without loss or pessimistic about their cognition. This holds in a probit regression (Figures 6-11) where ev en controlling for the cognitive score and the other covariates at baseline, slower response times are still associated with a higher probability of being unaware of one's cognitive decline.

Tables 18-20 confirm the findings from Mazzonna and Peracchi (2024) using the HRS: those who are unaware of their cognitive decline lose much more wealth than those who are aware of it.

Since response times are also positively correlated with cognitive decline unawareness, this new metric, which could be extracted from any survey incorporating information on cognitive functioning, could be helpful in identifying older individuals who are more at risk of losing their wealth due to a cognitive decline they do not know has already impaired their decision-making process.

Figure 1. Correlation between SHARE and Langa classification

	class_~n	class27
class_cogn~n	1.0000	
class27	0.4652	1.0000

Table 1. Descriptive Statistics for the Score, Langa Classification

	Mean	St. Dev.
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 2. Descriptive Statistics for the Score, HCAP Classification

	Mean	St. Dev.
Score	13.48958	4.584883
Fraction with normal Cognition	.6750552	.4684059
Fraction with CIND	.2218543	.4155395
Fraction with Dementia	.1030905	.3041106
Observations	2,494	2,494

Notes: The data come from SHARE. The classification is based HCAP

Table 3. Descriptive Statistics for the Time Stamps, Langa

	Mean	St.dev.	Min	Max	N
Overall	163.4737	51.64266	12	968	69,412
With normal Cognition 161.3035	49.18521	12	968	55,689	
With CIND	172.2267	57.88256	21	538	11,786
With Dementia	174.0961	70.46313	14	802	1,842

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

Table 4. Descriptive Statistics for the Time Stamps, SHARE

	Mean	St.dev.	Min	Max	N
Overall	165.8633	48.78084	22	505	2,209
With normal Cognition	164.0013	48.03314	22	505	1,593
With CIND	169.3085	49.2102	59	367	457
With Dementia	174.6164	53.58405	45	340	159

Notes: The data come from SHARE. The scale based on HCAP

Table 5. Cognitive Health and Time Stamps, Wave 8

	(1) Score	(2) Score	(3) Score	(4) Score
Z-time	-0.4087***	-0.5075***	-0.5014***	-0.5812***
	(0.0217)	(0.0221)	(0.0236)	(0.0239)
Z_age	-1.7934***	-1.7755***	-1.8523***	-1.8378***
	(0.0263)	(0.0261)	(0.0249)	(0.0247)
Steady		-0.8791***		-0.7508***
		(0.0439)		(0.0419)
Observations	28,242	28,242	28,171	28,171
R^2	0.160	0.172	0.362	0.369
Interviewer FE	No	No	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.

Figure 2. Wave 8 Response Time, Seconds

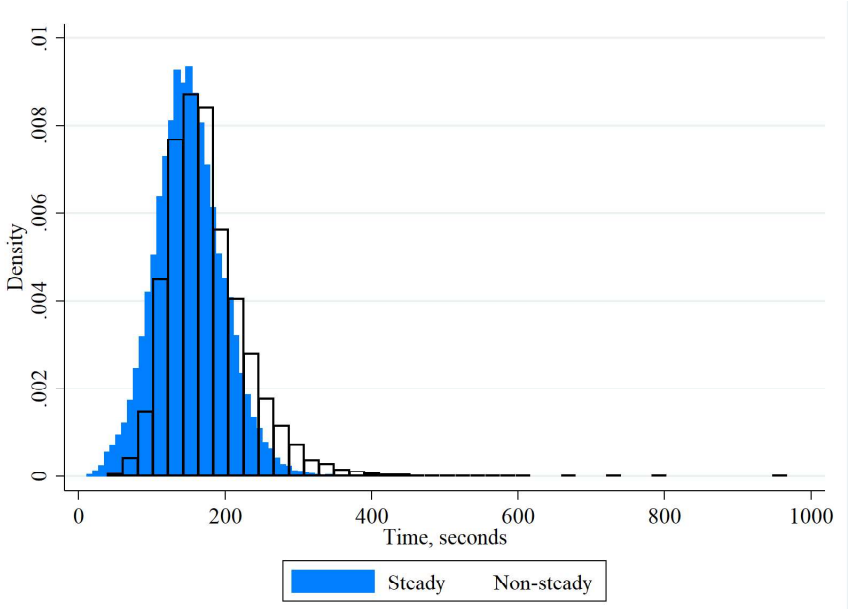


Figure 3. Wave 8 Response Time with Common Support, Seconds

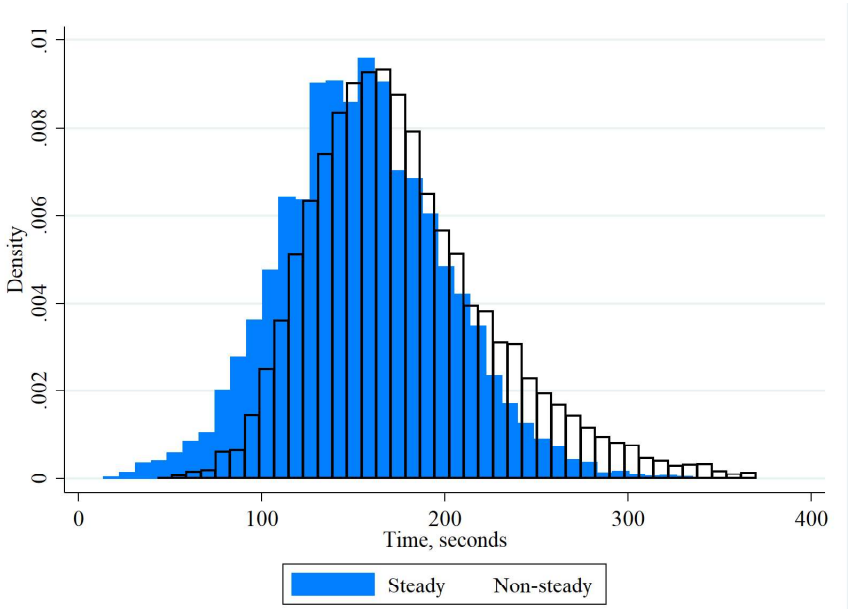


Figure 4. Wave 8 Weighted Response Time, Seconds

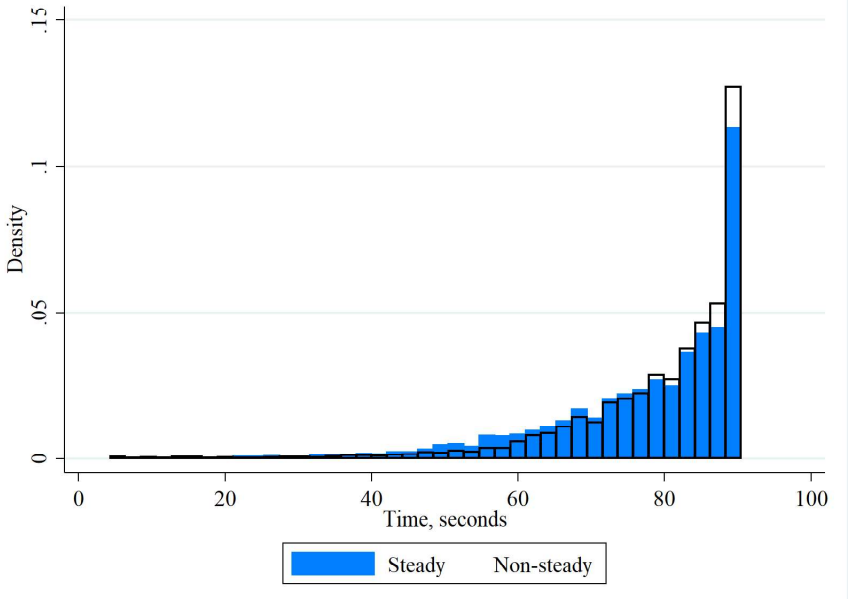


Table 6. Cognitive Health and Time Stamps with Common Support

	Unweighted		Propensity Weighted	
	(1)	(2)	(3)	(4)
	Score	Score	Score	Score
Z-time	-0.5108***	-0.5992***	-0.3035***	-0.4798***
	(0.0232)	(0.0250)	(0.0245)	(0.0270)
Z-age	-1.7728***	-1.8349***	-1.6992***	-1.7598***
	(0.0262)	(0.0248)	(0.0260)	(0.0248)
steady	-0.8801***	-0.7539***	-0.8471***	-0.7234***
	(0.0439)	(0.0419)	(0.0544)	(0.0508)
Observations	28141	28071	28141	28071
R^2	0.170	0.369	0.148	0.357
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	-0.1759***	-0.1755***		-0.2148***	-0.2179***	
	(0.0211)	(0.0217)		(0.0245)	(0.0250)	
Z-age	-0.9199***	-0.9199***	-1.6669***	-1.0346***	-1.0347***	-1.7855***
	(0.0283)	(0.0283)	(0.0325)	(0.0290)	(0.0290)	(0.0314)
Steady		0.0035			-0.0270	
		(0.0428)			(0.0432)	
Z-time*Normal			-0.3163***			-0.3620***
			(0.0292)			(0.0314)
Z-time*MCI			-0.9886***			-0.9857***
			(0.0568)			(0.0574)
Z-time*Dementia			-1.6523***			-1.7237***
			(0.1341)			(0.1287)
Steady*Normal			0.1314**			0.0667
			(0.0533)			(0.0516)
Steady*MCI			-3.6345***			-2.8893***
			(0.0951)			(0.0916)
Steady*Dementia			-7.7340***			-6.1200***
			(0.2886)			(0.2732)
Observations	21,674	21,674	21,674	21,589	21,589	21589
R^2	0.464	0.464	0.236	0.554	0.554	0.416
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)	(2)	(3)	(4)
	Score	Score	Score	Score
Z-time	-0.1827***	-0.2262***	-0.1560***	-0.2574***
	(0.0228)	(0.0261)	(0.0240)	(0.0281)
Z-age	-0.9170***	-1.0351***	-0.8643***	-0.9906***
	(0.0283)	(0.0290)	(0.0281)	(0.0288)
Steady	0.0010	-0.0294	0.0073	-0.0400
	(0.0428)	(0.0432)	(0.0528)	(0.0519)
Observations	21,596	21,512	21,596	21,512
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) Poor health	(2) Dead
Score	-0.1174***	-0.1403***
	(0.0066)	(0.0107)
Z-age	0.3685***	0.9711***
	(0.0311)	(0.0511)
Z-time	0.0553**	0.0959**
	(0.0240)	(0.0378)
Steady	0.0025	0.0022
Observations	22,792	22,792

Notes: The data come from SHARE. The dependent variable is the factor variable which takes values 1 (baseline), 2 (poor health), and 3 (deceased). The variable of interest is the standardized time needed to answer the questions.

Table 10. Health Outcomes and Time Stamps, with Common Support and Weighted

	(1) Poor health	(2) Dead
Score	-0.1143***	-0.1409***
	(0.0067)	(0.0109)
Z-age	0.3656***	0.9741***
	(0.0313)	(0.0518)
Z-time	0.0690***	0.0976**
	(0.0254)	(0.0413)
Steady	-0.0012	0.0056
	(0.0500)	(0.0838)
Observation	22,707	22,707

Notes: The data come from SHARE. The dependent variable is the factor variable which takes values 1 (baseline), 2 (poor health), and 3 (deceased). The variable of interest is the standardized time needed to answer the questions.

Table 11. Health Outcomes and Time Stamps

	(1) ADL limitation	(2) Chronic diseases	(3) Depression scale	(4) Mobility limitations
Z-time	0.0068***	0.0144***	0.0963***	0.1216***
	(0.0025)	(0.0039)	(0.0170)	(0.0175)
Z-age	0.0698***	0.0918***	0.3055***	0.7595***
	(0.0030)	(0.0047)	(0.0202)	(0.0206)
Observations	21,996	22,004	21,543	22,004
R^2	0.157	0.158	0.223	0.276

Notes: The data come from SHARE. The dependent variables in columns one and two are indicator variables that take value one if a respondent has at least one ADL limitation and at least two chronic diseases, respectively. The dependent variables in columns two and three 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

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