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Ştefania Simion

Tomasz Sulka

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**Editor:**

Prof. Dr. Hans-Theo Normann  
Düsseldorf Institute for Competition Economics (DICE)  
Tel +49 (0) 211-81-15125, E-Mail [normann@dice.hhu.de](mailto:normann@dice.hhu.de)

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# Multidimensional Cognitive Ability, Intermediate Channels, and Financial Outcomes\*

Ştefania Simion<sup>†</sup>

Tomasz Sulka<sup>‡</sup>

May 2023

## Abstract

In this paper, we examine which dimensions of cognitive ability are most predictive of key financial outcomes and what pathways could account for the observed relationships. We begin by proposing a conceptual framework that accounts for several plausible “channels” through which differences in cognitive ability might influence financial outcomes. Subsequently, we put the framework to test using the English Longitudinal Study of Ageing. We find that numeracy and literacy are strong predictors of different measures of wealth level and composition, after controlling for a rich set of demographic characteristics. We also find that our end-node channels, planning and self-control, have an even greater predictive power. Nevertheless, despite the fact that these channels are strongly correlated with both numeracy and literacy, they do not fully account for the pathways from cognitive ability to financial outcomes.

*JEL:* C13, D91, J14, J24

*Keywords:* Cognitive Ability, Numeracy, Financial Literacy, Planning, Self-Control

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<sup>†</sup>The University of Bristol, UK; email: stefania.simion@bristol.ac.uk

<sup>‡</sup>DICE, University of Düsseldorf, Germany; email: sulka@dice.hhu.de

# 1 Introduction

A rapidly expanding strand of the economic literature attempts to explain differences in choices and financial outcomes by accounting for variation in cognitive ability (see Table 1). Importantly, different measures of cognitive ability have been used as predictors across studies. This appears to be dictated partly by data availability and partly by a lack of a unifying framework that would capture how particular dimensions of cognitive ability may be reflected in financial outcomes. Moreover, with the exception of financial knowledge accumulation (Gustman et al. 2012; Jappelli and Padula 2013; Hung et al. 2018), the existing studies make little attempt to formalise, and test the validity of, specific pathways through which the reported relationships might materialise.

Acknowledging that cognitive ability is inherently a multidimensional trait, in this paper we ask two fundamental questions: (i) Which dimensions of cognitive ability are most predictive of financial outcomes?; (ii) What pathways could account for the observed relationships?<sup>1</sup> We begin by proposing a conceptual framework that accounts for several “channels” through which differences in cognitive ability might feed into financial outcomes, namely revealed preferences, financial literacy, planning behaviour, and ability to exercise self-control. Subsequently, we put the framework to test by estimating some key relationships using the first wave of the English Longitudinal Study of Ageing (ELSA), a representative dataset containing reliable measures of different dimensions of cognitive ability as well as various financial outcomes.

More specifically, we construct measures of five different dimensions of cognitive ability (numeracy, working memory, verbal fluency, literacy, accuracy and speed of mental processing), two ultimate-node channels (planning and self-control), and six financial outcomes (financial wealth, total wealth, net total wealth, being in debt, stock ownership, having a tax-advantaged saving account). We find that numeracy and literacy are strong predictors of all financial outcomes, save for indebtedness, after controlling for a rich set of demographic characteristics.

Regarding planning and self-control, we find that these channels (especially planning) have an even greater predictive power. Including these variables reduces the coefficient on numeracy and literacy, but

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<sup>1</sup>American Psychological Association defines *cognitive ability* as “the skills involved in performing the tasks associated with perception, learning, memory, understanding, awareness, reasoning, judgment, intuition, and language”, thus indicating that cognitive ability should be viewed as a multidimensional object. Since Spearman (1904), most psychologists organise various dimensions of cognitive ability into a hierarchical order, with more general, higher-order factors being predictive of performance across a wider range of tasks. While there appears to be consensus that a single, first-order factor  $g$  is unable to explain all variation in task performance (Horn and McArdle 2007), the precise number of required lower-order factors remains uncertain and is likely context-dependent. For example, Cattell (1971, 1987) proposed a very influential distinction between “fluid” and “crystallised” intelligence as two second-order factors, while in a meta-analysis of over 460 studies Carroll (1993) estimates a model with eight second-order factors.

only slightly, with the change in estimates being statistically insignificant. For instance, a one standard deviation increase in numeracy index is associated with a 0.11 standard deviation increase in financial wealth, irrespective of whether or not the channels are controlled for. At the same time, the change in financial wealth associated with a one standard deviation increase in literacy drops from an increase of 0.07 standard deviations, when we do not control for channels, to an increase of 0.05 standard deviations, when we do control for the channels.

Thus, it appears that a priori plausible channels informed by prevailing theories do not fully account for the pathways from cognitive ability to financial outcomes, despite the fact that in our setting these channels are indeed strongly correlated with the relevant dimensions of cognitive ability. We interpret this puzzle as highlighting an important gap between the empirical and theoretical strands of the literature in cognitive economics. Moreover, given that concerns related to bounded rationality have an increasing impact on policy design in the domain of household finance (see the reviews by [Bernheim and Taubinsky \(2018\)](#) and [Beshears et al. \(2018\)](#)), emphasising and addressing this discrepancy should have important practical implications.

We contribute to a recent strand of the empirical literature documenting the correlation between particular measures of cognitive ability and financial outcomes of interest (see Table 1 for a summary).<sup>2</sup> In the most closely related papers, [Banks and Oldfield \(2007\)](#) and [Banks et al. \(2010\)](#) also use the initial waves of the ELSA and find strong correlations between numeracy and variables related to financial preparation for retirement, such as financial wealth holdings, portfolio composition, savings, and self-reported preparedness for retirement. Complementing these studies, we formulate a novel conceptual framework aimed at explaining the pathways through which heterogeneity in cognitive ability may manifest itself, which we then use to guide our empirical analysis.

The rest of the paper is structured as follows. Section 2 discusses the theoretical framework. Section 3 presents the main data and section 4 describes the empirical strategy. Section 5 reports the results and section 6 concludes.

## 2 Theoretical Framework

As a starting point of our analysis, we propose a novel conceptual framework, aiming to account in a coherent way for multiple different pathways, or channels, through which the associations between cognitive ability and economic outcomes may arise. In doing so, we hope to bridge several seemingly

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<sup>2</sup>[Borghans et al. \(2008\)](#) provide a comprehensive review of using cognitive abilities and personality traits as explanatory variables in psychology and in economics.

disconnected strands of the applied behavioural literature, which in most cases have speculated about a single plausible pathway but did not consider the alternatives put forward elsewhere.

Following the theoretical model laid out in [Sulka \(2022\)](#), suppose that an economic outcome of interest reflects a combination of “planning” (i.e., identifying the desired action) and “self-control” (i.e., the ability to carry out the desired action). These two stages of decision-making are often separated, either in time (e.g., saving for retirement throughout one’s working life) or in space (e.g., exercising at a gym). Of course, some tasks can have either a trivial planning component (e.g., smoking is generally known to be unhealthy) or a trivial self-control component (e.g., opening a bank account with the lowest fees is not any more difficult to execute), but the important financial outcomes that we analyse later on would rely on both planning and self-control.

Below, we discuss the empirical evidence consistent with the notion that cognitive ability is correlated with the agent’s propensity to plan, features of the plan they come up with, their ability to exert self-control, as well as any remaining mistakes in their decision-making.

**Planning.** Empirically, a strong effect of planning behaviour on important economic outcomes has been documented by multiple studies ([Ameriks et al., 2003](#); [Lusardi and Mitchell, 2007, 2011](#)), but the determinants of planning itself remain largely unexplored. Despite an intuitive notion that planning, which relies heavily on the ability to accumulate and process information, might reflect one’s cognitive ability, we are unaware of any existing empirical tests of the relationship between cognitive ability and planning behaviour.

Conditional on engaging in planning, how might the resulting plans vary across individuals? We posit that the agent’s accumulated financial knowledge and their revealed preferences act as inputs into the planning stage, affecting the efficiency and the objectives of their plan, respectively. In other words, while preferences determine the agent’s goals, financial knowledge enables them to achieve those goals in an efficient manner (e.g., by not taking on uncompensated financial risks).

Cognitive ability can be seen as a trait determining the cost of information processing in models of endogenous financial knowledge accumulation ([Jappelli and Padula, 2013](#); [Lusardi et al., 2017](#)). Naturally, a lower cost of information processing should result in greater financial knowledge and, consequently, improved economic outcomes.<sup>3</sup> While the financial knowledge channel has been explicitly proposed in the existing literature as a pathway between cognitive ability and financial outcomes, the available results indicate that it does not account fully for the predictive power of cognitive ability ([Banks et al., 2010](#);

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<sup>3</sup>See [Lusardi and Mitchell \(2014\)](#) for a review of an established literature on the measurement of financial literacy and its effects on a range of financial outcomes.

Gustman et al., 2012; Banks et al., 2015).

Another strand of the literature has put forward that cognitive ability influences revealed time and risk preferences, as its specific dimensions are correlated with the displayed patience and risk-taking (Frederick, 2005; Dohmen et al., 2010; Benjamin et al., 2013). The association between cognitive ability and patience as well as risk-taking (in small-stakes gambles) could be rationalised by a greater cognitive ability enabling an individual to overcome their impulsivity and to bracket the risks more broadly.

**Self-Control.** In a similar vein, the variation in cognitive ability could manifest itself via self-control, understood as a capability to forego short-term temptations for the sake of implementing a predetermined plan (Gul and Pesendorfer, 2001; Benhabib and Bisin, 2005; Fudenberg and Levine, 2006). Empirical support for this channel comes from the above studies reporting a strong link between cognitive ability and patience, the observation that exogenous increases in cognitive load lead to more impulsive choices (Benjamin et al., 2013), and the neuroscientific research on the processes behind impulse control (Camerer, 2013; Duckworth et al., 2018).<sup>4</sup>

**Residual Mistakes.** Most directly, cognitive ability can affect the quality of decision-making by facilitating deliberation and numerical reasoning, thus minimising the chance of “residual mistakes”, conditional on a specific plan and the ability to carry it out. For instance, Agarwal and Mazumder (2013) find that the members of the US military who perform worse on a math test are also more likely to make a financial mistake when using their credit card or applying for a home loan.<sup>5</sup>

We illustrate the proposed framework diagrammatically in Figure 1. In the diagram, the individual’s multidimensional cognitive ability influences their economic decisions via three end-node channels, i.e. planning, self-control, and residual mistakes. Moreover, cognitive ability affects the individual’s financial knowledge and revealed preferences, which feed into the planning node.

In Appendix A, we additionally present a formal application of the framework to an inter-temporal consumption smoothing problem, in order to illustrate how these different considerations can be captured within a standard economic model of decision-making.

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<sup>4</sup>While the self-control channel reflects the agent’s actual ability to carry out a plan, any misperceptions thereof can be captured by the preference channel. For example, in the notation of a quasi-hyperbolic model (Strotz, 1955; Laibson, 1997), the agent’s actual present bias  $\beta$  would be reflected in the self-control channel, while their beliefs about future present bias  $\hat{\beta}$  would affect their “seemingly optimal” plan via the preference channel.

<sup>5</sup>Choi et al. (2010) and Choi et al. (2011) document the prevalence of clearly sub-optimal behaviours in the financial domain, but do not test for the association between such tendencies and cognitive ability.

### 3 Data

In this section, we describe the data used in the analysis, presenting summary statistics for the main controls, the different measures of cognitive ability, the channels, and the financial outcomes.

We use the first wave of the English Longitudinal Study of Ageing (ELSA), a longitudinal database which follows a representative sample of individuals living in England, aged 50 or more. ELSA is a very rich dataset, containing detailed measures reflecting the respondent's financial situation, demographic characteristics, and cognitive ability, which makes it uniquely suited to the purposes of our analysis (Banks et al., 2003).

The survey has been conducted biannually since 2002, but not all measures of cognitive ability have been collected in every wave. Thus, our main sample is based on the first wave, which has collected data on most of our measures of cognitive ability (see details in Subsection 3.2). The initial sample of wave 1 includes 7,912 household heads, but as we restrict the sample to individuals between 50 and 70 years old, we remain with 5,216 individuals. The sample gets further restricted to 4,838 individuals once we account for missing information on the main demographic measures. We lose a further 1,095 individuals once we account for missing information on the measures of cognitive ability and channels. This gives us a final sample of 3,743 individuals.

#### 3.1 Demographics

In Table 2, we present the main demographic characteristics of the individuals in our sample. On average, people are around 59 years old, 35% are females, and 97% are white. Moreover, 86% report to have had children and most of the individuals are married or co-habiting (66%), while 12% are widowed, and 16% are separated or divorced. Around 47% of the sample report an excellent or a very good health status. Regarding education, the majority of individuals have less than a high-school degree (62%). Finally, as a proxy for socio-economic background, we use the main carer's job during the respondent's childhood to define their social class. Approximately 25% of individuals belong to a high social class, while 36% belong to an intermediate social class.<sup>6</sup>

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<sup>6</sup>Specifically, we define an individual as belonging to a high social class if their main carer's occupation was as a manager or senior official in someone else's business, professional, technical, or running their own business. We define an individual as belonging to an intermediate social class if their main carer's occupation was administrative, clerical or secretarial, in a skilled trade, or in the armed forces.



## 3.2 Measures of Cognitive Ability

We next turn to the measures of cognitive ability we use in our analysis. After defining them, we present the summary statistics in Table 3 Panel A.

**Numeracy.** First, we derive a measure of numeracy based on the accuracy of arithmetic calculations. The respondents were asked up to five (out of six) progressively more difficult questions involving arithmetic calculations. Because the respondents were answering different questions based on their performance, we create a numeracy index ranging from 1 (lowest) to 4 (highest) for all individuals in our sample, as in [Banks and Oldfield \(2007\)](#).<sup>7</sup> Table 3 shows that the average of the numeracy index is around 2.6. Although our measure of numeracy is correlated with standard demographic characteristics, such as gender, age, and education, we still observe considerable variation when conditioning on these characteristics, see Figure 6. For example, while a share of respondents who have either the highest or the second highest level of numeracy is increasing in the level of education, we observe a full range of numeracy levels within each education group.

**Working Memory.** Second, we construct a measure of working memory, by summing up the number of words that a respondent is able to recall immediately and after a delay, from a set of 10 random words, each time. This working memory score thus varies from 0 to 20, with an average of 10.4 words in our sample (see Table 3). Equivalent indicators of memory are also considered in [Christelis et al. \(2010\)](#) and [Smith et al. \(2010\)](#), among others.

**Verbal Fluency.** Third, we derive a measure of verbal fluency from a performance in a word finding exercise. A respondent has 60 seconds to name as many different animals as they possibly can and we treat the number of animals recalled as a measure of their verbal fluency, as in [Christelis et al. \(2010\)](#). The maximum observed number of animals named is 50, while the minimum is 0. On average, the respondents were able to name around 21 animals in 60 seconds (see Table 3).

**Literacy.** Fourth, we create a literacy score based on the understanding of a hypothetical medicine label. After reading the label, a respondent is asked four questions testing their level of understanding. We take the number of correct answers to be their literacy score, similarly to [Banks et al. \(2010\)](#). As the survey in wave 1 did not collect information on literacy, we use the longitudinal aspect of ELSA to create this measure based on the wave 2 data, collected 2 years afterwards. In particular, we directly use the

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<sup>7</sup>Additional details of the derivation of the numeracy index are provided in Appendix B.

literacy displayed in the second wave to calculate our literacy score. As a robustness check, we find that the literacy score based on the data recorded in waves 2 and 5 (i.e., 6 years apart) is exactly the same for 62% of the individuals surveyed in both waves. Thus, since we are using the data collected only 2 years apart, we expect that our extrapolated literacy score is close to the respondent's "true" literacy at the time of wave 1. Moreover, given that the within-cohort rank of individual's cognitive ability stabilises already in childhood, and is even more stable over time than the raw test scores (Borghans et al., 2008), we also control for age in our regressions to address any potential concerns related to the extrapolation. Table 3 shows that in our sample the average literacy score is relatively high at 3.6, with a minimum of 0 and a maximum of 4.

**Accuracy and Speed.** Fifth, we use a visual letter cancellation task to measure the accuracy and speed of mental processing. A respondent's score is simply the sum of the letters correctly crossed-out from a page containing a random collection of letters, densely organised into rows and columns. Table 3 shows that in our sample the average measure of accuracy and speed is 19.6 letters correctly crossed, with a minimum value of 0 and a maximum value of 59.

In order to see how these measures relate to each other, we look at the pairwise correlations in Table 4. What emerges from this table is that the correlations are far from perfect, with some measures exhibiting low correlations, e.g. accuracy and speed is not strongly correlated with either numeracy or literacy.

For completeness, note that the ELSA questionnaires contain additional measures of cognitive ability, based on the respondent's orientation in time (identifying the date and the day of the week), backward counting, or object naming. These indicators, however, measure very basic aspects of cognitive ability and contain almost exclusively perfect scores. We therefore exclude these measures from our analysis. In Appendix C, we also use an additional measure of cognitive ability, namely fluid intelligence. Table C1 shows that while this measure is correlated with all the other dimensions of cognitive ability, the correlation is not perfect - the highest correlation coefficient of 0.52 is with numeracy. However, as the measure of fluid intelligence is extrapolated from data which are 10 years apart, we do not include it among our main measures of cognitive ability, but we test the robustness of our findings to its inclusion.

### 3.3 Financial Outcomes and Channels

We utilise finely dis-aggregated measures of financial outcomes contained in ELSA, capturing wealth levels as well as propensity for being in debt, holding any tax-advantaged saving accounts, and holding

any risky assets. We also create proxies for our two end-node channels, i.e. planning and self-control.<sup>8</sup> The financial outcomes that we use are comparable with the existing literature (see Table 1). The summary statistics are presented in Panels B and C of Table 3.

**Wealth Levels.** We distinguish between three different measures of wealth: (1) financial wealth - defined as the gross value of all financial assets, excluding housing and pension wealth; (2) total wealth - defined as the sum of financial wealth and net non-financial wealth (i.e., real estate); (3) net total wealth - defined as total wealth minus any outstanding debt. For these measures of wealth, we apply the inverse hyperbolic sine transformation (rather than log) to be able to account for zeros and negative values. Panel B, Table 3 shows that in our sample there is considerable variation in all three measures of wealth.

**Wealth Composition.** We create three different measures to reflect the composition of wealth. First, we define a binary dummy variable indicating whether an individual has any debt, be it owed on credit card, to individuals, or on loans, but excluding any mortgages. Table 3 shows that in our sample around 43% of individuals have some form of debt. Second, we create a binary dummy variable indicating whether an individual has any tax-advantaged saving accounts (i.e., cash, life, or shares ISA). Third, we define a binary dummy variable indicating whether an individual has any risky assets (i.e., stocks, shares, or trusts). Panel B in Table 3 shows that while around 51% of people have a tax-advantaged saving account, 48% have some risky assets.

**Planning.** ELSA contains explicit measures of the respondent's planning behaviour. Thus, we are able to classify an individual as a "planner" if they reported that they plan their household's consumption and saving over a period longer than the next year. Based on the answer to the same question, we classify an individual as a "non-planner" if they reported planning their household's consumption and saving over the next few weeks or spontaneously. In our sample, 54% of respondents are classified as planners and 19% as non-planners (see Panel C in Table 3).

**Self-Control.** We proxy for self-control based on the propensity to undertake activities that are widely known to yield long-term benefits, albeit at some short-term cost. In particular, we look at how often respondents reported exercising moderately, which we interpret as a flow variable reflecting the respon-

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<sup>8</sup>Due to data limitations, in our main results we do not control for the two intermediate nodes illustrated in Figure 1, namely revealed preferences and financial knowledge. For completeness, in Appendix D we consider a proxy for the respondent's financial literacy, which is available for only 15% of our sample. While ELSA included a battery of questions designed to measure the respondent's time and risk preferences, these were asked only to a very small subsample and as late as wave 5. We therefore do not include the preference measures in our analysis.

dent’s repeated, deliberate effort and thus a suitable proxy for self-control. This measure is categorical, with values ranging from 1 for “hardly ever or never”, 2 for “one to three times a month”, 3 for “once a week”, to 4 for “more than once a week”. Panel C in Table 3 shows that on average individuals self-report exercising moderately once a week.<sup>9</sup>

## 4 Empirical Identification

Although our conceptual framework is presented using a directed graph, we use observational data on standard cognitive tests to proxy for different dimensions of the underlying cognitive ability. Thus, similar to recent strands of cognitive economics we cannot interpret correlations that we might find in the data as evidence of causal relationship between cognitive ability and the outcomes of interest. Nonetheless, the empirical approach we adopt is consistent with a large and long-established literature in psychology examining linear relationships between measures of cognitive ability, implicitly taken as exogenous, and performance on various tasks in order to establish the predictive power of various forms of intelligence (Borghans et al., 2008). To facilitate the interpretation of our results, it is also worth highlighting the evidence showing that these measures of cognitive ability can be interpreted as an endowment that remains stable between early adulthood and the age of 55-60 (Craik and Bialystok, 2006). Even more so, Deary et al. (2013) and Deary (2014) report the correlation of 0.7 between intelligence test scores measured at the ages of 11 and 70, which provides an argument against reverse causality between financial outcomes and cognitive ability.

In order to determine which dimensions of cognitive ability predict our measures of financial outcomes, after accounting for planning and self-control, we estimate the below equation by Ordinary Least Squares (OLS):

$$y_i = \alpha + Cognition_i' \beta + \delta_1 Planning_i + \delta_2 Self\_control_i + X_i' \gamma + u_i \quad (1)$$

where  $y_i$  is a financial outcome of interest for individual  $i$ .  $Cognition_i$  is a vector of the measures of cognitive ability, i.e. numeracy index, working memory, verbal fluency, accuracy and speed, and literacy score.  $Planning_i$  is a measure of whether individual  $i$  is a planner or non-planner and  $Self\_control_i$

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<sup>9</sup>Cobb-Clark et al. (2021) develop measures of self-control and one’s awareness thereof based on the individual’s actual, ideal, and predicted body weight and find that those are indeed correlated with exercising for health reasons, but not for fun. Although ELSA contains two additional measures of physical activity, namely exercising mildly and exercising vigorously, we decided to not include them in our main analysis, as the ability to exercise vigorously could also reflect physical ability or health of the respondent, over and above their self-control. Similarly, the examples of mildly vigorous exercises include doing laundry and vacuuming, which also seem questionable as proxies for self-control. Nonetheless, the results using those two measures are available upon request.

measures the level of self-control for individual  $i$ .  $X_i$  is a vector controlling for demographics, i.e. gender, ethnicity, age, education, health level, marital status, number of children, and social class.  $u_i$  is the error term.

Our main coefficients of interest are the estimates for the measures of cognitive ability (the  $\beta$ s) and of the end-node channels ( $\delta_1$  and  $\delta_2$ ). Our theoretical framework predicts that once we account for the channels, the predictive power of the measures of cognitive ability diminishes, or even disappears. So, we first estimate equation 1 without accounting for the channels, and then we add the channel measures as additional control variables.

## 5 Results

In this section, we first present our preliminary results, which look at the predictive power of the different measures of cognitive ability for financial outcomes and channels. We then proceed to our main results, which analyse the predictive power of the different measures of cognitive ability for financial outcomes, once we account for the proposed channels.

### 5.1 Preliminary Results

**Predictors of Financial Outcomes.** Table 5 shows results obtained from running an amended version of regression 1 in which we do not control for the end-node channels. Each column refers to a different regression, with the title identifying the outcome variable. Additionally, the even number columns use the survey weights.

Column (1) reveals that among the measures of cognitive ability, numeracy, working memory, accuracy and speed, and literacy are all statistically significant predictors of financial wealth. The biggest predictor is numeracy (a one standard deviation increase in the numeracy index is associated with a 0.11 standard deviation increase in financial wealth), followed by literacy and working memory (around 0.06 standard deviations each). Column (2) shows that the results are robust when we use the survey weights. When focusing on the predictors of total wealth (Columns (3) and (4)) numeracy is still the most important predictor (around 0.12 standard deviations), with only literacy being the other statistically significant predictor, although of a smaller magnitude (0.06 standard deviations). Columns (5) and (6) show similar results for net total wealth - the only predictors that are statistically significant are numeracy and literacy, with the former having a larger coefficient. Overall, these findings are in line with the established literature arguing that numeracy is the strongest predictor of wealth levels and stock holding (see, e.g.,

Banks and Oldfield, 2007; Smith et al., 2010).

In Columns (7) to (12), we consider the relationship between different dimensions of cognitive ability and our measures of wealth composition. What emerges very clearly from Table 5 is that none of the measures of cognitive ability is statistically significant when the outcome is whether or not an individual has any debt. For measures of holding any tax-advantaged saving accounts and holding any risky assets, numeracy, working memory, and literacy are statistically significant predictors. In particular, an increase of one standard deviation in the numeracy score is associated with an increase of around 0.09 standard deviations in the probability to have any ISA holdings (Columns (9) and (10)) or any stocks, shares or trusts holdings (Columns (11) and (12)). The predictive power of working memory is smaller, at around 0.05 - 0.06 standard deviations. For literacy, the estimate is also statistically significant although the magnitude is smaller, at around 0.03 - 0.05 standard deviations.

**Predictors of Channels.** Following the conceptual framework, we also investigate how strongly the measures of cognitive ability predict the end-node channels. Table 6 has a similar structure to Table 5 - each column refers to a different outcome, identified in the name of the column, and even number columns use survey weights. Columns (1) and (2) show that for planning, numeracy, working memory and literacy are the only statistically significant predictors, with the latter having the largest magnitude (a one standard deviation increase in the literacy is associated with a 0.05 standard deviation increase in the probability of being a planner). These findings are supported by the results in columns (3) and (4), where we show the results for the probability of being a non-planner. Columns (5) and (6) show that when analysing the proxy for self-control based on moderate exercise, working memory and verbal fluency are the only statistical significant predictors, with the latter having the largest magnitude (around 0.07 standard deviations). Overall, these results indicate that certain dimensions of cognitive ability are indeed correlated with the end-node channels that we propose, preempting our hypothesis that these can account for at least part of the relationship between cognitive ability and financial outcomes.

## 5.2 Main Results

We next discuss the main results, which focus on the predictors of the financial measures, when accounting for the proposed channels. Tables 7 to 12 report the results for each of the financial outcomes, with even-numbered columns using survey weights.

**Wealth Levels.** Table 7 focuses on financial wealth. Across all specifications, we see that both channels (planning and self-control) are statistically significant predictors of financial wealth, but controlling for them does not reduce the predictive power of numeracy, working memory, accuracy and speed, or literacy. In fact, the associated coefficients are only slightly smaller when we account for the channels (see Columns (7) to (10)), compared to the ones reported in Table 5 (see Columns (1) and (2)), and the differences are not statistically significant. In terms of magnitudes, planning is the largest predictor (around 0.22 standard deviations), followed by numeracy and self-control (each with around 0.10 standard deviations).

Table 8 shows the predictors for total wealth. What is clear across all columns is that planning, whether it is measured as being a planner or a non-planner, predicts total wealth, on top of self-control as well as numeracy and literacy (which were the only measures of cognitive ability statistically significant in Table 5 in Columns (3) and (4)). In fact the magnitude of planning is about 60 - 100% higher than the one of self-control or numeracy, each with an estimate of around 0.11 standard deviations (Columns (7) to (10)). When comparing Columns (3) and (4) in Table 5 and Table 8 we can again see that there is only a small reduction in the coefficients for numeracy and literacy, once we account for the end-node channels, with the difference in estimates being statistically insignificant.

Finally, when looking at net financial wealth, Table 9 shows that planning, self-control, numeracy and literacy are again the only statistically significant predictors, with planning having the greatest predictive power (around 0.17 - 0.18 standard deviations), followed by numeracy (around 0.10 - 0.11 standard deviations), self-control (around 0.08 standard deviations), and literacy (around 0.03 - 0.04 standard deviations). Similarly to the previous two measures of wealth levels, accounting for the end-node channels does not substantially reduce the predictive power of the key cognitive ability measures, but the differences in estimates are not statistically significant (Columns (5) and (6) in in Table 5 vs Table 9).

To sum up, we find that even after controlling for planning and self-control, numeracy and literacy are still important predictors for all three measures of wealth. All results are robust to the use of survey weights.<sup>10</sup>

**Wealth Composition.** Table 10 reports the predictors of having any debt. The only predictor that is statistically significant across all estimations is planning, when measured as whether an individual is a planner (Columns (1), (2), (7) and (8)). None of the measures of cognitive ability has a statistically significant estimate, similarly to the results reported in Columns (7) and (8) of Table 5. Tables 11 and 12

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<sup>10</sup>For all our outcome measures, it should be noted that accounting for planning and self-control does not affect the predictive power of the other demographic variables.

show that planning, self-control, numeracy and working memory are statistically significant predictors of both having any tax-advantaged saving accounts and holding any risky assets. For the latter outcome, literacy also has a statistically significant coefficient (Table 12). In terms of magnitudes, planning is the strongest predictor (with an estimate of around 0.13 - 0.17 standard deviations), followed by numeracy and self-control (around 0.08 - 0.09 standard deviations). Analogously to the results corresponding to wealth levels, accounting for the end-node channels has little impact on the predictive power of cognitive ability measures, with no statistically significant differences in estimates.

In Appendix C, Tables C2 to C4, we repeat our analysis using an additional measure of cognitive ability, namely fluid intelligence. As we are able to create this variable for only two thirds of our main sample, we first check robustness of the main results for this smaller sample. While the difference between Tables C2 and C3 is the measure of planning, Table C4 uses survey weights. What emerges from these tables, is that independently of the measure of planning used, restricting the sample does not seem to alter our main results. When including the fluid intelligence, its predictive power depends on the outcome variable and the definition of planning. Fluid intelligence is a good predictor for financial wealth, having tax-advantaged saving accounts and holding any risky assets, independently of whether we use the planner or non-planner variables (Columns (2), (10) and (12) in Tables C2 and C3), with a magnitude of around 0.04 - 0.08 standard deviations. For total wealth and net total wealth, the estimate of fluid intelligence is statistically significant only at the 10% significance level when we use the planner variable (Columns (4) and (6) in Table C2), while for debt it is not statistically significant independently of whether we use the planner or non-planner variables (Column (8) in Tables C2 and C3).<sup>11</sup>

## 6 Conclusion

The aim of this paper is to provide a systematic analysis of the link between various dimensions of cognitive ability and financial outcomes. Our contribution is twofold. First, we propose a conceptual framework that synthesises findings from several strands of the empirical literature by accounting for different channels through which heterogeneity in cognitive ability may manifest itself, that is revealed preferences, financial literacy, planning, self-control, and residual mistakes.

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<sup>11</sup>As mentioned before, in Appendix D we define an additional channel, financial literacy, using three different measures. The sample available for this channel is very small - around 550 - 600 observations, depending on which measure we use. Table D2 shows that numeracy is the only statistically significant predictor (ranging from 0.12 to 0.20 standard deviations) for all measures of financial literacy. The results for the financial outcomes, available upon request, show that for this restricted sample, only the estimate of planning is statistically significant.



Second, we test the framework using the representative ELSA dataset, containing measures of multiple dimensions of cognitive ability as well as finely dis-aggregated financial outcomes. We find that numeracy and literacy are strong predictors of different measures of wealth level and composition, after controlling for a rich set of demographic characteristics. The end-node channels we propose, i.e. planning and self-control, have an even greater predictive power. Nevertheless, despite the fact that these channels are strongly correlated with both numeracy and literacy, they do not statistically significantly reduce the coefficients on the cognitive ability measures for any of our financial outcomes.

Accordingly, future research should prioritise a more precise understanding of the pathways through which differences in particular dimensions of cognitive ability influence key financial outcomes, in order to address the above puzzle. In our view, a more accurate representation of the underlying decision-making processes would allow to design more effective policy interventions in the domain of household finance. More specifically, the reviews by [Bernheim and Taubinsky \(2018\)](#) and [Beshears et al. \(2018\)](#) highlight the fact that empirical evidence on the effectiveness of various interventions motivated by bounded rationality, such as financial education and choice simplification, is far from conclusive. This is likely to be the case not only because these interventions vary substantially in their design, but also due to the lack of evidence on the underlying mechanisms. To that end, our findings indicate that even after controlling for planning behaviour and ability to exercise self-control, there exist important differences in outcomes attained by respondents differing in their underlying cognitive ability. This suggests that interventions targeting specifically the end-nodes of the decision-making process (see Figure 1), such as providing planning tools or information in a simplified format, can mitigate the effects of heterogeneous cognitive ability on financial outcomes only to a limited extent.

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# Figures and Tables

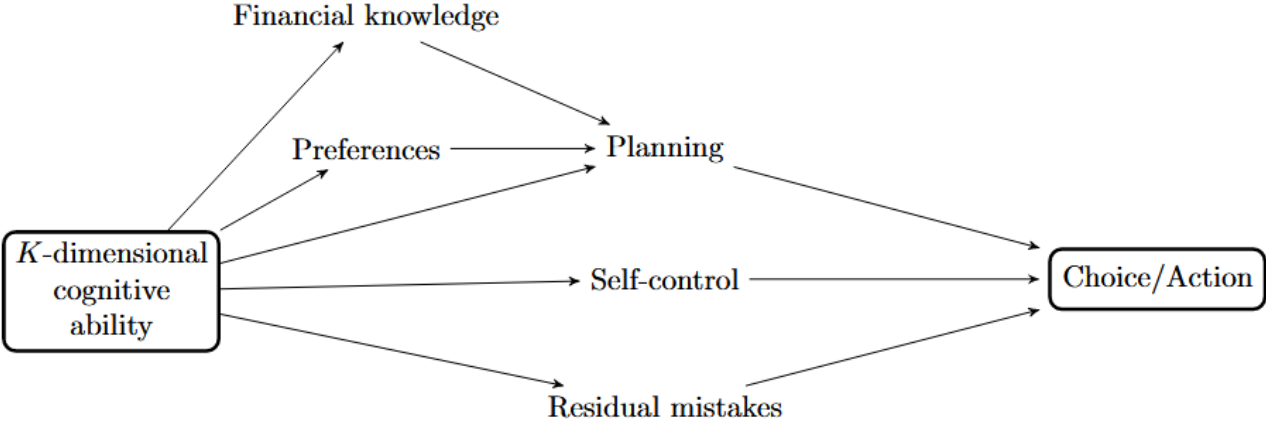
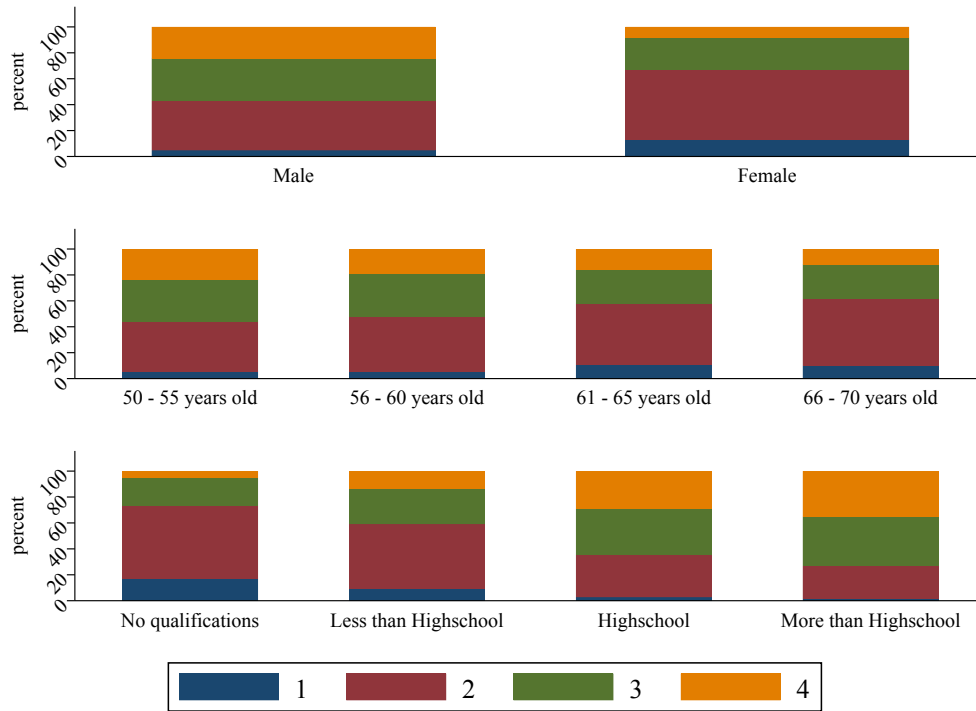


Figure 1: CONCEPTUAL FRAMEWORK

Figure 2: DISTRIBUTION OF NUMERACY INDEX BY DEMOGRAPHICS



Notes: This figure shows the distribution of numeracy by three characteristics. The top panel distinguishes between men and women, the middle panel shows the distribution by age groups, while the lower panel shows the distribution by education level. The numeracy is defined as 1, 2, 3, or 4, with the lowest level being 1 and the highest being 4.

Table 1: PREVIOUS STUDIES ON THE RELATIONSHIP BETWEEN COGNITIVE ABILITY AND FINANCIAL OUTCOMES

Paper	Dataset	Dependent variables	Key explanatory variables	Main findings
Agarwal and Mazumder 2013	AFQT	Financial mistakes in credit card usage and home loan applications	Mathematical ability, verbal ability, education	Mathematical, but not verbal, ability is a strong predictor of lower probability of making a financial mistake in either domain.
Banks and Oldfield 2007	ELSA	Financial wealth, portfolio composition, financial knowledge, self-assessed preparedness for retirement	Numeracy, executive function, memory, education, wealth level	Numeracy is as strong a predictor of financial wealth level and stock ownership as education, but has a greater effect on financial knowledge and preparedness for retirement.
Banks et al. 2010	ELSA	Financial wealth trajectory, replacement rate, expectations regarding retirement, subjective well-being	Numeracy, executive function, memory, literacy, education, wealth level	Higher numeracy associated with a more 'hump-shaped' wealth trajectory, but has no effect on replacement rates and well-being.
Banks et al. 2015	ELSA	Annuitisation choices	Numeracy, financial literacy (proxy), executive function, memory, education, wealth level	Numeracy has a strong effect on the propensity to 'shop around' for an annuity, but not on the income drawdown.
Christelis et al. 2010	SHARE	Stock ownership	Numeracy, executive function, memory, education, social activity	All 3 dimensions of cognitive ability have strong, comparable effects on holding stocks, but not bonds.
Gustman et al. 2012	HRS	Pension and non-pension wealth, knowledge of pensions	Numeracy, cognitive status, education	No evidence that pension-specific knowledge accounts for the impact of numeracy on wealth.
Hung et al. 2018	UAS (HRS)	Dedicated retirement savings, contributing to a workplace pension, planning, self-assessed preparedness for retirement (Withdrawing retirement funds, claiming social security benefits)	Fluid intelligence, crystallised intelligence, financial literacy, education (General cognition, education)	Financial literacy has the largest effect on 'prudent' saving behaviours and accounts for some of the effect of cognitive abilities. (Steeper cognitive decline is associated with pension wealth decumulation and claiming social security.)
Smith et al. 2010	HRS	Total wealth, financial wealth, proportion of financial wealth held in stocks, financial decision-maker (FDM)	Numeracy, cognitive status, memory, education, financial respondent	Numeracy, especially of FDM, has the strongest effect on wealth levels and stock holding. Husband's numeracy is the strongest determinant of FDM.

Table 2: SUMMARY STATISTICS - DEMOGRAPHICS

	Mean (1)	SD (2)	Min (3)	Max (4)	N (5)
Age	59.470	5.925	50	70	3,743
Year of birth	1,942.161	5.936	1,931	1,952	3,743
Female	0.351	0.477	0.000	1.000	3,743
White	0.974	0.160	0.000	1.000	3,743
Whether kids	0.859	0.348	0.000	1.000	3,743
<i>Marital Status</i>					
Married/co-habitation	0.660	0.474	0.000	1.000	3,743
Single	0.062	0.241	0.000	1.000	3,743
Widowed	0.115	0.319	0.000	1.000	3,743
Separated/Divorced	0.163	0.369	0.000	1.000	3,743
<i>Health Status</i>					
Excellent/Very Good Health	0.470	0.499	0.000	1.000	3,743
Good Health	0.305	0.460	0.000	1.000	3,743
Fair/Poor Health	0.225	0.418	0.000	1.000	3,743
<i>Highest education level attained</i>					
No Qualifications	0.076	0.265	0.000	1.000	3,743
Less than High-school	0.620	0.485	0.000	1.000	3,743
High-school	0.138	0.345	0.000	1.000	3,743
More than High-school	0.166	0.372	0.000	1.000	3,743
<i>Social Class</i>					
High	0.248	0.432	0.000	1.000	3,743
Intermediate	0.362	0.481	0.000	1.000	3,743
Routine	0.142	0.349	0.000	1.000	3,743
Disadvantaged	0.044	0.204	0.000	1.000	3,743
Other	0.204	0.403	0.000	1.000	3,743

Notes: The sample is based on wave 1 of ELSA. The table shows the mean, standard deviation, minimum and maximum value and the number of observations for each variable.



Table 3: SUMMARY STATISTICS

	Mean	SD	Min	Max	N
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Measures of cognition</i>					
Numeracy index (calculations)	2.591	0.875	1.000	4.000	3,743
Working memory (word recall)	10.407	3.146	0.000	20.000	3,743
Verbal fluency (word finding)	20.986	6.207	0.000	50.000	3,743
Literacy score	3.584	0.763	0.000	4.000	3,743
Accuracy and speed	19.563	5.601	0.000	59.000	3,743
<i>Panel B: Financial Outcomes</i>					
Financial wealth	9.418	3.122	0.000	15.701	3,743
Total wealth	11.618	3.153	-12.176	16.173	3,743
Net total wealth	10.974	5.098	-12.176	16.173	3,743
Whether any debt	0.433	0.496	0.000	1.000	3,743
Whether any ISAs	0.508	0.500	0.000	1.000	3,743
Whether any stocks, ISA shares or trusts	0.477	0.500	0.000	1.000	3,743
<i>Panel C: Channels</i>					
Planner	0.539	0.499	0.000	1.000	3,743
Non-planner	0.189	0.391	0.000	1.000	3,743
Self-control (moderately exercising)	3.335	1.045	1.000	4.000	3,743

Notes: The sample is based on wave 1 of ELSA. The table shows the mean, standard deviation, minimum and maximum value and the number of observations for each variable. Panel A includes the measures of cognition, Panel B refers to the financial outcomes and Panel C shows the channels. The measures of wealth (financial wealth, total wealth and net total wealth) are expressed as the inverse hyperbolic sine transformation, to account for negative values and values of wealth equal to zero.

**Table 4: PAIRWISE CORRELATIONS - MEASURES OF COGNITION**

	Numeracy index	Working memory	Literacy score	Verbal fluency	Accuracy and speed
Numeracy index	1.000				
Working memory	0.3064	1.000			
Literacy score	0.2680	0.2744	1.000		
Verbal fluency	0.3017	0.3562	0.2106	1.000	
Accuracy and speed	0.1318	0.2093	0.1401	0.2309	1.000

Notes: The sample is based on 3,743 individuals from wave 1 of ELSA.

Table 5: PREDICTORS OF FINANCIAL OUTCOMES

	Financial wealth (1)	Financial wealth (2)	Total wealth (3)	Total wealth (4)	Net total wealth (5)	Net total wealth (6)	Debt (7)	Debt (8)	ISAs (9)	ISAs (10)	Risky assests (11)	Risky assests (12)
Numeracy index (calculations)	0.398*** (0.059) [0.112]	0.412*** (0.059) [0.116]	0.425*** (0.061) [0.118]	0.440*** (0.061) [0.122]	0.638*** (0.103) [0.109]	0.675*** (0.104) [0.114]	-0.003 (0.011) [-0.005]	-0.001 (0.011) [-0.002]	0.049*** (0.010) [0.085]	0.049*** (0.010) [0.086]	0.052*** (0.010) [0.092]	0.053*** (0.010) [0.094]
Working memory (word recall)	0.063*** (0.016) [0.063]	0.064*** (0.016) [0.064]	0.026 (0.017) [0.026]	0.027 (0.017) [0.027]	0.042 (0.028) [0.026]	0.047 (0.029) [0.028]	-0.002 (0.003) [-0.011]	-0.002 (0.003) [-0.016]	0.010*** (0.003) [0.065]	0.010*** (0.003) [0.063]	0.008*** (0.003) [0.048]	0.008*** (0.003) [0.051]
Verbal fluency (word finding)	0.011 (0.008) [0.021]	0.006 (0.008) [0.011]	0.016* (0.008) [0.031]	0.010 (0.008) [0.019]	0.007 (0.014) [0.009]	-0.005 (0.014) [-0.006]	0.000 (0.001) [0.001]	0.001 (0.001) [0.006]	0.001 (0.001) [0.014]	0.000 (0.001) [0.005]	0.000 (0.001) [0.001]	-0.000 (0.001) [-0.004]
Accuracy and speed	0.018** (0.008) [0.032]	0.019** (0.008) [0.034]	0.013 (0.009) [0.023]	0.013 (0.009) [0.022]	-0.003 (0.015) [-0.003]	-0.006 (0.015) [-0.007]	0.002 (0.001) [0.027]	0.003* (0.002) [0.031]	0.002 (0.001) [0.022]	0.002 (0.001) [0.022]	0.000 (0.001) [0.004]	0.001 (0.001) [0.006]
Literacy score	0.272*** (0.062) [0.066]	0.253*** (0.062) [0.062]	0.276*** (0.064) [0.067]	0.241*** (0.064) [0.058]	0.342*** (0.108) [0.051]	0.317*** (0.109) [0.047]	0.015 (0.011) [0.023]	0.015 (0.011) [0.023]	0.022** (0.011) [0.033]	0.020* (0.011) [0.031]	0.031*** (0.011) [0.047]	0.030*** (0.011) [0.047]
Observations	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743
R-squared	0.263	0.261	0.241	0.242	0.169	0.169	0.073	0.073	0.108	0.105	0.155	0.152

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. The outcomes for each regression are reported in the title of each column, where all measures are expressed as the inverse hyperbolic sine transformation. The regressions in columns (2), (4), (6), (8), (10) and (12) use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respond has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 6: PREDICTORS OF THE CHANNELS

	Planner (1)	Planner (2)	Non-planner (3)	Non-planner (4)	Self-control (5)	Self-control (6)
Numeracy index (calculations)	0.022** (0.010) [0.038]	0.022** (0.010) [0.039]	-0.018** (0.008) [-0.040]	-0.019** (0.008) [-0.043]	0.025 (0.021) [0.021]	0.026 (0.021) [0.022]
Working memory (word recall)	0.007** (0.003) [0.043]	0.006** (0.003) [0.038]	-0.008*** (0.002) [-0.062]	-0.007*** (0.002) [-0.058]	0.012** (0.006) [0.036]	0.011* (0.006) [0.032]
Verbal fluency (word finding)	0.001 (0.001) [0.015]	0.001 (0.001) [0.013]	-0.001 (0.001) [-0.013]	-0.001 (0.001) [-0.013]	0.012*** (0.003) [0.074]	0.012*** (0.003) [0.074]
Accuracy and speed	0.000 (0.001) [0.001]	-0.000 (0.001) [-0.001]	-0.000 (0.001) [-0.003]	-0.000 (0.001) [-0.002]	0.004 (0.003) [0.021]	0.003 (0.003) [0.016]
Literacy score	0.034*** (0.011) [0.053]	0.033*** (0.011) [0.050]	-0.040*** (0.009) [-0.079]	-0.038*** (0.009) [-0.074]	0.018 (0.022) [0.013]	0.026 (0.022) [0.019]
Observations	3,743	3,743	3,743	3,743	3,743	3,743
R-squared	0.101	0.098	0.104	0.104	0.150	0.149

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. The outcomes for each regression are reported in the title of each column. The measure of self-control is based on moderately exercising. Regressions in columns (2), (4) and (6) use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 7: PREDICTORS OF FINANCIAL WEALTH

	Financial wealth (1)	Financial wealth (2)	Financial wealth (3)	Financial wealth (4)	Financial wealth (5)	Financial wealth (6)	Financial wealth (7)	Financial wealth (8)	Financial wealth (9)	Financial wealth (10)
Numeracy index (calculations)	0.367*** (0.058) [0.103]	0.380*** (0.058) [0.107]	0.363*** (0.057) [0.102]	0.375*** (0.057) [0.105]	0.390*** (0.059) [0.109]	0.403*** (0.059) [0.113]	0.360*** (0.057) [0.101]	0.373*** (0.057) [0.105]	0.357*** (0.057) [0.100]	0.368*** (0.057) [0.103]
Working memory (word recall)	0.053*** (0.016) [0.053]	0.055*** (0.016) [0.056]	0.048*** (0.016) [0.048]	0.050*** (0.016) [0.050]	0.059*** (0.016) [0.059]	0.060*** (0.016) [0.061]	0.049*** (0.016) [0.050]	0.052*** (0.016) [0.053]	0.044*** (0.016) [0.045]	0.047*** (0.016) [0.048]
Verbal fluency (word finding)	0.009 (0.008) [0.018]	0.004 (0.008) [0.008]	0.009 (0.008) [0.018]	0.004 (0.008) [0.008]	0.006 (0.008) [0.012]	0.001 (0.008) [0.003]	0.005 (0.008) [0.010]	0.001 (0.008) [0.001]	0.005 (0.008) [0.010]	0.001 (0.008) [0.001]
Accuracy and speed	0.018** (0.008) [0.032]	0.019** (0.008) [0.034]	0.018** (0.008) [0.032]	0.019** (0.008) [0.033]	0.017** (0.008) [0.030]	0.018** (0.008) [0.032]	0.017** (0.008) [0.030]	0.018** (0.008) [0.032]	0.016** (0.008) [0.030]	0.018** (0.008) [0.032]
Literacy score	0.223*** (0.060) [0.054]	0.206*** (0.060) [0.051]	0.193*** (0.060) [0.047]	0.180*** (0.060) [0.044]	0.265*** (0.062) [0.065]	0.244*** (0.062) [0.060]	0.218*** (0.060) [0.053]	0.200*** (0.060) [0.049]	0.189*** (0.060) [0.046]	0.175*** (0.060) [0.043]
Planner	1.426*** (0.090) [0.228]	1.423*** (0.090) [0.227]					1.393*** (0.089) [0.222]	1.387*** (0.090) [0.221]		
Non-planner			-1.953*** (0.114) [-0.245]	-1.915*** (0.115) [-0.240]					-1.902*** (0.114) [-0.238]	-1.862*** (0.114) [-0.233]
Self-control (moderately exercising)					0.353*** (0.045) [0.118]	0.344*** (0.046) [0.114]	0.317*** (0.044) [0.106]	0.304*** (0.044) [0.101]	0.306*** (0.044) [0.102]	0.294*** (0.044) [0.098]
Observations	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743
R-squared	0.310	0.307	0.317	0.312	0.275	0.272	0.319	0.316	0.325	0.321

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. Each column shows results from a different regression, with the outcome being financial wealth, expressed as the inverse hyperbolic sine transformation. The regressions in columns (2), (4), (6), (8) and (10) use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 8: PREDICTORS OF TOTAL WEALTH

	Total wealth (1)	Total wealth (2)	Total wealth (3)	Total wealth (4)	Total wealth (5)	Total wealth (6)	Total wealth (7)	Total wealth (8)	Total wealth (9)	Total wealth (10)
Numeracy index (calculations)	0.402*** (0.060) [0.111]	0.416*** (0.060) [0.115]	0.395*** (0.059) [0.110]	0.409*** (0.060) [0.113]	0.417*** (0.061) [0.116]	0.432*** (0.061) [0.120]	0.395*** (0.060) [0.110]	0.410*** (0.060) [0.114]	0.389*** (0.059) [0.108]	0.403*** (0.059) [0.112]
Working memory (word recall)	0.018 (0.016) [0.018]	0.021 (0.016) [0.021]	0.013 (0.016) [0.013]	0.015 (0.016) [0.015]	0.022 (0.017) [0.022]	0.024 (0.017) [0.024]	0.015 (0.016) [0.015]	0.018 (0.016) [0.018]	0.010 (0.016) [0.010]	0.013 (0.016) [0.013]
Verbal fluency (word finding)	0.014* (0.008) [0.028]	0.009 (0.008) [0.017]	0.014* (0.008) [0.028]	0.008 (0.008) [0.016]	0.012 (0.008) [0.023]	0.006 (0.008) [0.012]	0.011 (0.008) [0.021]	0.005 (0.008) [0.010]	0.011 (0.008) [0.021]	0.005 (0.008) [0.010]
Accuracy and speed	0.013 (0.008) [0.023]	0.013 (0.009) [0.023]	0.012 (0.008) [0.022]	0.013 (0.008) [0.022]	0.012 (0.009) [0.021]	0.012 (0.009) [0.021]	0.012 (0.008) [0.021]	0.012 (0.009) [0.021]	0.011 (0.008) [0.020]	0.012 (0.008) [0.021]
Literacy score	0.239*** (0.063) [0.058]	0.206*** (0.063) [0.050]	0.208*** (0.062) [0.050]	0.179*** (0.062) [0.043]	0.270*** (0.063) [0.065]	0.233*** (0.063) [0.056]	0.235*** (0.063) [0.057]	0.200*** (0.062) [0.048]	0.205*** (0.062) [0.050]	0.174*** (0.062) [0.042]
Planner	1.061*** (0.094) [0.168]	1.072*** (0.094) [0.169]					1.031*** (0.093) [0.163]	1.040*** (0.094) [0.164]		
Non-planner			-1.662*** (0.119) [-0.206]	-1.637*** (0.119) [-0.202]					-1.617*** (0.118) [-0.201]	-1.591*** (0.119) [-0.196]
Self-control (moderately exercising)					0.314*** (0.046) [0.104]	0.301*** (0.047) [0.099]	0.288*** (0.046) [0.096]	0.271*** (0.046) [0.089]	0.275*** (0.045) [0.091]	0.258*** (0.046) [0.085]
Observations	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743
R-squared	0.266	0.268	0.279	0.278	0.250	0.250	0.274	0.274	0.286	0.285

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. Each column shows results from a different regression, with the outcome being total wealth, expressed as the inverse hyperbolic sine transformation. The regressions in columns (2), (4), (6), (8) and (10) use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 9: PREDICTORS OF NET TOTAL WEALTH

	Net total wealth (1)	Net total wealth (2)	Net total wealth (3)	Net total wealth (4)	Net total wealth (5)	Net total wealth (6)	Net total wealth (7)	Net total wealth (8)	Net total wealth (9)	Net total wealth (10)
Numeracy index (calculations)	0.600*** (0.102) [0.103]	0.635*** (0.103) [0.108]	0.594*** (0.101) [0.102]	0.630*** (0.103) [0.107]	0.626*** (0.103) [0.107]	0.664*** (0.104) [0.113]	0.591*** (0.101) [0.101]	0.626*** (0.103) [0.106]	0.585*** (0.101) [0.100]	0.622*** (0.102) [0.105]
Working memory (word recall)	0.030 (0.028) [0.018]	0.036 (0.028) [0.022]	0.023 (0.028) [0.014]	0.029 (0.028) [0.018]	0.036 (0.028) [0.022]	0.042 (0.028) [0.026]	0.025 (0.028) [0.015]	0.032 (0.028) [0.020]	0.019 (0.028) [0.012]	0.026 (0.028) [0.016]
Verbal fluency (word finding)	0.005 (0.014) [0.006]	-0.007 (0.014) [-0.008]	0.005 (0.014) [0.006]	-0.007 (0.014) [-0.008]	0.001 (0.014) [0.002]	-0.010 (0.014) [-0.012]	-0.000 (0.014) [-0.000]	-0.011 (0.014) [-0.013]	0.000 (0.014) [0.000]	-0.011 (0.014) [-0.013]
Accuracy and speed	-0.003 (0.014) [-0.004]	-0.006 (0.015) [-0.007]	-0.004 (0.014) [-0.004]	-0.007 (0.015) [-0.007]	-0.005 (0.015) [-0.005]	-0.007 (0.015) [-0.008]	-0.005 (0.014) [-0.005]	-0.007 (0.015) [-0.008]	-0.005 (0.014) [-0.006]	-0.008 (0.015) [-0.008]
Literacy score	0.282*** (0.106) [0.042]	0.259** (0.107) [0.038]	0.244** (0.106) [0.036]	0.227** (0.107) [0.034]	0.334*** (0.108) [0.050]	0.307*** (0.109) [0.045]	0.276*** (0.106) [0.041]	0.251** (0.107) [0.037]	0.239** (0.106) [0.036]	0.221** (0.107) [0.033]
Planner	1.739*** (0.159) [0.170]	1.790*** (0.161) [0.172]					1.695*** (0.158) [0.166]	1.747*** (0.161) [0.168]		
Non-planner			-2.429*** (0.202) [-0.186]	-2.382*** (0.205) [-0.180]					-2.363*** (0.202) [-0.181]	-2.318*** (0.205) [-0.175]
Self-control (moderately exercising)					0.452*** (0.079) [0.093]	0.417*** (0.080) [0.084]	0.409*** (0.078) [0.084]	0.367*** (0.079) [0.074]	0.394*** (0.077) [0.081]	0.355*** (0.079) [0.071]
Observations	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743
R-squared	0.195	0.195	0.201	0.198	0.177	0.175	0.201	0.200	0.206	0.202

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. Each column shows results from a different regression, with the outcome being net total wealth, expressed as the inverse hyperbolic sine transformation. The regressions in columns (2), (4), (6), (8) and (10) use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 10: PREDICTORS OF HAVING ANY DEBT

	Debt (1)	Debt (2)	Debt (3)	Debt (4)	Debt (5)	Debt (6)	Debt (7)	Debt (8)	Debt (9)	Debt (10)
Numeracy index (calculations)	-0.002 (0.011) [-0.003]	0.000 (0.011) [0.000]	-0.003 (0.011) [-0.005]	-0.001 (0.011) [-0.002]	-0.003 (0.011) [-0.005]	-0.001 (0.011) [-0.002]	-0.002 (0.011) [-0.003]	0.000 (0.011) [0.000]	-0.003 (0.011) [-0.005]	-0.001 (0.011) [-0.002]
Working memory (word recall)	-0.001 (0.003) [-0.009]	-0.002 (0.003) [-0.013]	-0.002 (0.003) [-0.011]	-0.002 (0.003) [-0.016]	-0.002 (0.003) [-0.011]	-0.002 (0.003) [-0.015]	-0.001 (0.003) [-0.008]	-0.002 (0.003) [-0.013]	-0.002 (0.003) [-0.011]	-0.002 (0.003) [-0.015]
Verbal fluency (word finding)	0.000 (0.001) [0.002]	0.001 (0.001) [0.007]	0.000 (0.001) [0.001]	0.001 (0.001) [0.006]	0.000 (0.001) [0.002]	0.001 (0.001) [0.007]	0.000 (0.001) [0.002]	0.001 (0.001) [0.007]	0.000 (0.001) [0.002]	0.001 (0.001) [0.007]
Accuracy and speed	0.002 (0.001) [0.028]	0.003* (0.002) [0.031]	0.002 (0.001) [0.027]	0.003* (0.002) [0.031]	0.002 (0.001) [0.028]	0.003* (0.002) [0.031]	0.002 (0.001) [0.028]	0.003* (0.002) [0.031]	0.002 (0.001) [0.028]	0.003* (0.002) [0.031]
Literacy score	0.017 (0.011) [0.026]	0.016 (0.011) [0.025]	0.015 (0.011) [0.023]	0.015 (0.011) [0.022]	0.015 (0.011) [0.023]	0.015 (0.011) [0.023]	0.017 (0.011) [0.026]	0.017 (0.011) [0.026]	0.015 (0.011) [0.023]	0.015 (0.011) [0.023]
Planner	-0.060*** (0.017) [-0.060]	-0.059*** (0.017) [-0.059]					-0.059*** (0.017) [-0.060]	-0.059*** (0.017) [-0.059]		
Non-planner			0.003 (0.021) [0.003]	-0.001 (0.021) [-0.001]					0.002 (0.021) [0.002]	-0.002 (0.021) [-0.001]
Self-control (moderately exercising)					-0.005 (0.008) [-0.010]	-0.003 (0.008) [-0.006]	-0.003 (0.008) [-0.007]	-0.001 (0.008) [-0.002]	-0.005 (0.008) [-0.010]	-0.003 (0.008) [-0.006]
Observations	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743
R-squared	0.076	0.077	0.073	0.073	0.073	0.073	0.076	0.077	0.073	0.073

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. Each column shows results from a different regression, with the outcome being a dummy variable equal to 1 if an individual had any debt and zero otherwise. The regressions in columns (2), (4), (6), (8) and (10) use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.



Table 11: PREDICTORS OF ISA HOLDINGS

	ISAs (1)	ISAs (2)	ISAs (3)	ISAs (4)	ISAs (5)	ISAs (6)	ISAs (7)	ISAs (8)	ISAs (9)	ISAs (10)
Numeracy index (calculations)	0.045*** (0.010) [0.079]	0.045*** (0.010) [0.080]	0.045*** (0.010) [0.079]	0.046*** (0.010) [0.081]	0.047*** (0.010) [0.083]	0.048*** (0.010) [0.084]	0.044*** (0.010) [0.077]	0.044*** (0.010) [0.078]	0.044*** (0.010) [0.078]	0.045*** (0.010) [0.079]
Working memory (word recall)	0.009*** (0.003) [0.057]	0.009*** (0.003) [0.057]	0.009*** (0.003) [0.056]	0.009*** (0.003) [0.055]	0.010*** (0.003) [0.061]	0.010*** (0.003) [0.060]	0.009*** (0.003) [0.054]	0.009*** (0.003) [0.054]	0.008*** (0.003) [0.053]	0.008*** (0.003) [0.052]
Verbal fluency (word finding)	0.001 (0.001) [0.011]	0.000 (0.001) [0.002]	0.001 (0.001) [0.012]	0.000 (0.001) [0.003]	0.001 (0.001) [0.006]	-0.000 (0.001) [-0.003]	0.000 (0.001) [0.004]	-0.000 (0.001) [-0.004]	0.000 (0.001) [0.005]	-0.000 (0.001) [-0.004]
Accuracy and speed	0.002 (0.001) [0.022]	0.002 (0.001) [0.022]	0.002 (0.001) [0.021]	0.002 (0.001) [0.021]	0.002 (0.001) [0.020]	0.002 (0.001) [0.020]	0.002 (0.001) [0.020]	0.002 (0.001) [0.020]	0.002 (0.001) [0.020]	0.002 (0.001) [0.020]
Literacy score	0.016 (0.011) [0.025]	0.015 (0.011) [0.022]	0.015 (0.011) [0.023]	0.014 (0.011) [0.021]	0.021* (0.011) [0.032]	0.019* (0.011) [0.029]	0.015 (0.011) [0.024]	0.014 (0.011) [0.021]	0.014 (0.011) [0.022]	0.013 (0.011) [0.020]
Planner	0.169*** (0.016) [0.169]	0.172*** (0.016) [0.172]					0.164*** (0.016) [0.164]	0.167*** (0.016) [0.167]		
Non-planner			-0.176*** (0.021) [-0.138]	-0.176*** (0.021) [-0.138]					-0.169*** (0.021) [-0.132]	-0.168*** (0.021) [-0.132]
Self-control (moderately exercising)					0.048*** (0.008) [0.100]	0.048*** (0.008) [0.100]	0.044*** (0.008) [0.091]	0.043*** (0.008) [0.090]	0.044*** (0.008) [0.091]	0.044*** (0.008) [0.091]
Observations	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743
R-squared	0.134	0.132	0.125	0.122	0.117	0.114	0.141	0.139	0.132	0.129

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. Each column shows results from a different regression, with the outcome being a dummy variable equal to 1 if an individual had any ISAs and zero otherwise. The regressions in columns (2), (4), (6), (8) and (10) use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 12: PREDICTORS OF STOCKS, SHARES OR TRUSTS HOLDINGS

	Risky assets (1)	Risky assets (2)	Risky assets (3)	Risky assets (4)	Risky assets (5)	Risky assets (6)	Risky assets (7)	Risky assets (8)	Risky assets (9)	Risky assets (10)
Numeracy index (calculations)	0.049*** (0.010) [0.086]	0.050*** (0.010) [0.087]	0.049*** (0.010) [0.087]	0.050*** (0.010) [0.088]	0.052*** (0.010) [0.091]	0.053*** (0.010) [0.093]	0.048*** (0.010) [0.085]	0.049*** (0.010) [0.086]	0.049*** (0.010) [0.086]	0.050*** (0.010) [0.087]
Working memory (word recall)	0.006** (0.003) [0.040]	0.007*** (0.003) [0.044]	0.006** (0.003) [0.040]	0.007** (0.003) [0.043]	0.007*** (0.003) [0.046]	0.008*** (0.003) [0.049]	0.006** (0.003) [0.039]	0.007** (0.003) [0.043]	0.006** (0.003) [0.038]	0.007** (0.003) [0.042]
Verbal fluency (word finding)	-0.000 (0.001) [-0.001]	-0.001 (0.001) [-0.006]	-0.000 (0.001) [-0.000]	-0.000 (0.001) [-0.006]	-0.000 (0.001) [-0.003]	-0.001 (0.001) [-0.008]	-0.000 (0.001) [-0.004]	-0.001 (0.001) [-0.010]	-0.000 (0.001) [-0.004]	-0.001 (0.001) [-0.009]
Accuracy and speed	0.000 (0.001) [0.004]	0.001 (0.001) [0.006]	0.000 (0.001) [0.004]	0.001 (0.001) [0.006]	0.000 (0.001) [0.003]	0.000 (0.001) [0.005]	0.000 (0.001) [0.003]	0.001 (0.001) [0.006]	0.000 (0.001) [0.003]	0.000 (0.001) [0.005]
Literacy score	0.025** (0.011) [0.038]	0.025** (0.010) [0.038]	0.024** (0.011) [0.037]	0.024** (0.011) [0.037]	0.030*** (0.011) [0.046]	0.030*** (0.011) [0.046]	0.025** (0.011) [0.038]	0.024** (0.010) [0.037]	0.024** (0.011) [0.036]	0.024** (0.011) [0.036]
Planner	0.167*** (0.016) [0.167]	0.173*** (0.016) [0.173]					0.165*** (0.016) [0.165]	0.171*** (0.016) [0.171]		
Non-planner			-0.165*** (0.020) [-0.129]	-0.171*** (0.020) [-0.134]					-0.162*** (0.020) [-0.127]	-0.167*** (0.020) [-0.131]
Self-control (moderately exercising)					0.025*** (0.008) [0.052]	0.025*** (0.008) [0.053]	0.021*** (0.008) [0.043]	0.021*** (0.008) [0.043]	0.021*** (0.008) [0.043]	0.021*** (0.008) [0.044]
Observations	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743	3,743
R-squared	0.180	0.179	0.170	0.168	0.158	0.154	0.182	0.180	0.172	0.169

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. Each column shows results from a different regression, with the outcome being a dummy variable equal to 1 if an individual had any stocks, shares or trusts and zero otherwise. The regressions in columns (2), (4), (6), (8) and (10) use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respond has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

# Appendix

## A Application of the Theoretical Framework

Consider a stylised application of our unifying theoretical framework to an inter-temporal consumption smoothing problem. An agent is characterised by cognitive ability  $\mathbf{x} \in \mathbb{R}_+^K$ ,  $K \geq 1$ . She derives utility  $U(\mathbf{c}|\boldsymbol{\theta})$  from a consumption path  $\mathbf{c} = (c_1, c_2, \dots, c_T)$ ,  $T > 1$ , where  $\boldsymbol{\theta}(\mathbf{x}) : \mathbb{R}_+^K \rightarrow \mathbb{R}_+^L$ ,  $L \geq 1$ , denotes a vector of her preferences, which is allowed to be a function of cognitive ability. Finally, define a “default” consumption path  $\mathbf{c}^d$  corresponding to status quo, which is determined by past actions and current decision environment.

To account for the notion of cognitive costs of planning, suppose that departures from the default consumption path impose a fixed cost  $\phi(\mathbf{x}) \geq 0$ . The agent’s cost of planning is decreasing in her cognitive ability, with  $\frac{\partial \phi}{\partial x_i} \leq 0$  capturing the impact of a specific dimension  $i$  of cognitive ability.

If the agent engages in costly planning, her objective is to maximise utility subject to the budget constraint:

$$\max_{\mathbf{c}} U(\mathbf{c}|\boldsymbol{\theta}), \quad \text{s.t. } \mathbf{c} \in \mathcal{C}$$

To account for the role of financial literacy, suppose that acquiring financial knowledge allows the agent to relax her budget constraint. This is represented by a “budget wedge”  $\lambda$ , which is strictly decreasing in financial knowledge. However, accumulating financial knowledge is costly, with the cost associated with wedge  $\lambda$  denoted by  $\psi(\lambda|\mathbf{x})$ . Then, the agent’s budget set is:

$$\mathcal{C} \equiv \left\{ \mathbf{c} \mid \sum_{t=1}^T \frac{c_t}{(1+r)^{t-1}} + \lambda - \psi(\lambda|\mathbf{x}) \leq \sum_{t=1}^T \frac{c_t^d}{(1+r)^{t-1}} \right\}$$

As long as  $\psi(\lambda|\mathbf{x}) \geq 0$  is decreasing, strictly convex, and satisfies the Inada conditions  $\lim_{\lambda \rightarrow \infty} \frac{\partial \psi}{\partial \lambda} = 0$  and  $\lim_{\lambda \rightarrow -\infty} \frac{\partial \psi}{\partial \lambda} = +\infty$ , there exists a unique level of financial knowledge that the agent optimally acquires. Furthermore, if the marginal cost of financial knowledge is decreasing in cognitive ability, i.e.  $\frac{\partial^2 \psi}{\partial x_i \partial \lambda} \leq 0$ , then greater cognitive ability results in higher optimal financial knowledge and consequently in a smaller budget wedge.

Finally, having devised an optimal plan  $\mathbf{c}^*$ , the agent needs to exert enough self-control in order to execute it. Capturing the notion of costly self-control in a reduced form, suppose that the consumption path ultimately chosen by the agent  $\hat{\mathbf{c}}$  is a convex combination of her default path and the optimal plan:

$$\hat{\mathbf{c}} = \nu(\mathbf{x})\mathbf{c}^* + (1 - \nu(\mathbf{x}))\mathbf{c}^d$$

where the self-control parameter  $\nu(\mathbf{x}) \in [0, 1]$  is increasing in cognitive ability, i.e.  $\frac{\partial \nu}{\partial x_i} \geq 0$ .

In sum, the agent’s optimal plan  $\mathbf{c}^*$  and the resulting action  $\hat{\mathbf{c}}$  satisfy:

$$\max_{\mathbf{c}^*, \lambda} U(\hat{\mathbf{c}}|\boldsymbol{\theta}), \quad \text{s.t.:$$

1.  $\hat{\mathbf{c}} \in \mathcal{C} \equiv \left\{ \mathbf{c} \mid \sum_{t=1}^T \frac{c_t}{(1+r)^{t-1}} + \lambda - \psi(\lambda|\mathbf{x}) \leq \sum_{t=1}^T \frac{c_t^d}{(1+r)^{t-1}} \right\}$
2.  $\hat{\mathbf{c}} = \nu(\mathbf{x})\mathbf{c}^* + (1 - \nu(\mathbf{x}))\mathbf{c}^d$

provided that the above exceeds  $U(\mathbf{c}^d|\boldsymbol{\theta}) + \phi(\mathbf{x})$ . Otherwise,  $\hat{\mathbf{c}} = \mathbf{c}^* = \mathbf{c}^d$  at the optimum.

Without imposing further structure and additional assumptions, the model yields some natural predictions. First, greater cognitive ability (in relevant dimensions) increases the agent’s propensity to actively plan her consumption. Second, conditional on planning, cognitive ability affects the features of the optimal plan through its impact on the agent’s preferences and the optimal level of financial knowledge. Third, given the optimal plan, greater cognitive ability allows the agent to carry out the plan more thoroughly.

## B Measuring Numeracy

The six questions asked to the respondents that we used to create the measure of numeracy were:

1. If you buy a drink for 85 pence and pay with a one pound coin, how much change should you get?
2. In a sale, a shop is selling all items at half price. Before the sale a sofa costs £300. How much will it cost in the sale?
3. If the chance of getting a disease is 10 per cent, how many people out of 1,000 would be expect to get the disease?
4. A second hand car dealer is selling a car for £6,000. This is two-thirds of what it cost new. How much did the car cost new?
5. If 5 people all have the winning numbers in the lottery and the prize is £2 million, how much will each of them get?
6. Let's say you have £200 in a savings account. The account earns ten per cent interest per year. How much will you have in the account at the end of two years?

A respondent is initially asked questions 2-4. If they answer all of them incorrectly, they are asked question 1. Otherwise, they are asked question 5. If a respondent answered any of the questions 3-5 correctly, they are additionally asked question 6. Given that respondents might be answering different subsets of questions, we construct a numeracy index as in [Banks and Oldfield \(2007\)](#) by dividing the respondents into four groups:

- (i) Questions 2-4 all incorrect; or question 2 correct and questions 3-5 all incorrect.
- (ii) At least one of questions 2-5 incorrect and question 6 incorrect.
- (iii) Questions 2-5 all correct and question 6 incorrect; or question 6 correct and at least one of questions 2-5 incorrect.
- (iv) Questions 2-6 all correct.

## C Fluid Intelligence

We use the respondents performance on a number series test in order to construct a measure of fluid intelligence. In this test, a respondent is asked to deduct a missing number in a series following a logical, but unknown, pattern - for example, "what should be the next number in a series of 23, 26, 30, 35, ...?". The respondents were always asked six questions, but of varying difficulty. We thus construct a fluid intelligence score by summing up correct responses and weighting them by their difficult.<sup>a</sup>

The resulting score ranges from 0 to 7.5, with a sample average of 3.8 in our sample, restricted to only 2,410 individuals. One should note that the test used to create the measure of fluid intelligence was asked for the first time in wave 6, so we used this to extrapolate our measure in wave 1. While this is not ideal given that we are using data 10 years apart, our robustness check shows that there is a high level of correlation of 0.59 between the measure of fluid intelligence in waves 6 and 9 (i.e., 6 years apart), the only two years in which this test was run.

In Table C1 we look at the pairwise correlations of our measure of fluid intelligence and the other measures of cognitive ability. What emerges from this table is that despite high correlations between numeracy and fluid intelligence, the correlations are far from perfect.

Table C1: PAIRWISE CORRELATIONS - MEASURES OF COGNITION

	Numeracy index	Working memory	Literacy score	Verbal fluency	Accuracy and speed	Fluid intelligence
Fluid intelligence	0.5162	0.3368	0.2759	0.2893	0.1791	1.0000

Notes: The sample is based on 2,410 individuals from wave 1 of ELSA.

<sup>a</sup>The questions comprising the number series test are divided into 5 categories based on their difficulty. A respondent is first asked three 'medium-difficulty' questions and the number of their correct answers determines the difficulty of the subsequent three questions (i.e. each one of potential results 0-3 leads to a different set of followup questions). Examples of the easiest, medium, and most difficult sets of questions are given below:

- (a) 6 . . . 7 . . . BLANK . . . 9
- (b) 6 . . . BLANK . . . 4 . . . 3
- (c) 5 . . . 8 . . . 11 . . . BLANK
- ⋮
- (g) 8 . . . BLANK . . . 12 . . . 14
- (h) 23 . . . 26 . . . 30 . . . 35 . . . BLANK
- (i) 18 . . . 17 . . . 15 . . . BLANK . . . 8
- ⋮
- (m) BLANK . . . 20 . . . 26 . . . 38 . . . 62
- (n) 5 . . . BLANK . . . 11 . . . 19 . . . 35
- (o) 70 . . . BLANK . . . BLANK . . . 84

As each respondent is asked precisely six questions, we construct a fluid intelligence score by summing up their correct responses, weighted by their level of difficulty, with weights of 0.5, 0.75, 1.0, 1.25, and 1.5. The fluid intelligence score thus varies from 0 to 7.5.

Table C2: PREDICTORS OF FINANCIAL OUTCOMES

	Financial wealth (1)	Financial wealth (2)	Total wealth (3)	Total wealth (4)	Net total wealth (5)	Net total wealth (6)	Debt (7)	Debt (8)	ISAs (9)	ISAs (10)	Risky assets (11)	Risky assets (12)
Numeracy index (calculations)	0.404*** (0.068) [0.118]	0.313*** (0.072) [0.091]	0.398*** (0.072) [0.115]	0.352*** (0.076) [0.101]	0.588*** (0.119) [0.106]	0.512*** (0.126) [0.092]	-0.011 (0.013) [-0.020]	-0.004 (0.014) [-0.007]	0.040*** (0.013) [0.070]	0.027** (0.014) [0.047]	0.051*** (0.012) [0.089]	0.039*** (0.013) [0.068]
Working memory (word recall)	0.034* (0.019) [0.035]	0.025 (0.019) [0.025]	-0.004 (0.020) [-0.004]	-0.009 (0.020) [-0.009]	-0.004 (0.033) [-0.003]	-0.013 (0.033) [-0.008]	-0.003 (0.004) [-0.016]	-0.002 (0.004) [-0.012]	0.008** (0.004) [0.047]	0.006* (0.004) [0.039]	0.003 (0.003) [0.019]	0.002 (0.003) [0.011]
Verbal fluency (word finding)	0.014 (0.009) [0.029]	0.012 (0.009) [0.025]	0.014 (0.010) [0.030]	0.013 (0.010) [0.028]	0.008 (0.016) [0.011]	0.007 (0.016) [0.009]	0.001 (0.002) [0.012]	0.001 (0.002) [0.014]	-0.000 (0.002) [-0.000]	-0.000 (0.002) [-0.004]	-0.001 (0.002) [-0.006]	-0.001 (0.002) [-0.010]
Accuracy and speed	0.012 (0.010) [0.022]	0.009 (0.010) [0.016]	0.012 (0.010) [0.023]	0.011 (0.010) [0.020]	0.001 (0.017) [0.001]	-0.002 (0.017) [-0.002]	0.003* (0.002) [0.037]	0.004* (0.002) [0.040]	0.002 (0.002) [0.024]	0.002 (0.002) [0.020]	0.001 (0.002) [0.015]	0.001 (0.002) [0.011]
Literacy score	0.166** (0.076) [0.039]	0.135* (0.077) [0.032]	0.240*** (0.081) [0.056]	0.223*** (0.081) [0.053]	0.284** (0.134) [0.042]	0.258* (0.135) [0.038]	0.028* (0.015) [0.041]	0.031** (0.015) [0.044]	0.010 (0.014) [0.014]	0.005 (0.014) [0.008]	0.021 (0.014) [0.030]	0.017 (0.014) [0.024]
Fluid intelligence score (number series)		0.119*** (0.032) [0.078]		0.062* (0.034) [0.040]		0.101* (0.057) [0.041]		-0.009 (0.006) [-0.036]		0.017*** (0.006) [0.066]		0.016** (0.006) [0.064]
Planner	1.269*** (0.108) [0.210]	1.264*** (0.108) [0.209]	0.836*** (0.114) [0.137]	0.834*** (0.114) [0.136]	1.379*** (0.189) [0.141]	1.375*** (0.189) [0.141]	-0.066*** (0.021) [-0.066]	-0.065*** (0.021) [-0.065]	0.174*** (0.020) [0.173]	0.173*** (0.020) [0.172]	0.152*** (0.020) [0.151]	0.152*** (0.020) [0.151]
Self-control (moderately exercising)	0.318*** (0.055) [0.105]	0.307*** (0.055) [0.101]	0.251*** (0.058) [0.082]	0.245*** (0.058) [0.080]	0.409*** (0.097) [0.083]	0.399*** (0.097) [0.081]	-0.004 (0.011) [-0.007]	-0.003 (0.011) [-0.005]	0.041*** (0.010) [0.081]	0.040*** (0.010) [0.078]	0.019* (0.010) [0.038]	0.018* (0.010) [0.035]
Observations	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410
R-squared	0.325	0.328	0.265	0.266	0.210	0.211	0.081	0.082	0.134	0.136	0.189	0.192

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. The outcomes for each regression are reported in the title of each column, where all measures are expressed as the inverse hyperbolic sine transformation. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table C3: PREDICTORS OF FINANCIAL OUTCOMES

	Financial wealth (1)	Financial wealth (2)	Total wealth (3)	Total wealth (4)	Net total wealth (5)	Net total wealth (6)	Debt (7)	Debt (8)	ISAs (9)	ISAs (10)	Risky assets (11)	Risky assets (12)
Numeracy index (calculations)	0.394*** (0.067) [0.115]	0.316*** (0.072) [0.092]	0.389*** (0.071) [0.112]	0.351*** (0.076) [0.101]	0.577*** (0.118) [0.104]	0.515*** (0.126) [0.093]	-0.012 (0.013) [-0.020]	-0.005 (0.014) [-0.009]	0.039*** (0.013) [0.068]	0.028** (0.014) [0.049]	0.051*** (0.012) [0.088]	0.040*** (0.013) [0.070]
Working memory (word recall)	0.028 (0.019) [0.029]	0.021 (0.019) [0.022]	-0.010 (0.020) [-0.010]	-0.013 (0.020) [-0.013]	-0.011 (0.033) [-0.007]	-0.017 (0.033) [-0.011]	-0.003 (0.004) [-0.018]	-0.002 (0.004) [-0.014]	0.007** (0.004) [0.045]	0.006* (0.004) [0.038]	0.003 (0.003) [0.017]	0.002 (0.003) [0.011]
Verbal fluency (word finding)	0.013 (0.009) [0.028]	0.012 (0.009) [0.026]	0.014 (0.009) [0.028]	0.013 (0.009) [0.027]	0.008 (0.016) [0.010]	0.007 (0.016) [0.009]	0.001 (0.002) [0.012]	0.001 (0.002) [0.013]	-0.000 (0.002) [-0.001]	-0.000 (0.002) [-0.003]	-0.001 (0.002) [-0.007]	-0.001 (0.002) [-0.008]
Accuracy and speed	0.013 (0.010) [0.024]	0.010 (0.010) [0.018]	0.013 (0.010) [0.024]	0.012 (0.010) [0.022]	0.002 (0.017) [0.002]	-0.001 (0.017) [-0.001]	0.003* (0.002) [0.038]	0.004* (0.002) [0.041]	0.002 (0.002) [0.025]	0.002 (0.002) [0.021]	0.001 (0.002) [0.016]	0.001 (0.002) [0.011]
Literacy score	0.134* (0.075) [0.032]	0.124 (0.076) [0.029]	0.210*** (0.080) [0.049]	0.205** (0.080) [0.048]	0.248* (0.133) [0.036]	0.243* (0.134) [0.036]	0.027* (0.015) [0.039]	0.028* (0.015) [0.040]	0.007 (0.014) [0.010]	0.006 (0.015) [0.009]	0.019 (0.014) [0.027]	0.018 (0.014) [0.026]
Fluid intelligence score (number series)		0.112*** (0.032) [0.074]		0.055 (0.034) [0.036]		0.092 (0.056) [0.037]		-0.009 (0.006) [-0.037]		0.016*** (0.006) [0.063]		0.016*** (0.006) [0.062]
Non-planner	-1.350*** (0.158) [-0.168]	-1.819*** (0.141) [-0.227]	-1.252*** (0.167) [-0.154]	-1.488*** (0.149) [-0.183]	-1.567*** (0.278) [-0.121]	-2.060*** (0.248) [-0.158]	-0.056* (0.031) [-0.042]	-0.006 (0.028) [-0.004]	-0.104*** (0.030) [-0.078]	-0.185*** (0.027) [-0.138]	-0.070** (0.029) [-0.052]	-0.146*** (0.026) [-0.109]
Self-control (moderately exercising)	0.295*** (0.054) [0.097]	0.292*** (0.055) [0.096]	0.229*** (0.058) [0.075]	0.228*** (0.058) [0.074]	0.382*** (0.096) [0.078]	0.382*** (0.096) [0.078]	-0.004 (0.011) [-0.009]	-0.004 (0.011) [-0.009]	0.039*** (0.010) [0.078]	0.039*** (0.010) [0.078]	0.018* (0.010) [0.035]	0.018* (0.010) [0.035]
Observations	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410
R-squared	0.345	0.336	0.282	0.280	0.221	0.216	0.083	0.078	0.138	0.127	0.191	0.182

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. The outcomes for each regression are reported in the title of each column, where all measures are expressed as the inverse hyperbolic sine transformation. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.



Table C4: PREDICTORS OF FINANCIAL OUTCOMES (WEIGHTED)

	Financial wealth (1)	Financial wealth (2)	Total wealth (3)	Total wealth (4)	Net total wealth (5)	Net total wealth (6)	Debt (7)	Debt (8)	ISAs (9)	ISAs (10)	Risky assets (11)	Risky assets (12)
Numeracy index (calculations)	0.316*** (0.072) [0.092]	0.318*** (0.072) [0.093]	0.356*** (0.076) [0.103]	0.356*** (0.076) [0.103]	0.539*** (0.128) [0.096]	0.542*** (0.128) [0.096]	-0.005 (0.014) [-0.008]	-0.006 (0.014) [-0.010]	0.027** (0.014) [0.047]	0.028** (0.014) [0.049]	0.038*** (0.013) [0.068]	0.039*** (0.013) [0.069]
Working memory (word recall)	0.025 (0.019) [0.025]	0.021 (0.019) [0.021]	-0.007 (0.020) [-0.007]	-0.011 (0.020) [-0.011]	-0.004 (0.034) [-0.003]	-0.009 (0.034) [-0.006]	-0.002 (0.004) [-0.015]	-0.003 (0.004) [-0.017]	0.006* (0.004) [0.040]	0.006* (0.004) [0.039]	0.003 (0.003) [0.017]	0.003 (0.003) [0.016]
Verbal fluency (word finding)	0.006 (0.009) [0.013]	0.006 (0.009) [0.013]	0.006 (0.010) [0.012]	0.006 (0.010) [0.012]	-0.008 (0.016) [-0.010]	-0.008 (0.016) [-0.010]	0.002 (0.002) [0.020]	0.002 (0.002) [0.019]	-0.001 (0.002) [-0.014]	-0.001 (0.002) [-0.013]	-0.002 (0.002) [-0.020]	-0.002 (0.002) [-0.020]
Accuracy and speed	0.010 (0.010) [0.019]	0.011 (0.010) [0.021]	0.012 (0.010) [0.021]	0.013 (0.010) [0.023]	-0.004 (0.018) [-0.004]	-0.003 (0.018) [-0.003]	0.004** (0.002) [0.043]	0.004** (0.002) [0.044]	0.002 (0.002) [0.020]	0.002 (0.002) [0.021]	0.001 (0.002) [0.013]	0.001 (0.002) [0.013]
Literacy score	0.117 (0.077) [0.028]	0.113 (0.077) [0.027]	0.193** (0.081) [0.045]	0.182** (0.081) [0.043]	0.242* (0.137) [0.035]	0.239* (0.137) [0.035]	0.029** (0.015) [0.042]	0.026* (0.015) [0.037]	0.004 (0.014) [0.006]	0.006 (0.015) [0.008]	0.016 (0.014) [0.023]	0.018 (0.014) [0.026]
Fluid intelligence score (number series)	0.121*** (0.032) [0.079]	0.113*** (0.032) [0.074]	0.065* (0.034) [0.042]	0.058* (0.034) [0.038]	0.095* (0.057) [0.038]	0.086 (0.057) [0.034]	-0.007 (0.006) [-0.030]	-0.008 (0.006) [-0.031]	0.016** (0.006) [0.062]	0.015** (0.006) [0.059]	0.016*** (0.006) [0.063]	0.015*** (0.006) [0.061]
Planner	1.260*** (0.108) [0.208]		0.848*** (0.114) [0.138]		1.463*** (0.192) [0.147]		-0.063*** (0.021) [-0.063]		0.173*** (0.020) [0.172]		0.160*** (0.020) [0.158]	
Self-control (moderately exercising)	0.303*** (0.056) [0.099]	0.292*** (0.055) [0.096]	0.235*** (0.059) [0.076]	0.221*** (0.058) [0.071]	0.376*** (0.099) [0.075]	0.364*** (0.099) [0.072]	-0.004 (0.011) [-0.007]	-0.005 (0.011) [-0.011]	0.038*** (0.010) [0.075]	0.038*** (0.011) [0.076]	0.018* (0.010) [0.035]	0.018* (0.010) [0.036]
Non-planner		-1.782*** (0.143) [-0.220]		-1.475*** (0.150) [-0.180]		-2.056*** (0.255) [-0.154]		-0.008 (0.028) [-0.006]		-0.183*** (0.027) [-0.136]		-0.152*** (0.026) [-0.113]
Observations	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410	2,410
R-squared	0.325	0.330	0.265	0.277	0.209	0.212	0.082	0.079	0.133	0.123	0.190	0.179

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. The outcomes for each regression are reported in the title of each column, where all measures are expressed as the inverse hyperbolic sine transformation. All regressions use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

## D Financial Literacy

We also attempt to capture the respondent's financial literacy based on the questions measuring their understanding of the financial products they themselves own. Specifically, following [Banks and Oldfield \(2007\)](#) we look at the propensity to answer 'don't know' to questions about the pension benefit accumulation, the indexation of benefits, and the expected amount of the benefit for those who participate in an employer-sponsored DB pension scheme. Respondents who provided a numerical answer to those questions are interpreted as more financially literate than those who replied 'don't know'. Note that only a small number of individuals answered these questions, reducing the sample to around 550-600 observations. Table D1 shows that in this restricted sample, around 59% are financially literate if we use the knowledge of the pension benefit formula as an indicator, but the shares of financially literate are higher if we instead use the knowledge of the pension indexation rule or the amount of the expected pension benefit, are around 75%.

Table D1: SUMMARY STATISTICS

	Mean	SD	Min	Max	Observations
	(1)	(2)	(3)	(4)	(5)
Financial Literacy 1 (DB pension formula)	0.588	0.493	0.000	1.000	544
Financial Literacy 2 (DB pension indexation)	0.747	0.435	0.000	1.000	596
Financial Literacy 3 (DB pension benefit)	0.751	0.433	0.000	1.000	595

Notes: The sample is based on wave 1 of ELSA.

Table D2: PREDICTORS OF FINANCIAL LITERACY

	DB pension formula		DB pension indexation		DB pension benefit	
	(1)	(2)	(3)	(4)	(5)	(6)
Numeracy index (calculations)	0.079*** (0.027) [0.134]	0.081*** (0.027) [0.136]	0.069*** (0.023) [0.132]	0.068*** (0.023) [0.131]	0.098*** (0.023) [0.190]	0.102*** (0.023) [0.197]
Working memory (word recall)	-0.005 (0.008) [-0.029]	-0.006 (0.008) [-0.033]	0.003 (0.006) [0.022]	0.002 (0.006) [0.016]	0.014** (0.006) [0.097]	0.013** (0.006) [0.088]
Verbal fluency (word finding)	0.005 (0.004) [0.068]	0.005 (0.004) [0.064]	0.000 (0.003) [0.000]	0.001 (0.003) [0.008]	0.005 (0.003) [0.072]	0.004 (0.003) [0.060]
Accuracy and speed	0.007* (0.004) [0.080]	0.006 (0.004) [0.068]	-0.006* (0.003) [-0.075]	-0.006* (0.003) [-0.075]	0.001 (0.003) [0.015]	0.001 (0.003) [0.017]
Literacy score	0.050 (0.038) [0.058]	0.070* (0.037) [0.082]	0.030 (0.032) [0.038]	0.041 (0.032) [0.054]	-0.023 (0.032) [-0.029]	-0.021 (0.031) [-0.028]
Observations	544	544	596	596	595	595
R-squared	0.114	0.114	0.099	0.096	0.128	0.127

The sample is based on wave 1 of ELSA, including only individuals aged 50 to 70 years old. The outcomes for each regression are reported in the title of each column. Regressions in columns (2), (4) and (6) use the survey weights. All regressions control for a female dummy, a white dummy, age group dummies, health status dummies, social class dummies, marital status dummies and whether the respondent has any children. Standard errors in round brackets and standardised coefficients in square brackets. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

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**Heinrich-Heine-Universität Düsseldorf**

**Düsseldorfer Institut für  
Wettbewerbsökonomie (DICE)**

Universitätsstraße 1, 40225 Düsseldorf

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