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Finance and intelligence: An overview of the literature

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Abstract

Do more intelligent investors take better economic decisions than less intelligent ones? Is risk attitude, in particular risk/loss aversion, linked to cognitive ability? Does an investor's cognitive ability impact his/her patience? Is financial performance positively linked to investor's intelligence? These research questions have become highly relevant with the development of behavioral economics and behavioral finance, following the recognition that humans are not homo economicus. This paper reviews the several strands of literature devoted to answering the above questions. We first discuss the barely debated definitions and measures of intelligence/cognitive ability used in psychology, economics, and finance. We then review the results related to the (controversial) link between risk aversion and cognitive ability. We observe that the literature provides clear results for patience; individuals with a higher level of cognitive ability being more patient on average. Finally, we review the contributions linking (successfully or not) portfolio choice and financial performance to cognitive ability.

KEYWORDS
cognitive ability, decision-making, financial performance, intelligence, portfolio choice

1 INTRODUCTION

Research on cognitive ability/intelligence may be traced back to the end of the nineteenth century, more specifically to the launch of the first psychological laboratory by Wilhelm Wundt in 1879 at the University of Leipzig (Spearman, 1904; Tulsky et al., 2003). Even in early studies, the definition of intelligence was rarely debated. Binet and Simon (1905), the fathers of the first structured IQ test, define intelligence in terms of judgment, attention, practical sense, reasoning facilities, and adaptability. Wechsler (1958), 50 years later, states that intelligence is "the aggregate or global capacity of the individual to act purposefully, to think rationally, and to deal effectively with his/her environment." More recently, Plomin (1999) defines cognitive ability as the capacity to "reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience".

Researchers in experimental psychology first started to test relationships between physical/psychical characteristics and intelligence.[1] However, no validated measure of cognitive ability was available at that time. In most of the early studies, the cognitive ability of children was assessed by teachers; pupils were classified in three categories: dull, good, or smart/bright[2]. Laboratory tests had not revealed a relationship between intelligence and abilities in different domains until the beginning of the twentieth century, for various reasons including the small sample size of most studies and the poor assessment of intelligence/cognitive ability.

The development of research gave rise to more structured definitions and measures of intelligence, starting with the IQ test proposed by Binet and Simon (1905).[3] Their test became popular because it was able to "accurately predict teachers' assessments of their long-time students using a relatively short verbally administered test" (Dickens, 2008). Thousands of papers have been written since then illustrating that intelligence is a multi-dimensional concept whose definition continues to be discussed today (Otero et al., 2022).

In economics and finance, the link between intelligence and decision outcomes has become an important topic with the development of Behavioral Economics. Research in Behavioral Economics has shown that economic agents are quite different from the standard description of homo economicus. In particular, the fully rational homo economicus with unlimited cognitive capacities does not make mistakes and does not waste time and energy solving complex optimization problems. Everything is effortless for him/her and he/she takes, by assumption, the best economic decisions.

On October 9, 2017, Richard Thaler was awarded the Nobel Prize in Economics for his contributions to Behavioral Economics. During the press conference, a journalist asked Thaler "What is the most important impact of your research?" He answered "The recognition that economic agents are human and that economic models have to incorporate that." (quoted in Debondt et al., 2018). This short answer, which had already appeared 20 years before in Thaler's article *From homo economicus to homo sapiens* (Thaler, 2000), shows that studying the relationship between cognitive ability and investment behavior is important and highly relevant. Economic and financial decisions being characterized by risky/uncertain outcomes, it turns out that specific abilities, in particular the understanding of numerical and probabilistic information in the context of daily life, are likely to be important drivers of sound economic/financial decisions (Sobkow et al., 2020).

In this paper, we focus on the link between cognitive ability/intelligence[4] and investor behavior and preferences. This topic has become the focus of scientific attention for at least two decades, with renewed interest following crises like the burst of the dotcom bubble, the Great Financial Crisis of 2008 (Browning & Finke, 2015; Bucher-Koenen & Ziegelmeyer, 2011; Gerardi et al.,

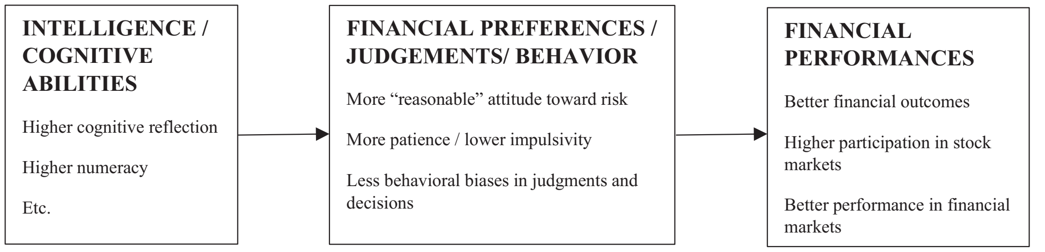
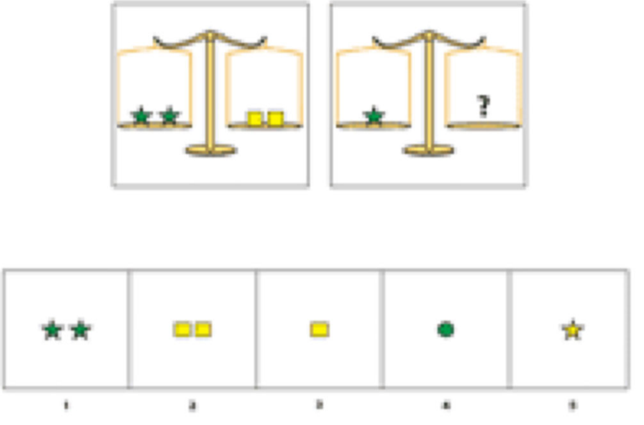


FIGURE 1 Mediated framework of intelligence effects on financial performances.

FIGURE 2 Example of an item in the WAIS test. [Colour figure can be viewed at wileyonlinelibrary.com]



2013; Nofsinger, 2012) or, more recently, the Covid-19 crisis (Bansal, 2020). We propose a conceptual framework of the link between cognitive abilities and financial performance. The main idea is that financial preferences and behavior, in particular risk-taking propensity, impatience and behavioral biases, are the behavioral mediators of the impact of cognitive abilities on financial performance. In short, cognitive abilities influence financial performance by affecting judgements and behavior. Figure 1 summarizes the relationships between the building blocks of the paper.

The aim of the paper is to overview the empirical literature in line with the framework depicted in Figure 2. Our contribution is to bring together several strands of literature so as to outline a global research agenda encompassing methodological issues (including definition and measures of cognitive abilities) and conceptual questions (behavioral mediators of the impact of cognitive abilities on financial performance).

More specifically, three facets of investment behavior are examined in this paper. First, we study the existence of a relationship between cognitive ability and risk attitude. If such a link exists, what are the consequences on stock market participation and portfolio choice? Second, we examine the relationship between cognitive ability and financial performance. Intuition tells us that smarter investors should perform better (Corgnet et al., 2018). However, one could also argue that smarter investors are likely to be active investors, who tend to lose money by trading too much (Odean, 1999). Third, we look at the mediating role of cognitive ability on the propensity of investors to suffer from behavioral biases.

The paper is organized as follows. In Section 2, we review and discuss the definitions and measures of cognitive abilities. Section 3 explores the theoretical links between cognitive skills and individual behavior in financial decisions. This investigation allows us to derive some theoretical propositions about the influence of cognitive abilities on individual preferences and investor behavior. In Section 4, we turn to the empirical evidence relating cognitive ability, preferences, and behavior; the literature provides controversial results on risk aversion (Section 4.1), while those about patience (Section 4.2) and behavioral biases (Section 4.3) seem to be more convincing. We also discuss the potential confounding factors such as gender, age, or other biological factors (e.g., testosterone) (Section 4.4). In Section 5, we present evidence of the influence of cognitive abilities on investor behavior, both on field data and in experimental financial markets.

2 | DEFINITIONS AND MEASURES OF COGNITIVE ABILITIES

The concept of cognitive ability reflects the generic concept of intelligence. Significant research activity has been devoted to both definitions (Section 2.1) and measures (Section 2.2) of cognitive ability.

2.1 | Definitions of cognitive ability/intelligence

Intelligence is one of the most controversial constructs in the field of psychology (Eysenck, 1998; Gottfredson, 1997). Roughly speaking, intelligence is a general mental capability including abilities of reasoning, problem solving, abstract thinking, understanding complex ideas and quick learning (Gottfredson, 1997). While intelligence is sometimes viewed as a general ability useful in various situations, it can also be represented as a diversified portfolio of specific abilities. However, identifying the "assets" composing the portfolio is a hard task.[5]

The seminal work of Cattell (1963), which distinguishes fluid and crystallized intelligence,[6] is an important source for the modern debate on cognitive abilities. Fluid intelligence refers to inductive/deductive reasoning abilities, that is, the ability to solve novel problems. Fluid intelligence mainly refers to innate abilities (processing speed, memory, etc.) related to biological factors. Crystallized intelligence manifests itself through the ability to use some acquired knowledge and skills, including verbal and numerical skills (and financial literacy as well). More specifically, McGrew (2009, p. 5) defines fluid intelligence as "the use of deliberate and controlled mental operations to solve novel problems that cannot be performed automatically", and crystallized intelligence as "the knowledge of the culture that is incorporated by individuals through a process of acculturation". Crystallized intelligence therefore depends on educational opportunities. It also depends on fluid intelligence since fluid intelligence clearly favors the acquisition of knowledge and skills (Kvist & Gustafsson, 2008).

The so-called Cattel–Horn–Carrol (CHC) model has been an influential approach to intelligence in recent years (McGrew, 2009). This theory assumes the existence of 10 broad abilities and more than 70 narrow abilities. The 10 broad abilities are: (i) comprehensive knowledge (Gc), which refers to crystallized intelligence, (ii) fluid reasoning (Gf), which refers to fluid intelligence, (iii) quantitative knowledge (Gq), (iv) reading and writing ability (Grw), (v) short-term memory (Gsm), (vi) long-term storage and retrieval (Glr), (vii) visual processing (Gv), (viii) auditory processing (Ga), (ix) processing speed (Gs), and (x) decision/reaction time/speed (Gt).[7]

In more specific studies of financial behavior, cognitive abilities refer to the ability to perform various tasks requiring the manipulation, evaluation, retrieval or processing of mental information (Lilleholt, 2019), notably numerical and probabilistic information.

2.2 | Measures of cognitive abilities

Measuring intelligence is at least as complicated as defining it. In the CHC approach, it is necessary to build a synthetic index accounting for these various abilities.

In a few studies, administrative data, including measures of cognitive skills (e.g., IQ scores from Army tests), have been used to evaluate the strength of the relationship between investor performance and cognitive ability (Christelis et al., 2010; Cole et al., 2014; Grinblatt et al., 2011, 2012; Talpsepp et al., 2020). Since the impact of cognitive abilities on financial decision-making is likely to be largely based on the basic abilities of reasoning, problem solving or abstract thinking, it is no surprise that in research papers the priority has been given to the assessment of fluid (instead of crystallized) intelligence.[8]

Although many IQ measures have been designed and tested over the last century, no universally accepted IQ test has emerged in the field of Economics and Finance. One of the reasons for this absence of consensus is that standard intelligence tests developed in cognitive psychology are usually time-consuming and, hence, difficult to implement in large samples. Instead, researchers in behavioral economics have chosen to use simpler tests that act as IQ proxies.

In the studies we review hereafter, different measures of cognitive abilities are used: the cognitive reflection test (Bergman et al., 2010; Bosch-Rosa et al., 2018; Breaban & Noussair, 2015; Charness & Neugebauer, 2019; Corgnet et al., 2018; Frederick, 2005; Haita-Falah, 2017; Hoppe & Kusterer, 2011; Noussair et al., 2016; Oechssler et al., 2009; Park, 2016), students' scores on a standardized math test (Benjamin et al., 2013; Brañas-Garza et al., 2008)[9], Raven's matrices test (Burks et al., 2009; Corgnet et al., 2018; Cueva & Rustichini, 2015), and others, in particular tests focused on numeracy or creativity.

2.2.1 | Standard IQ tests

Psychology research widely uses IQ tests to measure intelligence. Among the most widely used tests, we can mention the Stanford–Binet test and the Wechsler Adult Intelligence Scale (WAIS).

The Stanford–Binet test measures intelligence through five factors of cognitive ability, namely, fluid reasoning, knowledge, quantitative reasoning, visual-spatial processing, and working memory. The time-constrained test contains both verbal and nonverbal questions and leads to an IQ score. Examples of questions include:[10]

1. A 5-foot-tall women is standing near a flag pole which casts a shadow of 21 feet on level ground. If the women's shadow is 3 feet long, how tall is the flag pole? (Enter numerical value only) (correct answer: 35 feet)
2. If Thursday is in 3 days, what day was yesterday? (correct answer: Sunday)
3. Do the words credit and acclaim have opposite meanings, similar meanings, or no relation? (correct answer: similar meaning)
4. Karl owns 28 golf balls. Some are green, some are blue, and several are orange. One fourth are red. Are seven golf balls definitely green? Yes, No, Cannot say. (correct answer: Cannot say)
5. Which of these numbers is not like the others? 7, 8, 10, 22, 24 (correct answer: 7)
6. When the letters are rearranged in C C I I A P F, you get the name of a: State, Country, Continent, Ocean, Planet (answer: Ocean)

7. A bike travels 7 feet in 1/3 of a second. At the same speed, how many feet will it travel in 5 s? 21 feet, 35 feet, 105 feet, 155 feet (correct answer: 105 feet)
8. If one serving of cookie dough makes four cookies, how many cookies can be made with seven servings of cookie dough? Enter a numerical value only. (correct answer: 28)
9. What is the next letter in this sequence? N P O Q P R Q (correct answer: S)
10. A pair of shoes sell for $27 per pair. There is a sale tomorrow on shoes offering two pairs for $45. How much will three pairs of shoes cost today? $27, $72, $81 (correct answer: $81)

The Wechsler Adult Intelligence Scale (WAIS) is another IQ test frequently used in psychology.[11] It includes verbal and nonverbal modules. An example of a nonverbal problem is displayed in Figure 2 (correct answer: 3).

Examples of verbal problems are: (i) In what way are a bus and a car alike? (correct answer: they are both vehicles), (ii) In what way are a second and a month alike? (correct answer: they are both intervals of time), and (iii) In what way are rewards and penalties alike? (correct answer: both are used to change behavior).

Note that two submodules (symbol-digit correspondence and word fluency) of the WAIS test are used in the study by Dohmen et al. (2010), who explore the relationships between cognitive abilities and risk attitudes and impatience from a representative sample of German adults (see below).

Some research reviewed below (e.g., Grinblatt et al., 2011, 2012, 2016) use army IQ tests as measure of intelligence. However, as mentioned and explained above, research in behavioral economics and finance does not frequently use IQ tests. In particular, in experimental research, such tests are time-consuming, thus it is difficult to implement them in addition to the main tasks of the experiment. That is why researchers in behavioral economics extensively use other measures of cognitive abilities, such as IQ proxies.

2.2.2 | Cognitive reflection

Cognitive reflection is defined by Frederick (2005, p. 35) as “the ability or disposition to resist reporting the response that first comes to mind”. Interestingly, the elementary three-item cognitive reflection test (CRT) proposed by Frederick (2005) appears as a good predictor of cognitive reflection. The CRT consists of the following three items:

A bat and a ball together cost $1.10. The bat costs 1 dollar more than the ball. How much does the ball cost? (intuitive answer: 10 cents; correct answer: 5 cents)

If it takes five machines 5 min to make five widgets, how long would it take 100 machines to make 100 widgets? (intuitive answer: 100 min; correct answer: 5 min)

In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? (intuitive answer: 24 days; correct answer: 47 days)

Most often, the CRT score is defined as the number of correct answers. In some respect, the CRT allows to differentiate the intuitive/impulsive (low score) and reflective (high score) decision-makers. However, whether it is the best solution to measure cognitive reflection remains unclear. In fact, there are two possible incorrect answers: the one that corresponds to the intuitive answer, and the other answers that are neither correct nor intuitive. For example, Campitelli and Gerrans (2014) find 1901 correct answers, 3248 intuitive answers, and 908 neither correct nor intuitive answers (denoted “other”), from a sample of 2019 individuals.[12] On a much larger database of

43,974 individuals from 69 countries who have provided three answers to the CRT and for which the gender is known, Azevedo et al. (2023) found 49,236 correct answers, 60,912 intuitive answers, and 21,774 other answers[13]. In each of the above papers, the number of "other" answers is far from negligible. Therefore, the ratio of correct answers divided by the sum of correct and intuitive answers could lead to a better interpretation of cognitive reflection as defined by Frederick (2005).

The CRT naturally relates to the dual-process model of human cognition, first presented by Wason and Evans (1974) and popularized by Stanovich and West (2000) and Kahneman (2011). This model suggests that our brain works with two systems. System-1 is intuitive, automatic, and fast. It leads to effortless decisions that, in most cases, are correct. However, using System-1 is sometimes a source of errors. System-2 is slow and reflective, in order to generate deliberative decisions and to avoid errors. System-2 is therefore effortful and requires concentration. In the CRT, all three items are designed to induce an incorrect intuitive answer produced effortlessly by System 1. The control operated by the reflective System 2 allows analytical people to resist their intuition and to find the correct answer. Thus, a higher score on the CRT is interpreted as a sign of a higher level of System 2 cognition, which characterizes more analytical (or less intuitive) people.

An important issue with the CRT has to do with its popularity. Over the years, a large number of papers using the CRT have been published (see Brañas-Garza et al., 2019, for a meta-analysis of 118 CRT studies) and the method is frequently taught in lectures on experimental finance. As a result, participants in experiments may be familiar with the questions and thus know the correct answers (Haigh, 2016; Stieger and Reips, 2016). Although more elaborate questionnaires can be considered, that is, four or seven items CRT (Toplak et al., 2014), respondents who already took the test know that intuitive answers are incorrect, and thus think differently about the questions. Another issue with the CRT is that correctly answering the questions requires numerical skills. Thus, scoring high on the CRT may require not (only) high ability for cognitive reflection but also high numerical skills (Campitelli & Gerrans, 2014; Sinayev & Peters, 2015). In the same vein, Pennycook and Ross (2016) and Pennycook et al. (2016) show that CRT scores also relate to the propensity to think analytically and not only to the capacity of correcting erroneous intuitive answers.

2.2.3 | Raven's progressive matrices

The Raven's Progressive Matrices test (Raven, 1941; Raven et al., 2000) is a nonverbal logical (IQ) test that aims at measuring fluid intelligence. The test consists of five sets of 12 items. The difficulty of each item in a given set increases and each set is, on average, more complex than the previous one. The items consist of one or several visual geometric designs with a missing piece. Subjects are asked to find among the six (or eight) solutions offered, the missing piece. An illustration of an item can be found in Figure 3. Raven progressive matrices are intended to capture subjects' educative and reproductive abilities, the two components of fluid intelligence (Raven, 2000). The test has been widely used throughout the world over the last couple of decades and has a good test-retest reliability. The main advantage of Raven's Progressive Matrices is that the ability to complete the task does not depend on culture nor knowledge.

Hence, the test appears fit to assess fluid intelligence for all kind of populations. Raven's Progressive Matrices are, however, not exempt from limitations. First, the test exhibits a ceiling effect: it fails to discriminate subjects who are located in the tails of the score distribution. As a result, specific tests were designed to address this issue. Colored Progressive Matrices (CPM) and Advanced Progressive Matrices (APM) were introduced to consider, respectively, the lower tail (children

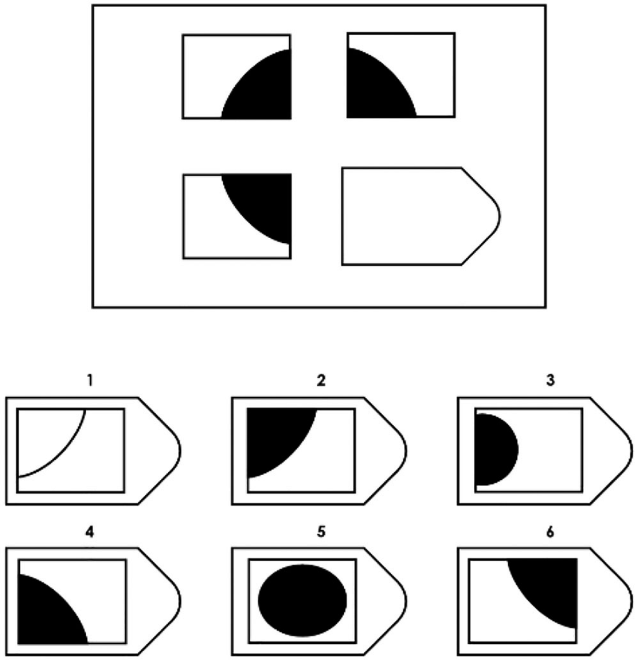


FIGURE 3 Example of an item in the Raven's Progressive Matrices Test.

and people with intellectual disability) and the upper tail. Second, the test requires a significant amount of time to be administered and completed (between 40 and 60 min, Van der Elst et al., 2013), which is particularly problematic when the Raven's Progressive Matrices test is part of a larger experiment/survey. To circumvent this issue, it is possible to either impose a time constraint or to consider only some of the 60 questions. Imposing a time constraint, however, changes the output of the test. In the case of time-bounded tests intellectual efficiency—and not intelligence—is evaluated (Raven et al., 1993). Regarding shorter versions, several attempts have been made to process a selection of items, both for SPM and APM. (Arthur & Day, 1994; Bilker et al., 2012; Bors & Stokes, 1998; Hamel & Schmittmann, 2006; Wytek et al., 1984). Overall, Bilker et al.'s (2012) selection of nine items appear to provide the best ratio of item reduction on score correlation. Indeed, the score on their nine-item version exhibit a correlation of 0.98 with the score on the standard Raven's Progressive Matrices test.

2.2.4 | Numeracy

Given that financial decision-making implies numerical and probabilistic computations (possibly approximate), and number manipulation as well, the specificity of numeracy skills has been widely studied.[14] In the psychology literature, numeracy is defined as the ability to process numerical concepts and basic probabilities (Peters et al., 2006) or, more generally, as the ability to understand numbers. For example, Peters et al. (2006), Peters and Levin (2008), or Estrada-Mejia et al. (2016) use a 11-item Numeracy scale proposed by Lipkus et al. (2001).[15]

The 11 items of Lipkus et al. (2001) are the following:

1. Imagine that we rolled a fair, six-sided die 1000 times. Out of 1000 rolls, how many times do you think the die would come up even (2, 4, or 6)? (correct answer: 500)

2. In the BIG BUCKS LOTTERY, the chances of winning a $10.00 prize is 1%. What is your best guess about how many people would win a $10.00 prize if 1000 people each buy a single ticket to BIG BUCKS? (correct answer: 10)
3. In the ACME PUBLISHING SWEEPSTAKES, the chance of winning a car is one in 1000. What percentage of tickets to ACME PUBLISHING SWEEPSTAKES win a car? (correct answer: 0.1%)
4. Which of the following numbers represents the biggest risk of getting a disease? one in 100, one in 1000, one in 10. (correct answer: one in 10)
5. Which of the following numbers represents the biggest risk of getting a disease? 1%, 10%, 5%. (correct answer 10%)
6. If Person A's risk of getting a disease is 1% in 10 years, and person B's risk is double that of A's, what is B's risk? (correct answer: 2%)
7. If Person A's chance of getting a disease is one in 100 in 10 years, and person B's risk is double that of A's, what is B's risk? (correct answer: two in 100)
8. If the chance of getting a disease is 10%, how many people would be expected to get the disease: A: Out of 100? (correct answer 10)
9. If the chance of getting a disease is 10%, how many people would be expected to get the disease: B: Out of 1000? (correct answer 100)
10. If the chance of getting a disease is 20 out of 100, this would be the same as having a ____% chance of getting the disease. (correct answer: 20)
11. The chance of getting a viral infection is .0005. Out of 10,000 people, about how many of them are expected to get infected? (correct answer: 5)

From their three highly educated samples ($n = 463$ in total), Lipkus et al. (2001) obtained the following percentages of correct answers: 55.3 for Q1, 59.8 for Q2, 20.9 for Q3, 78.2 for Q4, 83.6 for Q5, 90.5 for Q6, 86.6 for Q7, 80.8 for Q8, 77.5 for Q9, 70.4 for Q10, and 48.6 for Q11.

Cokely et al. (2012) propose another numeracy test, called the Berlin Numeracy Test (BNT), which is based on the four following items:

1. Out of 1000 people in a small town, 500 are members of a choir. Out of these 500 members in the choir, 100 are men. Out of the 500 inhabitants that are not in the choir, 300 are men. What is the probability that a randomly drawn man is a member of the choir? Please indicate the probability in percentage. (correct answer: 25%)
2. Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3, or 5)? (correct answer: 30)
3. Imagine we are throwing a loaded die (six sides). The probability that the die shows a six is twice as high as the probability of each of the other numbers. On average, out of these 70 throws how many times would the die show the number 6? (correct answer: 20).
4. In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red? (correct answer: 50%)

This four-item test has been validated by Cokely et al. (2012) (with diverse samples from 15 countries) as a good measure of statistical numeracy and a strong predictor of risk understanding. It was then confirmed by Lindskog et al. (2015) from both a student sample and a representative sample of the Swedish population.

Numeracy skills are also strongly linked to the approximate number system (ANS), a cognitive system that allows humans and many animal species to evaluate quantities without using exact calculations (also referred to as approximate numeracy). Adapting measures from the psychology literature (Booth and Siegler, 2006; Siegler and Booth, 2004; Siegler and Opfer, 2003), Roger et al. (2022) use a Number Line Estimation (NLE) task to elicit the acuity of the ANS of subjects participating in experimental markets.[16] In such a task, subjects are facing an empty number line on a computer screen. The left end is marked with number 0 and the right end is marked with number 100. A randomly selected number between 0 and 100 appears on the subject's screen for 10 s. Participants are asked to locate this number on the empty number line using a slider initially positioned at the left end (i.e., 0). At the end of the 15 trials, an indicator of the subjects' accuracy is computed and interpreted as a measure of their number sense, and a proxy for their numeracy skills.

Research in psychology has also developed self-assessment measures of numeracy. In particular, Fagerlin et al. (2007) propose an eight-item measure called the Subjective Numeracy Scale (SNS). The SNS contains the following eight items:

Cognitive abilities (1 = not at all good, 6 = extremely good):

1. How good are you at working with fractions?
2. How good are you at working with percentages?
3. How good are you at calculating a 15% tip?
4. How good are you at figuring out how much a shirt will cost if it is 25% off?

Preference for display of numeric information:

1. When reading the newspaper, how helpful do you find tables and graphs that are parts of a story? (1 = not at all, 6 = extremely)
2. When people tell you the chance of something happening, do you prefer that they use words ("it rarely happens") or numbers ("there's a 1% chance")? (1 = always prefer words, 6 = always prefer numbers)
3. When you hear a weather forecast, do you prefer predictions using percentages (e.g., "there will be a 20% chance of rain today") or predictions using only words (e.g., "there is a small chance of rain today")? (1 = always prefer percentages, 6 = always prefer words; reverse coded)
4. How often do you find numerical information to be useful? (1 = never, 6 = very often)

Regarding the obvious concerns about the validity of self-assessment measures (Dunning et al., 2004), Fagerlin et al. (2007) and Zikmund-Fisher et al. (2007) found that the SNS correlates quite well with objective measures of numeracy such as the Lipkus et al.'s (2001) scale.

2.2.5 | Convergent thinking

The Remote Associates Test (RAT) has been designed by Mednick (1962) and is often assumed to assess creativity. This test measures subjects' convergent thinking or convergent creativity, that is, the ability to find the solution to a problem by applying established rules of logical reasoning. The test consists of several tasks where the subject is given three disparate related words and is asked to find a fourth related word. For example, for the three words "square/cardboard/open", the correct answer is "box". In the RAT, the final measure is simply determined by the number of

FIGURE 4 Dominant strategy in the Hit 15 game.

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
		X				X				X				X

correct answers. In the research we review below, a 13-item RAT is used by Amador-Hidalgo et al. (2021) in addition to a slightly modified version of the CRT. Note that while the CRT measures reflective versus intuitive thinking, the RAT measures convergent thinking.

2.2.6 | Other measures

Burks et al. (2009) and Cueva and Rustichini (2015) use, in addition to the standard Raven's matrices test, a simple game called Hit 15, played against a computer. In this Nim-type game, the winner is the first player to reach number 15, starting from number 1 and adding at each round a number between 1 and 3. Applying backward induction reasoning enables finding a dominant strategy for the starting player, that is, to reach successively numbers 3, 7, 11, and finally 15. The dominant strategy is illustrated in Figure 4, where the (starting) player marks her moves with a cross.

This game is a good instrument to assess the subject's ability to reason backwards and, more generally, test his/her planning ability and strategic thinking.

Other measures include scores at mathematical tests. For example, Benjamin et al. (2013) ask calculations of expected values, that is, questions of the following form: "Please circle whichever number is larger, (a) 250, (b) $(X \times 1/2) + (0 \times 1/2)$", where X took, in the different questions, the values 200, 350, 500, 650, and 800. The subject's score is simply the sum of his/her correct answers.

Haita-Falah (2017) uses a cognitive quiz that comprises the three questions of the CRT and the following three mathematics questions (inspired by Benjamin et al., 2013):

Which number is larger? (a) 250, (b) $(800 \times 1/2) + (0 \times 1/2)$. (correct answer: b)

y and z are two numbers with the following properties: If we subtract 2 from y, z is obtained and by multiplying y and z, we obtain 48. Which of the following CANNOT be NEITHER y NOR z? (a) 6, (b) 8, (c) 12, (d) – 6, (e) – 8. (correct answer: c)

Which number is larger? (a) 250, (b) $(200 \times 1/2) + (0 \times 1/2)$. (correct answer: a)

Basic calculations may also be used as a proxy for mathematical skills. For example, Amador-Hidalgo et al. (2021) propose an exercise aiming at measuring mathematical proficiency in a stressful environment. They use a variant of the task introduced by Niederle and Vesterlund (2007) who asked subjects to solve the most possible correct summations of five two-digit numbers in 5 min (for instance, 21, 35, 48, 29, and 83).

Finally, some survey research relies on a proxy deduced from subjects' self-assessment of their own mathematical skills. One example is the experimentally validated Global Preference Survey (GPS),[17] developed and exploited (in particular for cross-country comparisons) by Falk et al. (2018), where the proxy for cognitive skills is the self-reported degree of agreement with the statement "I am good at math" on an 11-point Likert scale.[18]

2.2.7 | Summing up and relating the different measures

While some of the papers reviewed above use only one measure (e.g., the CRT in Bergman et al., 2010; Frederick, 2005; Hoppe and Kusterer, 2011; Oechssler et al., 2009), others rely on the combination of several measures. A natural question relates to the existence of correlations between the different measures. Burks et al. (2009) note strong correlations between their three measures of cognitive ability, namely, Raven's matrices test, Hit 15 task and a numeracy test. Their results hold with the different measures, even when they use the first common factor of a factor analysis of the three measures. The same approach is used in Rustichini et al. (2016).

In the same vein, Anderson et al. (2016) find unchanged conclusions about the effect of cognitive ability on risk preferences with alternative measures of cognitive ability (i.e., Raven scores vs. CRT scores).

Cueva and Rustichini (2015) also observe a strong correlation between their two measures of cognitive abilities (Raven's Advanced Progressive Matrices test and the Hit 15 game). Both measures yield the same regression results and the authors finally combine the two measures in a weighted average. Using a factor analysis of three correlated measures of cognitive abilities (CRT, summations exercise, 13-item RAT), Amador-Hidalgo et al. (2021) build a general and robust measure, in order to minimize measurement errors.

Corgnet et al. (2018) note that their three measures of cognitive abilities (CRT score, Raven score and Theory-of-Mind score) correlate only moderately, so that they use the three measures independently in their regression analyses. An alternative methodology is adopted by Chapman et al. (2018) who construct an aggregate score from different measures, including answers to Raven's matrices and answers to CRT questions.

Since a vast literature uses the CRT, it is of special interest to look at the correlations between the CRT scores and other standard measures. Some research has shown that CRT scores are significantly correlated with SAT quantitative scores ($r = .46$ in Frederick, 2005; $r = .45$ in Obrecht et al., 2009) and with numeracy scores based on variants of Lipkus et al.'s (2001) Numeracy scale ($r = .31$ in Cokely and Kelley, 2009; $r = .53$ in Finucane and Gullion, 2010; $r = .51$ and $r = .40$ in Brazilian and US samples, respectively, and in Liberali et al., 2012).

From a methodological perspective, two of the most commonly used measures, the CRT and the 11-item Numeracy scale (Lipkus et al., 2001), raise problems. Indeed, in several samples, most of the participants perceive that the CRT is too difficult and that the Lipkus et al.'s items are too easy. To illustrate, 33% of the Frederick (2005) sample (Table 1, p. 29) obtain a null score, 28% a score of one. Moreover, zero is the modal score in nearly half of Frederick's sub-samples. The distribution of CRT scores is therefore far from symmetric and clearly right-skewed. On the opposite side, the score on the Lipkus et al.'s numeracy questionnaire is heavily left-skewed as shown in Table 1 of Peters et al. (2006, p. 408). The authors find a median score of 9 for this 11-item test. Weller et al. (2013) note that the skewedness of both measures could be an issue because these measures do not discriminate numeracy levels. However, it should be noted that the CRT is not a numeracy measure. In short, these two measures make it difficult to analyze the role of numeracy with linear methods. Weller et al. (2013) propose to tackle the issue by introducing four additional (more complex) numeric questions[19] in the 11 items of Lipkus et al. (2001) and three new items in the CRT. These additions should lead to a new (almost) symmetric measure, well suited for predicting risk judgments in a linear approach, compared to the two separate initial measures.

3 | THE THEORETICAL BACKGROUND OF THE LINK BETWEEN COGNITIVE ABILITIES AND INDIVIDUAL BEHAVIOR

As mentioned in the introduction, the homo economicus does not make mistakes, and does not waste time and energy to solve complex optimization problems. In practice, however, all

TABLE 1 Summary of the main results about cognitive abilities and risk preferences.

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of risk preferences	Effect of higher cognitive abilities on risk aversion	Statistical method
Frederick (2005)	Experimental survey (non-incentivized)	Undergraduate students, $N = 3428$	CRT	Hypothetical lottery choices	–	Comparisons of means and proportions, p-values from t-tests or chi-square tests
Brañas-Garza et al. (2008)	Controlled experiment (incentivized with bonus points in the final grade)	Undergraduate students, $N = 192$	Score on a GRE-like math test	Six lottery choice sequences	0	Comparisons of medians, p-values from Kruskal–Wallis and Median non-parametric tests
Burks et al. (2009)	Laboratory experiment (incentivized)	Trainee truckers, $N = 1066$	Raven's Progressive Matrices test + Hit 15 game + Numeracy test	Four sets of six lottery choices	–	Regression estimations, p-values from OLS estimates
Cokely and Kelley (2009)	Experiment (non-incentivized)	Undergraduate students, $N = 80$	CRT + working memory capacity task + numeracy task	40 hypothetical lottery choices	–	Intercorrelations, p-values from hierarchical linear regression estimates
Oechssler et al. (2009)	Online web-experiment (incentivized)	Online recruitment, $N = 564$	CRT	Two questions on small-stakes lottery choices	–	Comparisons of proportions, p-values from two-sided chi-square tests
Campitelli and Labollita (2010)	Experimental survey (non-incentivized	Volunteers, $N = 157$	CRT	Hypothetical lottery choices	–	Bivariate correlations, p-values from Pearson r correlation test
Dave et al. (2010)	Experiment (incentivized)	Sample of Canadian adults, $N = 881$	Numeracy test	Multiple lottery choices (Eckel & Grossman (2002, 2008) and Holt & Laury tasks)	0	Regression model, p-values

(Continues)

TABLE 1 (Continued)

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of risk preferences	Effect of higher cognitive abilities on risk aversion	Statistical method
Dohmen et al. (2010)	Experiment (incentivized)	Representative sample German adults, $N = 1012$	Submodules of WAIS IQ test	Multiple lottery choices (Holt & Laury task)	–	Econometric interval regression model, p-values
Sousa (2010)	Laboratory experiment (incentivized)	Undergraduate students, $N = 106$	CRT	Multiple lottery choices	0	Comparisons of means, p-values from Mann–Whitney tests; regression estimations, p-values from OLS estimates
Brañas-Garza and Rustichini (2011)	Experiment (non-incentivized)	College students, $N = 188$	Raven Progressive Matrices test	Hypothetical lottery choices	–	p-values from correlation and regression estimates
Benjamin et al. (2013)	Laboratory experiments (incentivized)	Chilean high-school students, $N = 92$ (study 1) and 81 (study 2)	Score on a standardized math test	Five questions on small-stakes bet choices	–	Econometric ordered probit models, p-value from the estimates
Booth and Katic (2013)	Survey study (non-incentivized)	Random sample of young Australians (age 18), $N = 1586$	Percentile ranking for university entrance at age 18	Questions about risk attitudes and hypothetical lottery investment	0	Econometric ordered probit models, p-values
Sutter et al. (2013)	Experiments (incentivized)	Austrian children and adolescents aged 10–18, $N = 661$	Math grades	Multiple lottery choices	0	Regression estimations, p-values
Taylor (2013)	Laboratory experiments (incentivized and non-incentivized))	Undergraduate students, $N = 98$	CRT + 5 items from the Numeracy scale (Lipkus et al., 2001)	Multiple lottery choices (Holt–Laury task)	– (hypothetical payoffs) + (real payoffs)	Regression model, p-values

(Continues)

TABLE 1 (Continued)

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of risk preferences	Effect of higher cognitive abilities on risk aversion	Statistical method
Booth et al. (2014)	Experiment (incentivized)	Undergraduate students, $N = 219$	Raven's Advanced Progressive Matrices test	Multiple lottery choices (Holt–Laury task)	–	Regression estimations, *p*-values
Mandal and Roe (2014)	Administrative data	Representative US population samples: National Longitudinal Survey of Youth (NLS), Health and Retirement Study (HRS), $N = 7682$	Armed Forces Qualifications Test (AFQT) score	Survey questions about risky job scenarios	Non linear (lower risk aversion among respondents with the lowest and highest cognitive abilities)	Econometric interval regression model, *p*-values
Andersson et al. (2016)	On-line experiment (incentivized)	Random sample of the adult Danish population (aged 18–80), $N = 3663$	Raven's Progressive Matrices test + CRT	Multiple lottery choices (two different presentations)	0 (negative effects on errors)	Regression estimations, *p*-values from OLS and interval regressions estimates
Cueva et al. (2016)	Laboratory experiments (incentivized)	University students, $N = 1180$	CRT	Multiple lottery choices (two different protocols)	0 (results task-dependent)	*p*-values from maximum likelihood estimates
Park (2016)	Experimental survey (non-incentivized)	Sample of adult South Korean financial consumers, $N = 243$	CRT	Hypothetical lottery choices	–	Comparisons of means, *p*-values from *t*-tests
Rustichini et al. (2016)	Laboratory experiment (incentivized)	Trainee truckers, $N = 1065$	Raven's Progressive Matrices test + Hit 15 game + Numeracy test	Four sets of six lottery choices	–	*p*-values from regression estimates

(Continues)

TABLE 1 (Continued)

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of risk preferences	Effect of higher cognitive abilities on risk aversion	Statistical method
Taylor (2016)	Laboratory experiment (incentivized and non-incentivized))	University students, $N = 184$	CRT + 5 items from the Numeracy scale (Lipkus et al., 2001)	Multiple lottery choices (Holt–Laury task)	− (hypothetical payoffs) + (real payoffs)	*p*-values from Poisson regression estimates
Beauchamp et al. (2017)	Administrative data	Population-based sample of twins, $N = 11{,}000$	Sweden military service IQ test	Self-reported measure of willingness to take risks	−	Ordered probit models, *p*-value from the estimates
Chapman et al. (2018)	Experimental survey (incentivized)	Representative sample of the U.S. population, $N = 2000$	Raven's Progressive Matrices + CRT	Multiple lottery choices	−	*p*-values from regression estimates
Falk et al. (2018)	Experimentally validated survey (Global Preference Survey)	Representative population samples from 76 countries, $N = 78{,}445$	Self-assessment of math skills (on an 11-point Likert scale)	Lottery choice sequence + self-assessment: willingness to take risks in general	−	Regression estimations, *p*-values from OLS estimates
Andersson et al. (2020)	On-line experiment (incentivized)	Random sample of the adult Danish population (aged 18–80), $N = 1396$	Raven's Progressive Matrices test	Multiple lottery choices (two different presentations)	0 (negative effects on errors)	Econometric structural model, *p*-values from estimates
Amador-Hidalgo et al. (2021)	Online laboratory experiment (incentivized)	Undergraduate Spanish students, $N = 556$	CRT, RAT (Remote Associates Test), 4-digit summations exercise	Multiple lottery choices (Holt–Laury task)	0 (negative effect on inconsistent choices)	Structural equation model, *p*-values from OLS or Logit estimates

individuals exhibit limited cognitive abilities. Empirical research in Behavioral Economics has shown that the reality is far from the idealized description of economic agents behaving as homo economicus. The existence of limits in cognitive abilities raises the question of departures from the normative decision-making process, leading to potential errors and suboptimal choices. Research in economics and psychology goes in at least three directions.

First, below average cognitive abilities could be associated with "pathological" risk aversion. Although Expected Utility Theory (EUT) assumes stable risk attitudes, Rabin (2000) shows that risk aversion on small stakes implies absurd levels of risk aversion on large stakes. In other words, expected utility maximizers should be close to risk neutral when stakes are small. Accordingly, rational people should be virtually risk neutral in economic experiments where stakes tend to be small (Rabin & Thaler, 2001).

Second, impatience could be greater in people with low cognitive abilities. According to rational choice theory, agents should optimize intertemporally, obeying the standard exponential discounting model. However, many people display some forms of impatience in short-term decisions. In fact, their behavior is more in line with the hyperbolic discounting model (Laibson, 1997), compared to the standard EUT model.

Third, a wealth of evidence from behavioral economics and finance sheds light on anomalies in respect to the predictions of the rational choice model (see, e.g., Barberis & Thaler, 2003; Rabin, 1998). People are prone to a number of behavioral biases when making judgements and decisions. They rely on heuristics and fall prey to many biases or fallacies (status quo bias, overconfidence, conjunction and gambler fallacies, etc.)

The link between behavioral biases and cognitive abilities seems straightforward because the above three directions of investigation ("pathological" risk aversion, unreasonable impatience, behavioral biases and fallacies) require some form of bounded rationality. Thus, we expect the behavior of people with higher cognitive abilities to be closer to what is predicted by standard rational models, compared to the behavior of people with lower cognitive abilities.

In economics and finance, a popular theory that formalizes the link between behavior and cognitive abilities relies on the dual process of human cognition.[20] As mentioned above, these two processes have been named System 1 and System 2. System 1 is automatic, mainly unconscious, and relatively effortless. Kahneman (2011) uses the metaphor of a "machine for jumping to conclusions" to describe the way System 1 works. On the contrary, System 2 is effortful, slow, voluntary, and designed to take reflective decisions. We could therefore conjecture that people with high cognitive abilities primarily use their reflective System 2 and rely less on their intuitive System 1, thus avoiding biases in information treatment. A likely consequence is that these "reflective" people eventually perform better in making decisions. This conjecture has been confirmed by the results of a number of experiments studying the link between cognitive load and decision quality; for example, Benjamin et al. (2013) find that adding a distracting task to subjects induces less efficient decisions (i.e., more risk-averse choices in small-stake lottery experiments).

Another related two-system approach relies on the interplay between a short-run myopic self, embodied by an impulsive emotional system, and a long-run rational self, embodied by a deliberative patient system (e.g., Bernheim and Rangel, 2004; Brocas and Carrillo, 2008; Fudenberg and Levine, 2006; McClure et al., 2004). In this approach, it can also be conjectured that people with higher cognitive skills have better abilities to resist short-term temptations and are less prone to various System-1 related biases.[21]

"Narrow bracketing" (Rabin and Weizsacker, 2009; Read et al., 1999) is another reason to link cognitive ability and economic decisions. Individuals with better cognitive skills may be able to "see the big picture" and view the short-run small-stakes laboratory choices with a broader perspective, leading them to adopt a more patient, and close to risk-neutral, behavior.

The above review leads to the following propositions on the link between cognitive abilities and individual preferences:

P1: People with higher cognitive abilities display less risk aversion for small stakes.

Following Rabin (2000) and Rabin and Thaler (2001), proposition P1 means that people with high cognitive abilities should be close to standard EU maximization when making decisions. As a consequence, they should be approximately risk-neutral in small-stakes laboratory experiments. That is, the causal impact of cognitive ability on risk aversion could be mediated by the link between cognitive abilities and control of decisions by the balance between reflective System 2 and intuitive System 1 (Dohmen et al., 2018).[22]

P2: People with higher cognitive abilities are more patient.

Two elements make intertemporal choices cognitively demanding. First, there is a multiplicity of interdependent numerators in the expected utility formula. Second, the structure of the denominators is exponential, even with a constant discount rate. Ensthaler et al. (2018) show that individuals are not well calibrated for compounding, especially when outcomes are random. Roughly speaking, people confuse geometric and linear growth. On the discounting side, Chen and Rao (2007) find that retailers strategically use this bias by proposing double dip price discounts. A discount of 30% followed by a discount of 20% is perceived as a 50% reduction, not the actual 44%. We therefore conjecture that people with higher cognitive abilities are better at managing compounding and discounting, leading them to be more patient.

P3: People with higher cognitive abilities are less prone to behavioral biases in judgement and decision making.

These first three propositions are general and deal with the individual behavior of agents. More specific assumptions about the link between cognitive abilities and investor behavior are developed below. If better cognitive skills imply better information processing, better memory, less biases and, possibly, less risk aversion and more patience, then financial decisions (and, eventually, financial outcomes, should be impacted (participation to the stock market or portfolio diversification for example). Thus, more skilled people should achieve better financial outcomes in the fields of budgeting, investment or wealth accumulation. Accordingly, we formulate the three following propositions:

P4: People with higher cognitive abilities achieve better financial outcomes.

People with higher cognitive abilities should be more efficient in their financial management, for example because they make less mistakes when using their credit cards or have a better understanding of the diversification principle in their wealth management.

P5: People with higher cognitive abilities participate more in stock markets.

Investors who maximize their expected utility should invest in risky assets when the risk premium is positive (Arrow, 1974). The intuition is the same as in Rabin's (2000) argument. Participation in the stock market simply means you invest a positive amount of money in stocks. This amount can be small (in fact close to 0), meaning almost risk-neutrality for small stakes. A positive risk premium is therefore enough to guarantee the optimality of a stock market participation

P6: People with higher cognitive abilities obtain better performance in financial markets.

Finally, higher cognitive abilities could not only imply more participation in stock markets, but also cause individuals to perform better on these markets, either in terms of Sharpe ratios or in the way people trade (stock-picking, market timing).

4 | EMPIRICAL EVIDENCE ON THE LINK BETWEEN COGNITIVE ABILITIES AND INDIVIDUAL BEHAVIOR

In this section, we review the empirical evidence on propositions P1 (risk aversion), P2 (impatience), and P3 (behavioral biases).

4.1 | Cognitive abilities and risk preferences

There is extensive literature on the relationship between cognitive abilities and risk preferences, starting with the seminal paper of Frederick (2005),[23] which introduced the CRT and provided the first results linking cognitive ability with risk and time preferences. Frederick (2005) found that people who exhibit a high CRT score tend to be less risk averse and more patient. A lot of empirical studies, mainly based on laboratory experiments, have investigated the robustness of these early results. Following Amador-Hidalgo et al. (2021), we classify these studies in three categories:

(i) Studies that confirm the link between higher cognitive abilities and lower risk aversion,
(ii) Studies that conclude to the absence of relationship between cognitive abilities and risk preferences,
(iii) Studies showing that whatever the result, it is highly sensitive to the experimental design, thus lacking robustness, at least for methodological reasons.

In the first category, Dohmen et al. (2010), using a random sample of 1000 German adults, confirm that people with higher cognitive abilities are, on average, significantly more risk tolerant and significantly less impatient. The authors measure cognitive abilities using scores on two submodules (a symbol-digit correspondence test and a word fluency test) of a widely used IQ test, the Wechsler Adult Intelligence Scale—WAIS (see Section 2.2.1). Controlling for education and income does not change the result. Several experimental studies further confirmed the positive relationship between cognitive ability and risk tolerance (Benjamin et al., 2013;[24] Booth et al., 2014; Brañas-Garza & Rustichini, 2011; Burks et al., 2009; Campitelli & Labollita, 2010; Cokely & Kelley, 2009; Oechssler et al., 2009; Park, 2016; Rustichini et al., 2016). For example, Oechssler et al. (2009), using the CRT score as a measure of cognitive abilities, find a lower risk aversion for individuals with higher CRT scores (2 or 3). Benjamin et al. (2013) obtain a similar result on a sample of high-school students when cognitive ability is measured using scores obtained from standardized math exams. Several papers based on survey research found similar results (Beauchamp et al., 2017; Chapman et al., 2018[25]; Falk et al., 2018). In particular, Falk et al. (2018) in their experimentally validated survey, the Global Preference Survey (GPS), include two measures of risk preferences, that is, a standard lottery choice sequence and a self-assessment question about the willingness to take risks in general. As noted above (Section 4.2), Falk et al. (2018) use self-assessment of math skills[26] as a proxy for cognitive abilities. Using representative samples from 76 countries, they find that both measures of risk taking are positively impacted by the measure of cognitive ability, so that risk aversion appears to indeed be less pronounced for individuals with higher cognitive skills.[27]

In the second category, which concludes the relationship between cognitive abilities and risk preferences is absent, Brañas-Garza et al. (2008) find no relationship between mathematical skills (measured by the score at a GRE-like math test) and risk attitudes. Similar results are reported by Sousa (2010) and Sutter et al. (2013) from experimental studies, and by Booth and Katic (2013) from survey data. Mandal and Roe (2014) also use survey data and observe a nonlinear relationship between cognitive ability and risk aversion. The respondents with the highest or the lowest cognitive ability scores exhibit a lower risk aversion compared to respondents whose cognitive ability scores are close to the average. Though this second category contains a lower number of references than the first one, Nelson (2014) shows that an absence of result is less likely to be published, possibly because authors have a tendency to under-report experiments that do not provide "conventional" results.

Finally, the third category includes studies that show the high sensitivity of results to the choice of experimental measures of risk preferences, whatever the direction of the results obtained. First, Taylor (2013, 2016) finds that the correlation between cognitive abilities and risk attitudes observed for hypothetical choices, tends to disappear once real payoffs are introduced. More importantly, Dave et al. (2010) and Andersson et al. (2016, 2020) find that the method that is implemented to infer risk preferences, namely, the framing of the risk elicitation task, has a crucial impact on the results. These authors argue that the impact of cognitive abilities on risky choices is in fact related to low-ability subjects making noisier choices rather than differences in risk preferences.[28] Cueva et al. (2016) also find that differences in risk attitudes across CRT groups depend on the choice of the elicitation task. In a similar vein, Amador-Hidalgo et al. (2021) recently showed that cognitive abilities do play a role in the errors made by subjects during the complex tasks of lottery choices. However, cognitive abilities do not influence risk preferences. Individuals with high cognitive abilities are able to avoid mistakes and thus make less inconsistent choices, which, given the properties of the lottery choice tasks, make them appear less risk averse.[29] In a nutshell, the studies from this third category suggest that the impact of cognitive abilities on risk preferences is task-contingent and, hence, correlations found in previous works may be spurious, coming from an artifact caused by the choice of the elicitation method.

What can we conclude from this overview? On one side, Dohmen et al. (2018) defend the idea that cognitive ability is, in general, negatively correlated with risk aversion in financial decision making.[30] On the other side, two recent meta-analyses have been conducted on the link between cognitive abilities and risk aversion (Lilleholt, 2019; Mechera-Ostrovsky et al., 2022), and both suggest that the link is ambiguous. Lilleholt (2019) concludes that the relationship between cognitive ability and risk aversion is domain specific and not as strong as suggested by previous studies, while Mechera-Ostrovsky et al. (2022) emphasize that the apparent correlations between cognitive abilities and risk preferences are spurious and mediated by decision errors. Given these results and those summarized in Table 1, we formulate the following observation:

Observation 1: The effect of cognitive abilities on risk preferences appears to be ambiguous.

4.2 | Cognitive abilities and patience

Some of the aforementioned studies (e.g., Benjamin et al., 2013; Burks et al., 2009; Chapman et al., 2018; Dohmen et al., 2010; Falk et al., 2018; Frederick, 2005; Oechssler et al., 2009; Sutter et al., 2013) find a clear relationship between cognitive abilities and patience: people with higher cognitive abilities are, on average, significantly less impatient in their intertemporal choices.[31] For example, in an online web-based experiment, Oechssler et al. (2009) find that subjects with high CRT score (2 or 3) are indeed more patient than subjects with low CRT scores (0 or 1).

Benjamin et al. (2013) find, in two separate studies conducted on Chilean high-school students, that higher cognitive abilities, proxied by the students' scores on a standardized mathematical test, are associated with less short-term discounting. In an experiment on 661 children and adolescents, Sutter et al. (2013) also find that better mathematical grades are associated with more patience. Applying their survey-based experimental procedure to a representative sample of the U.S. population, Chapman et al. (2018) confirm that higher cognitive ability participants are more patient.

The aforementioned Global Preference Survey (GPS) of Falk et al. (2018), also includes two measures of patience: a standard intertemporal choice sequence and a self-assessment question about the willingness to wait. Using self-assessment of mathematical skills as a proxy for cognitive abilities, the authors find, using representative samples from 76 countries, that both measures of patience are positively linked to their measure of cognitive ability; again, patience appears to be more pronounced among individuals with higher cognitive abilities. In a similar vein, using new macro data, Potrafke (2019) confirms a positive correlation between IQ and patience, that is, higher patience in countries with high IQ populations than in countries with low IQ populations.

Note that in the case of time preferences, the causal effect of cognitive abilities also raises important questions. Indeed, the causation between cognitive abilities and time preferences could be reversed if, as reported by some research (e.g., Mischel et al., 1989), self-control ability in early childhood predicts cognitive skills in adolescence, which indicates that there is in fact a causal effect going from the inherited ability to delay gratification to the accumulation of cognitive skills. This potential reverse causation is addressed by Benjamin et al. (2013), with mixed results about the relation between elementary-school grades and short-time preferences as measured in their experiments at the end of high school.

As documented by the meta-analysis of Shamosh and Gray (2008) and subsequent studies summarized in Table 2, there seems to be a clear relationship between cognitive ability and impatience:

Observation 2: Higher cognitive abilities tend to be associated with higher levels of patience.

4.3 | Cognitive abilities and other behavioral biases

In the psychology literature, a number of papers conclude that higher cognitive abilities tend to reduce the intensity of biases in judgement and decision making such as the sunk cost fallacy or the conjunction fallacy (Stanovich & West, 1998; Stanovich, 1999).

TABLE 2 Summary of the main results about cognitive abilities and impatience.

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of time preferences	Effect of higher cognitive abilities on impatience	Statistical method
Frederick (2005)	Experimental survey (non-incentivized)	Undergraduate students, $N = 3428$	CRT	Hypothetical intertemporal choices	–	Comparisons of means and proportions, *p*-values from *t*-test or chi-square test
Burks et al. (2009)	Laboratory experiment (incentivized)	Trainee truckers, $N = 1066$	Raven's matrices test + Hit 15 game	Four sets of seven intertemporal choices	–	Regression estimations, *p*-values from OLS estimates
Oechssler et al. (2009)	Online web-experiment (incentivized)	Online recruitment, $N = 564$	CRT	One question on short-time preferences	–	Comparison of proportions, *p*-value from two-sided chi-square tests
Campitelli and Labollita (2010)	Experimental survey (non-incentivized	Volunteers, $N = 157$	CRT	Hypothetical intertemporal choices	0	Bivariate correlations, *p*-values from Pearson r correlation test
Dohmen et al. (2010)	Experiment (incentivized)	Representative sample of German adults, $N = 1012$	Submodules of WAIS IQ test	Multiple intertemporal choices	–	Econometric interval regression model, *p*-values from the estimates

(Continues)

TABLE 2 (Continued)

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of time preferences	Effect of higher cognitive abilities on impatience	Statistical method
Benjamin et al. (2013)	Laboratory experiments (incentivized)	Chilean high-school students, $N = 92$ (study 1) and 81 (study 2)	Score on a standardized math test	Six questions on short-time preferences	–	Econometric ordered probit models, p-value from the estimates
Sutter et al. (2013)	Experiments (incentivized)	Austrian children and adolescents aged 10–18, $N = 661$	Math grades	Multiple intertemporal choices	–	Regression estimations, p-values from OLS estimates
Chapman et al. (2018)	Experimental survey (incentivized)	Representative sample of the U.S. population, $N = 2000$	Raven's Progressive Matrices + CRT	10 intertemporal choices	–	p-values from regression estimates
Falk et al. (2018)	Experimentally validated survey (Global Preference Survey)	Representative population samples from 76 countries, $N = 78{,}501$	Self-assessment of math skills (on an 11-point Likert scale)	Intertemporal choice sequence + self-assessment: willingness to wait	–	Regression estimations, p-values from OLS estimates

Peters and Levin (2008) use five variants of Tversky and Kahneman's (1981) Asian disease problem to test whether numeracy skills tend to mitigate the risky-choice framing effect arising from this problem.[32] They measure numeracy with two tests: the 18-item Need for Cognition scale[33] and the 11-item Numeracy scale (Lipkus et al., 2001) presented in Section 4.2. They find that better numeracy skills tend indeed to reduce the intensity of the framing effect.[34]

Using the CRT, Oechssler et al. (2009) and Hoppe and Kusterer (2011) show that most behavioral biases are reduced (though not completely cancelled) for people with higher cognitive abilities. More specifically, Oechssler et al. (2009) observe that people with higher CRT scores (2 or 3) display lower incidences of the conjunction fallacy in the well-known Linda problem of Tversky and Kahneman (1983), and less conservatism in a standard problem of probability updating taken from Edwards (1968). The result from the conservatism bias was replicated by Hoppe and Kusterer (2011). These authors also find that individuals with higher CRT scores (2 or 3) are less affected by the base rate fallacy, indicating that they probably rely less on the representativeness heuristics and perceive more clearly base-rate probabilities. Hoppe and Kusterer (2011) also document that subjects with higher CRT scores have a more precise self-assessment of their number of correct answers to a general knowledge quiz, hence are less affected by overconfidence.[35] However, the authors find that CRT score is unrelated to the occurrence of the endowment effect.[36] Replicating the design proposed by Ariely et al. (2003) for testing anchoring effects, Bergman et al. (2010) find that the anchoring intensity is a decreasing function of the CRT score.[37]

In a more general approach, Toplak et al. (2011) analyze observations from a sample of standard tasks from the heuristics-and-biases literature and find that subjects' CRT score is a good predictor of their performance on such heuristics-and-biases tasks.

Unfortunately, up to now there is no meta-analysis on the link between cognitive abilities and behavioral biases. However, based on the results summarized in Table 3, we propose the following observation.

Observation 3: Higher cognitive abilities seem to reduce significantly (though do not eliminate) some of the behavioral biases identified in the behavioral economics and finance literature.

4.4 | Confounding factors: Gender, age, and other biological factors

Potential confounding factors of the link between cognitive abilities and risk are gender, age and biological characteristics. In particular, ageing tends to decrease both cognitive abilities and risk tolerance.

First, most studies conclude there is a gender gap in risk aversion, with women being less tolerant than men towards risk (e.g., Charness & Gneezy, 2012; Croson & Gneezy, 2009; Niederle, 2016). These results are mainly based on statistical comparisons of averages. Nelson (2015, 2016) uses a similarity index to show that a difference on average scores does not mean that a randomly chosen man is different from a randomly chosen women.

Second, risk aversion tends to increase with age: there is a continuous trend to greater risk aversion from the onset of adulthood to old age, though this trend tends to smoothen out after age 65 (Dohmen et al., 2017; Schildberg-Hörisch, 2018).[38]

Psychological evidence indicates that both physical and cognitive abilities, especially memory, decline with age. Korniotis and Kumar (2011) show that because of declining cognitive abilities, older investors' decisions deteriorate in spite of their greater experience.

TABLE 3 Summary of the main results about cognitive abilities and behavioral biases.

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of behavioral biases	Effect of higher cognitive abilities on behavioral biases	Statistical method
Peters and Levin (2008)	Experiment (non-incentivized)	Undergraduate students, $N = 108$	18-item Need for Cognition scale + 11-item Numeracy scale (Lipkus et al., 2001)	Asian disease problem (framing effect)	− framing effect	*p*-values from regression estimates
Oechssler et al. (2009)	Online web-experiment (incentivized)	Online recruitment, $N = 564$	CRT	Linda problem (conjunction), Edwards problem (conservatism), anchoring question (anchoring)	− conjunction fallacy − conservatism bias 0 anchoring	Comparison of proportions (conjunction), *p*-value from two-sided chi-square test; comparisons of means (conservatism and anchoring), *p*-values from Mann–Whitney U tests

(Continues)

TABLE 3 (Continued)

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of behavioral biases	Effect of higher cognitive abilities on behavioral biases	Statistical method
Bergman et al. (2010)	Laboratory experiment (incentivized)	Undergraduate students, $N = 116$	CRT	Ariely et al.'s (2003) design (anchoring)	– anchoring	p-values of Pearson correlation tests
Hoppe and Kusterer (2011)	Laboratory experiment (incentivized)	University students, $N = 414$	CRT	Problem of evaluating a conditional probability (base-rate fallacy), Edwards problem (conservatism), self-assessment of the number of correct answers to a 5-question general knowledge quiz (overconfidence), pricing of a 'Stabilo Boss' highlighter (endowment effect)	– base rate fallacy – conservatism bias – overconfidence 0 endowment effect	Comparison of proportions (overconfidence, endowment effect), p-value from two-sided chi-square test; comparisons of means (base rate fallacy, conservatism), p-values from two-sided Mann–Whitney U tests
Haita-Falah (2017)	Laboratory experiment (incentivized)	Undergraduate students, $N = 138$	CRT + 3 mathematics questions	Level of investment in an experimental game with sunk investment	0 sunk-cost fallacy	p-values from GLS estimates

Another question is the relationship between gender and the different measures of cognitive ability. Several papers show that the average CRT score of men is significantly higher than the CRT score of women (e.g., Brañas-Garza et al., 2012, 2019; Cueva et al., 2016; Frederick, 2005; Hoppe and Kusterer, 2011; Oechssler et al., 2009). As noted by Bosch-Domènech et al. (2014, p. 2) "While many reasons can account for this result, including differences in upbringing and education of males and females, the sex differences in CRT answers may suggest a role for prenatal organizational hormones, particularly testosterone". Indeed, the link between testosterone and cognitive abilities and risk preferences is well documented. For example, taking the second-to-fourth digit ratio (2D:4D) as a biomarker of prenatal (in utero) testosterone exposure, recent research concludes that higher exposure to testosterone (lower 2D:4D) may be associated with better cognitive abilities (Brañas-Garza & Rustichini, 2011; Cueva et al., 2016), higher risk-tolerance (Brañas-Garza & Rustichini, 2011; Garbarino et al., 2011; Sapienza et al., 2009; Stenstrom et al., 2011), and success in real financial markets (Coates et al., 2009). Brañas-Garza and Rustichini (2011) show that the negative relationship between testosterone and risk aversion is partially mediated by cognitive abilities. Bosch-Domènech et al. (2014) find that the effect of 2D:4D on CRT scores is not affected when controlling for mathematical skills. Neyse et al. (2020) argue that the controversial results obtained in the literature could be caused by the measures and tasks used to assess risk preference, them being designed in the framework of EU theory. They build different ("Prospect Theory friendly") tasks and measures and do not find any relationship between risk preferences and the 2D:4D ratio. Moreover, Juanchich et al. (2020) argue that the gender gap in the CRT comes from a greater anxiety of miscalculations among women, not from a difference of cognitive reflection.

One of the most interesting discussions related to the potential gender gap in cognitive abilities was developed in Nelson (2015, 2016). The author argues that a result stated as "the average CRT score of men is higher than the average CRT score" does not allow to conclude that a randomly chosen man has a better cognitive ability than a randomly chosen women. To illustrate this important remark, we consider two studies for which the raw 3-item CRT data are available. The first one is the paper by Campitelli and Gerrans (2014) that deals with 2019 individuals, and the second one is Azevedo et al. (2023) for which 43,974 detailed CRT scores are available. We calculate the proportion of correct answers for each of the three items and the aggregate score. The proportions of correct answers are higher for men on each item and the difference is highly significant (see Table A1 in the appendix). The t-values for the difference lie between 3.177 and 7.16 in the Campitelli and Gerrans (2014) study, and between 15.63 and 28.04 in the Azevedo et al. (2023) study. These corresponding *p*-values are close to 0. We perform a stochastic dominance analysis (Table A2) to strengthen our results and find that the distribution of men's scores dominates (in the first-order stochastic dominance sense) the distribution of women's scores in the two studies. However, as an additional test, we also calculate the similarity index used by Nelson (2016)—which measures the percentage of men and women in the sample that can be matched with the same CRT score. We find, in Table A3, very high values for the similarity index when we consider the similarity between correct answers. These values are, respectively, 0.86 and 0.88 for the Campitelli and Gerrans (2014) the Azevedo et al. (2023) studies. It is a remarkable result because in the Azevedo et al. (2023) study, the *t*-values (in Table A1) were very high. Nevertheless, more than 85% of women can be matched with men who have the same CRT score. It is therefore important to state the gender gap in specific terms, namely, "the average CRT score of men is higher than the average score of women". This statement does not permit to conclude at the individual level.

Another important area of research deals with the link between cognitive ability and personality. Many psychology studies investigate the complex relationships between the different facets of cognitive abilities (fluid vs. crystallized intelligence) and the Big Five personality traits (e.g., Rammstedt et al., 2016, 2018). These personality-linked confounding factors could partially explain the controversial nature of the results concerning risk preferences and cognitive abilities. However, they do not seem to impact the results on the relationship between cognitive abilities and time preferences or behavioral biases. Thus, even when taking these confounding factors into account, the three general results presented above still persist.

To conclude, even after controlling for the confounding factors of gender, age and biological characteristics, there remains direct relationships between cognitive abilities and individual behavior, as described by observations 1, 2, and 3.

5 | EMPIRICAL EVIDENCE ON THE LINK BETWEEN COGNITIVE ABILITIES AND INVESTOR DECISIONS

Section 4 showed that people with higher cognitive abilities are less prone to pathological risk aversion and impatience as well as to many other behavioral biases. Moreover, these people appear to have better financial literacy (Muñoz-Murillo et al., 2020; Skagerlund et al., 2018).[39] Those results lead to conjecture that people with higher cognitive abilities take more efficient financial decisions. This section presents evidence of the influence of cognitive abilities on financial behavior, in line with propositions P4 (People with higher cognitive abilities achieve better financial outcomes), P5 (People with higher cognitive abilities are more willing to participate in stock markets), and P6 (People with higher cognitive abilities perform better in financial markets).

Note that such potential effects of cognitive abilities may be more difficult to establish if participants in financial markets have rather good cognitive abilities (selection bias). However, there remains a large heterogeneity in the level of the participants and the vast majority of studies mentioned above show that behavioral biases are reduced but not eliminated among people with high cognitive abilities (e.g., Benjamin et al., 2013; Oechssler et al., 2009).

5.1 | Cognitive abilities and financial outcomes

In the following, we restrict our review to studies that use direct measures of cognitive abilities and we set aside research based on age or education.[40]

Agarwal and Mazumder (2013) construct a dataset of members of the US military that includes a measure of cognitive skills—the Armed Forces Qualifying Test (AFQT) score—and information on financial decisions. They find that individuals with higher cognitive abilities are less likely to make mistakes when using credit cards or in home loan applications.[41] The authors also show that these results are primarily driven by mathematical skills and not by verbal skills since the correlations between test scores and mistakes only hold for mathematical scores but not for non-mathematical verbal test scores.

Estrada-Mejia et al. (2016) use the 11-item Numeracy scale of Lipkus et al. (2001) as a measure of numeracy, on a panel of 1019 Dutch adults. They find a positive and statistically significant correlation between numeracy and wealth, even after controlling for differences in education, risk preferences, financial knowledge, and other variables. The same type of results is found by Estrada-Mejia et al. (2020) in a field study conducted with 218 adults in agrarian communities in Peru's Andean highlands.

Using data from the U.S. Health and Retirement Study (HRS), Tang (2021) confirms that higher cognitive abilities are associated to better financial outcomes. HRS contains both measures of cognitive abilities coming from standard cognition tests (on counting, naming, recalling, etc.), and information about the financial profile of respondents. The author creates a financial behavior score based on six indicators that target the different aspects of financial behavior: meeting monthly bills, having enough money to buy food, paying mortgage on time, diversifying portfolios, following the stock market, having a better-than-median financial wealth growth rate. The analyses done with a global score but also with separate scores for "routine tasks" and "advanced tasks". Tang (2021) finds that cognitive abilities have a positive effect on both types of tasks but the effect is clearly stronger for advanced tasks. Thus, the effect of cognitive abilities on financial outcomes is stronger in areas where tasks require more cognitive skills (diversification of portfolio, accumulation of financial wealth, following the stock market) than in the routine tasks of basic budget management (having money in the checking account, paying bills on time, etc.).

We can summarize these findings in the following general observation.

Observation 4: People with higher cognitive abilities tend to achieve better financial outcomes.

5.2 | Cognitive abilities and stock market participation

While there is an abundant literature on the effects of financial literacy (e.g., van Rooij et al., 2011) and education (e.g., Campbell, 2006; Christiansen et al., 2008; Cole et al., 2014; Guiso et al., 2003; Gottesman and Morey, 2006)[42] on stock market participation, evidence of a direct effect of cognitive abilities on market participation is scarcer, primarily because it is difficult to collect reliable individual data.[43] Indeed, the study of the link between cognitive abilities and stock market participation requires datasets that comprise both direct measures of cognitive abilities and detailed data on investing choices.

In the working paper of Benjamin et al. (2013), the authors use data from the National Longitudinal Survey of Youth 1979 (NLSY) that includes the score in the Army IQ test as a measure of cognitive abilities and two questions related to financial decisions (level of wealth accumulation, stock market participation). Benjamin et al. (2006) find that people with higher cognitive abilities report higher wealth and participate more in the stock market, even after controlling for income and family background. Similar results are found in research that uses the Health and Retirement Survey (HRS) in the U.S. (e.g., Kézdi and Willis, 2003; McArdle et al., 2011).

In Europe, Christelis et al. (2010) use the Survey of Health, Ageing and Retirement in Europe (SHARE) to show that there is a strong association between the propensity to invest in stocks and cognitive abilities. SHARE is a large dataset (19,548 households and 32,405 individuals) covering 11 European countries and has a section devoted to cognitive ability measures. Christelis et al. (2010) used three measures: an indicator of numeracy (mathematical skills), an indicator of verbal fluency (executive function) and a memory indicator (recall skills). The authors find a positive relationship between the three measures of cognitive abilities and the level of participation in the stock market, both for direct participation and for indirect participation through mutual funds or investment accounts. They verify that this positive correlation between cognitive abilities and stockholding is still valid when controlling for age, education, health and economic resources. However, they observe that such a relationship does not hold for less information-intensive assets (e.g., bonds). The authors conclude that the relationship between cognitive abilities and stockholding is likely due to information constraints rather than to preferences or psychological traits.

The results of Christelis et al. (2010) were confirmed by subsequent studies (Cole et al., 2014; Grinblatt et al., 2011). In particular, Grinblatt et al. (2011) use data from Finland that include a measure of cognitive ability (IQ scores coming from the Finnish Armed Forces intelligence test completed by each Finnish man aged 18–20 when joining the army) and information on financial investment. They find a positive impact of IQ on stock market participation, after controlling for wealth, income, age, and other usual familial and demographic variables. We can summarize these findings in the following general observation.

Observation 5: People with higher cognitive abilities are more willing to participate in stock markets.

5.3 | Cognitive abilities and performance in financial markets

Most of the empirical evidence provided in this section comes from experimental markets. The reason is simple: collecting measures of cognitive abilities and real financial data at the same time is challenging, both for retail and professional investors.

5.3.1 | Evidence from the field

Grinblatt et al. (2011), who find, as mentioned above, a positive correlation between IQ and stock market participation, also document that investors with high IQs exhibit better investment performance, that is, less risky portfolios and larger Sharpe ratios. This result is confirmed by a subsequent analysis of the same database. Grinblatt et al. (2012) document a positive link between IQ and a wide range of indicators of investor performance (market timing, stock-picking, trade execution). In the same vein, Grinblatt et al. (2016) find that investors with high IQ choose mutual funds with lower fees. However, this result has two interpretations. On the one hand, high-IQ investors are less in need of costly services because they are able to take sound financial decisions without external help. On the other hand, they do not overpay for financial services because they are more able to value the price charged for financial services. Grinblatt et al. (2016) conclude that the two interpretations are at work. High-IQ investors avoid funds linked to expensive services. They prefer a simple mix of equity and bond funds, compared to (expensive) packaged balanced funds. At the same time, the authors observe that IQ and fees are negatively correlated, even after controlling for many confounding factors. The above results are also indirectly confirmed by Talpsepp et al. (2020) who find that, in Estonian financial markets, investors who exhibit higher academic abilities have more profitable investments and better financial performance. The results are especially strong for those with higher grades in mathematics and English exams at the end of high school.[44]

Farago et al. (2022) study the decisions of professional fund managers in a sequence of experiments and questionnaires. First, they find that the risk tolerance of fund managers is positively linked to fund risk, controlling, among others, for fund benchmark and fund category. A more original (nevertheless intuitive) result is that the ambiguity tolerance of fund managers has a positive correlation with the funds' tracking error (calculated with respect to the benchmark).

However, the authors find that cognitive skills are unable to explain excess returns of funds, even if fund managers with a high CRT score compose funds at lower risk.

5.3.2 | Evidence from laboratory experiments

Most laboratory studies show that people with higher cognitive abilities perform better in experimental asset markets (Baghestanian et al., 2015; Bosch-Rosa et al., 2018; Breaban & Noussair, 2015; Charness & Neugebauer, 2019; Corgnet et al., 2015, 2018; Cueva & Rustichini, 2015; Holt et al., 2017; Miklánek & Zajíček, 2020; Noussair et al., 2016; Roger et al., 2022; Shestakova et al., 2019; Tai et al., 2018).[45] In contrast, Weitzel et al. (2020) do not find that cognitive skills impact market performance, both on a pool of finance professionals and students. However, they indicate that their sample lacks variance in cognitive skills, which could explain the absence of difference. The presence of participants with higher cognitive abilities seems to lead to more efficient markets (Breaban & Noussair, 2015; Charness & Neugebauer, 2019; Cueva & Rustichini, 2015; Noussair et al., 2016; Roger et al., 2022). The relationship between cognitive abilities and mispricing can be explained by the fact that subjects exhibiting higher cognitive abilities tend to better understand the instructions of the experiment and show less confusion. Indeed, previous research (Huber & Kirchler, 2012; Kirchler et al., 2012; Lei & Vesely, 2009) indicates that mispricing decreases when rules and procedures are easily understood.

Baghestanian et al. (2015) propose a heterogeneous agent model for experimental closed-book call market design. The model discriminates subjects between fundamental traders, who buy when the price is below the fundamental value (hereafter FV) of the risky asset and sell when the price is above the FV, speculators, whose trades are function of the trades of the noise traders, and noise traders, who are equally likely to buy or sell during each period with respect to a reference price (the last period clearing price in the experiment). They find higher CRT scores for fundamental traders and speculators, compared to noise traders. Fundamental traders and speculators also reach a higher terminal wealth at the end of the experiment.

Breaban and Noussair (2015) analyze the role of individual characteristics—specifically risk aversion, loss aversion and cognitive ability—in explaining mispricing in standard experimental markets. The difference between their setup and the one of Smith et al. (1988) is the dynamics of the FV. They consider two treatments, bear markets and bull markets, in which the FV remain constant in the first seven periods and then decreases (increases) from period 8 to the end of the market (period 15). Similar to Baghestanian et al. (2015), they find that high CRT subjects are more likely to behave as fundamental traders. In terms of market outcomes, Breaban and Noussair (2015) document a positive influence of cognitive ability on market efficiency. When the average CRT score of a session is high, smaller price deviations from FV are observed. Regarding individual outcomes, the authors find a positive and significant association between CRT score and individual earnings. Corgnet et al. (2015), in a paper studying the effect of house money on bubbles, obtain similar results on the impact of CRT. They find that high CRT subjects tend to buy (sell) when prices are below (above) FV. They behave as fundamental traders, therefore earning more than their low CRT counterparts. In a contemporaneous article, Cueva and Rustichini (2015) use alternative measures of cognitive abilities, namely, the "Hit 15" game[46] and Raven matrices. They obtain comparable findings. Individuals with higher (lower) cognitive abilities earn significantly more (less). Sessions with individuals characterized by high cognitive abilities tend to exhibit a lower than average market volatility.

Noussair et al. (2016) consider two setups: one is a standard asset market and the second is a setup with both a spot and a futures market. Their results on the spot market are in line with previous findings. However, on the futures market, the average CRT score of the participants does not correlate with the level of mispricing, contrary to what is observed on the spot market.

In one of the few articles that completely focuses on cognitive abilities, Bosch-Rosa et al. (2018) examine whether bubbles tend to inflate or to disappear when markets are populated only by individuals with high (or low) cognitive abilities. Consistent with previous papers and with the idea that misunderstanding of procedures and rules induce mispricing (Huber & Kirchler, 2012; Kirchler et al., 2012; Lei & Vesely, 2009), Bosch-Rosa et al. (2018) observe standard bubble and crash patterns in "low cognitive abilities" markets. Bubbles and crashes, however, do not appear in "high cognitive abilities" markets.

Akiyama et al. (2017) postulate that mispricing is caused both by confusion (misunderstanding of procedures and instructions) and strategic uncertainty (uncertainty about the behavior of others). To test the role of strategic uncertainty, the authors run two types of markets: one type where the market is composed of 6 human traders (6H) and one where there is only one human subject and 5 computer traders (1H5C). This setup allows them to assess the importance of strategic uncertainty. Indeed, in the 1H5C market because of how computers behave, prices should be equal to the FV. Thus, deviations of forecasts from the FV should result from confusion. The deviations in the 6H setup should be caused by both confusion and strategic uncertainty. The intensity of strategic uncertainty is observed by looking at the difference in forecast price deviation from FV between both types of markets. Overall, Akiyama et al. (2017) find that strategic uncertainty accounts for about half of the forecast deviation from the FV. The relative importance of strategic uncertainty increases in markets where traders score high on the CRT (about 70% of the median initial forecast deviation from the FV).

Another important article dedicated to the role of cognitive abilities in explaining financial performance is Corgnet et al. (2018). Contrary to Bosch-Rosa et al. (2018), Corgnet et al. (2018) do not focus on mispricing but rather on subject performance. They measure cognitive abilities using the CRT and Raven's matrices. In addition, they also consider the influence of the Theory of Mind (i.e., a psychological trait related to empathy and the ability to infer others' intentions, which play a key role in some disorders such as autism). Finally, they include controls such as financial literacy, personality traits and risk attitude. Using an experimental market setup similar to Plott and Sunder (1988), they find that both cognitive reflection and fluid intelligence are associated with higher individual earnings.

Charness and Neugebauer (2019) test the invariance theorem of Modigliani and Miller using experimental asset markets where two twin shares are traded simultaneously. The expected value of the dividends associated with the two shares differs by a constant amount. Hence, the difference in prices between the two types of shares should be equal to that amount. Price discrepancies, however, do exist; especially when there are limits to arbitrage. Charness and Neugebauer (2019) nonetheless find that these price discrepancies are smaller in sessions populated by high CRT subjects.

In a recent paper, Roger et al. (2022) show that approximate numeracy, measured with a Number Line Estimation (NLE) task, is a strong predictor of subjects' performance in a continuous double auction market. More specifically, they observe that high-ability subjects obtain higher earnings. The two sources of performance for the high-ability subjects are: (1) a better use of limit orders (in short, buying low and selling high) and, (2) an ability to jump quickly on trading opportunities. The results are robust to controlling for differences in risk aversion, background education or demographic characteristics.

Based on the above review and the results summarized in Table 4, we propose the following observation.

Observation 6: People with higher cognitive abilities tend to obtain better performance in financial markets (real and experimental) and to mitigate mispricing.

6 | CONCLUSION

While the topic intelligence/cognitive abilities have been under scrutiny for more than a century, it has only recently attracted interest in the fields of economics and finance. In standard economic models, agents are homo economicus and thus take rational decisions. Therefore, the question of the link between intelligence and economic/financial performance was irrelevant. After three Nobel prizes attributed to researchers in Behavioral Economics and Behavioral Finance (Daniel Kahneman in 2002, Robert Shiller in 2013 and Richard Thaler in 2017), studying the relationship between the intelligence of homo sapiens and his/her decision-making processes has become; however, fully legitimate.

In this paper we reviewed the literature that explores this aforementioned relationship. Our contribution is to bring together several strands of literature to outline a global research agenda encompassing methodological issues (definition and measures of cognitive abilities, field and experimental data, etc.) and conceptual questions (behavioral mediators of the impact of cognitive abilities on financial performances). We acknowledge that each of the above elements would deserve further investigations, in particular through meta-analyses. For some subfields, recent meta-analyses already exist: Lilleholt (2019) and Mechera-Ostrovsky et al. (2022) link cognitive abilities and risk preferences in their respective meta-analyses, and Shamosh and Gray (2008) survey the impact of cognitive abilities on patience. Some other topics would need in themselves new meta-analyses. However, the possibly most important topic of the paper, namely, the effect of cognitive abilities on financial performances, does not yet offer a large number of studies, and the papers are based on two completely different types of data, that is field data and laboratory data from experimental studies.

A summary of our conclusions from the overview of the literature is as follows:

- The effect of cognitive abilities on risk tolerance remains controversial. Some studies find a positive link, some others do not find any, and the third category of papers finds that the link, whatever the direction, is largely contingent on the measures that are used and the experimental framework.
- Results are more clearcut for patience. Individuals with higher (lower) cognitive abilities are more (less) patient.
- High cognitive abilities reduce the propensity to fall prey to most behavioral biases.
- People with higher cognitive abilities achieve better financial outcomes (when using credit cards, in managing loans, etc.).
- People with higher cognitive abilities are more willing to participate in stock markets. At the country level, a positive relationship was found between the mean IQ score and the development of the financial and banking systems
- People with higher cognitive abilities perform better in financial markets. They achieve higher earnings in experimental markets and they get higher Sharpe ratios in real markets.

TABLE 4 Summary of the main results about cognitive abilities and investor performance.

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of investor performances	Effect of cognitive abilities on investor performance	Statistical method
Christelis et al. (2010)	Administrative data	Representative sample of individuals ages 50+ in 11 European countries, $N = 19{,}548$	Indicators of numeracy, verbal fluency and memory	Participation in the stock market	+ stock market participation	Econometric probit models, *p*-values
Grinblatt et al. (2011)	Administrative data	Finnish males, $N = 158{,}044$	IQ score from Finnish Armed Forces (FAF) Intelligence Assessment	Participation is stock markets, portfolio Sharpe ratios	+ stock market participation + portfolio Sharpe ratios	Econometric models, *p*-values from Probit (stock market participation) or OLS (Sharpe ratios) estimates
Cole et al. (2014)	Administrative data	National Longitudinal Survey of Youth (NLSY), $N = 14{,}913{,}356$	Various measures of cognitive ability in the NLSY	Investment outcome, ownership of stocks, bonds or mutual funds	+	Regression estimations, *p*-values from OLS estimates
Baghestanian et al. (2015)	Laboratory experiments (incentivized)	Undergraduate students, $N = ?$	CRT	Earnings in experimental asset markets	+	*p*-values of Kendall and Spearman correlation tests
Breaban and Noussair (2015)	Laboratory experiments (incentivized)	University students, $N = \sim 120$	CRT	Price deviations from fundamental values	+ (lower price deviations from fundamental values)	*p*-values from regression estimates
Corgnet et al. (2015)	Laboratory experiments (incentivized)	?	CRT	Earnings in experimental asset markets	+	Comparisons of means and medians, *p*-values from Mann–Whitney–Wilcoxon test

(Continues)

TABLE 4 (Continued)

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of investor performances	Effect of cognitive abilities on investor performance	Statistical method
Cueva and Rustichini (2015)	Laboratory experiments (incentivized)	University students, $N = 284$	Raven's Advanced Progressive Matrices test + Hit 15 game	Price deviations from fundamental values + market volatility + earnings	+ (lower price deviations from fundamental values, lower market volatility, higher earnings)	Regression estimations, *p*-values
Noussair et al. (2016)	Laboratory experiments (incentivized)	University students, $N = 218$	CRT	Performances in experimental asset markets (earnings, price discovery)	+	Regression estimations, *p*-values
Akiyama et al. (2017)	Laboratory experiments (incentivized)	University students, $N = 173$	CRT	Forecast deviations	+ (lower forecast deviations) in one treatment (1H5C)	Comparisons of distributions, *p*-values from two-tailed Kolmogorov–Smirnov or Mann–Whitney tests
Bosch-Rosa et al. (2018)	Laboratory experiments (incentivized)	Undergraduate students, $N = 352$	CRT + Guessing game (Nagel) + Race to 60 game	Price deviations from fundamental value	+	Regression estimations, *p*-values

(Continues)

TABLE 4 (Continued)

Study	Type of study	Subject pool, number of observations	Measure of cognitive ability	Measure of investor performances	Effect of cognitive abilities on investor performance	Statistical method
Corgnet et al. (2018)	Laboratory experiments (incentivized)	University students, $N = 204$	CRT, Raven's progressive matrices test, Theory of mind (ToM) test	Earnings in experimental asset markets	+	*p*-values from linear panel regression estimates
Charness and Neugebauer (2019)	Laboratory experiments (incentivized)	University students, $N = 174$	CRT	Price deviations from fundamental values	+ (lower price deviations from fundamental values)	Regression estimations, *p*-values
Weitzel et al. (2020)	Laboratory experiments (incentivized)	University students, $N = 502$; Finance professionals, $N = 412$	CRT, Raven's progressive matrices test, Theory of mind (ToM) test, Hit 15 game	Price deviations from fundamental value	0	Regression estimations, *p*-values
Farago et al. (2022)	Online experiments (incentivized)	Fund managers, $N = 94$	CRT, Raven's progressive matrices test, Theory of mind (ToM) test	Net return of the fund, riskiness of the fund	0 return of the fund − riskiness of the fund	Regression estimations, *p*-values
Roger et al. (2022)	Laboratory experiments (incentivized)	University students or employees, $N = 216$	Number Line Estimation task (number sense)	Earnings in experimental asset markets	+	*p*-values from regression estimates

These conclusions have potential implications in several domains. First, financial institutions have to check whether their clients understand how their money is managed (either through personal decisions or through the advice of financial advisors). Thus, tests of cognitive abilities could be useful beyond standard tests used by financial institutions, to comply with the European MIFID regulation (Appropriateness and/or Suitability tests). The protection of investors would be enhanced by ensuring that clients are able to understand the products they purchase or sell.

Implications for public policies can also be important. As noted by Dohmen et al. (2018, p. 116) "the existing empirical evidence suggests that interventions to influence cognitive ability, should they be possible, might have spillovers on risky choice." People with lower cognitive abilities may be more sensitive to nudge effects in the financial domain, e.g., concerning the presentation of retirement or benefit options (Dohmen et al., 2018, p. 130).

More generally, the findings suggest that policy interventions, for example in financial education, should focus on people with lower-than-average cognitive ability. When taking into account the problem of cognitive decline with age, it is also necessary to tackle the issue of increased vulnerability caused by aging. Policy makers should give priority to regulatory protections or service programs, to manage the age-related cognitive decline.

Finally, many studies show the link between numeracy and the efficiency of financial decisions. Public efforts should be devoted to the improvement of numeracy in the general population. This can be done through various forms of number line training which improve people's sense of numbers (Kucian et al., 2011; Sobkow et al., 2019). Sobkow et al. (2019) find that mental number line training with feedback allows people to estimate more accurately the total price of everyday products presented on a shopping bill. As noted by Sobkow et al. (2020, p. 10) "These findings suggest that interventions focused on influencing approximate numeracy can be a promising method for enhancing decision making".

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ENDNOTES

[1] For example, Cattell and Galton (1890) defined ten tests to be passed in the Psychological Laboratory of the University of Pennsylvania: (1) Dynamometer pressure, (2) Rate of movement, (3) Sensation-areas, (4) Pressure causing pain, (5) Least noticeable difference in weight, (6) Reaction-time for sound, (7) Time for naming colors, (8) Bi-section of a 50 cm. line, (9) Judgment of 10 s time, and 10) Number of letters remembered on one hearing.

[2] For example, see Dresslar (1894).

[3] Measures of intelligence are often called "IQ" (for "intelligence quotient") because Binet and Simon (1905) measured the quotient mental age/physical age. The current version is called the Stanford-Binet test and was first applied at the Stanford Graduate School of Education. Examples of questions for this test can be found at https://stanfordbinettest.com/.

[4] We only focus on cognitive abilities, which means that we voluntarily set aside the impact of non-cognitive abilities, such as self-efficacy, on financial decisions (Kuhnen & Melzer, 2018; Tang, 2021).

[5] Some analyses identify up to 80 specific abilities.

[6] Note that research on intelligence goes back as far as Spearman's studies in the early 20th century and his proposition of the g-factor for general intelligence (Spearman, 1904).

[7] Alternative approaches are, for example: (a) Gardner's Multiple Intelligences Theory, which defines eight different types of intelligence: linguistic, logical/mathematical, spatial, bodily-kinesthetic, musical, interpersonal, intrapersonal, and naturalist – (Davis et al., 2011; Gardner, 1983, 2000) and, (b) Sternberg's theory of successful intelligences, which are defined along three dimensions: analytical, creative, and practical (Sternberg, 1985, 1997, 1999, 2011).

[8] Intelligence tests deal primarily with fluid intelligence whereas achievement tests (knowledge tests to evaluate educational attainment, used for selection at college, university, etc.) lean further towards crystallized intelligence.

[9] As noted by Benjamin et al. (2013, p. 1235), performance on standardized exams such as the SAT and more generally on mathematics test are often considered in the psychology literature as a good proxy for general cognitive ability (see, e.g., Frey & Detterman, 2004).

[10] The test is available at https://stanfordbinettest.com/.

[11] See, for example, Tulsky et al. (2003) for an historical overview of the factors that influence the Wechsler scale.

[12] The data of the authors are available at https://drive.google.com/drive/folders/0BxvQ-uHPASPvd3lwS2MzR3c0WlE?resourcekey=0-piMY44VD4EoiXHV5J8fU1g.

[13] The raw data are downloadable at https://osf.io/tfsza/

[14] The interplay between numeracy and other cognitive skills is explored by Sobkow et al. (2020), who find that numeric competencies predict decision outcomes beyond fluid intelligence and cognitive reflection. Recent psychology research documents that statistical numeracy may be the best predictor of superior decision making, even after controlling for other aspects of intelligence (Cokely et al., 2018). In their meta-analysis of the relationship between cognitive reflection, cognitive abilities and numeracy skills, Otero et al. (2022) find that cognitive reflection, as measured by the CRT, correlates with all cognitive abilities and numeracy skills.

[15] Note that Lipkus et al. (2001) expanded the three-item numeracy measure proposed by Schwartz et al. (1997) with one question assessing understanding of chance ("Imagine that we roll a fair, six-sided die 1,000 times. Out of 1,000 rolls, how many times do you think the die would come up as an even number?"), and two questions assessing the ability to convert a percentage to a proportion ("In the BIG BUCKS LOTTERY, the chances of winning a $10.00 prize are 1%. What is your best guess about how many people would win a $10.00 prize if 1,000 people each buy a single ticket from BIG BUCKS?") and to convert a proportion to a percentage ("In the ACME PUBLISHING SWEEPSTAKES, the chance of winning a car is 1 in 1,000. What percent of tickets of ACME PUBLISHING SWEEPSTAKES win a car?"). Lipkus et al. (2001) take these three questions as their three first items and then add eight new questions to form their 11-item scale.A modified version of the 11-item Lipkus et al.'s (2001) test is used by Estrada-Mejia et al. (2020); after running psychometric analyses using item response theory methods that reveal that only two items have acceptable discrimination, the authors finally retain only these two items, namely:• Imagine you were going to buy a raffle ticket and you had three different raffles to choose from. In the first raffle, one out of every 100 people wins. In the second raffle, one out of every 1000 people wins. In the third raffle, one out of every 10 people wins. Which raffle would you rather play?• If the chance of winning a raffle is 10%, how many people would you expect to win out of 1000?

[16] Other articles in the field of economics that use the Number Line Estimation (NLE) include Peters et al. (2008), Schley and Peters (2014), Peters and Bjalkebring (2015), and Sobkow et al. (2020). These articles focus on economic valuation and decision making.

[17] The GPS is "experimentally-validated" in the sense that the survey relies exclusively on questions that have been shown to have good correlations with standard experimental measures. For example, the question "Please tell me, in general, how willing or unwilling you are to take risks" (with an 11-point Likert scale for answers) is one of the proxy questions for assessing risk preferences since the answers to this question appear to be well correlated with usual lottery choice measures (Holt & Laury, 2002).

[18] According to Falk et al. (2018, pp. 1656–1657) "The GPS survey module also elicited a self-reported proxy for cognitive skills by asking people to assess themselves regarding the statement "I am good at math" on an 11-point Likert scale". They defend this "subjective math skills" measure, noting (p. 1666): "As a proxy for cognitive skills, our data set contains a measure of self-reported math skills that we use to proxy for cognitive skills. Although this is an imperfect proxy for cognitive ability, there is evidence that math skills are correlated with cognitive ability in general (Borghans et al., 2016), that subjective assessments of ability are correlated with measured cognitive ability, and that these have predictive power for academic achievement (Ackerman & Wolman, 2007; Chamorro-Premuzic et al., 2010; Marsh, 1990; Marsh et al., 2005; Spinath et al., 2006)." Surprisingly, however, the authors do not mention the potential flaws in respondents' answers on such self-assessment questions (Dunning et al., 2004), especially overconfidence, which can be of major concern given the link between overconfidence and risk attitudes documented in the financial literature (e.g., Broihanne et al., 2014).

[19] These four additional questions, taken from Peters et al. (2007), are: (i) Which of the following numbers represents the biggest risk of getting a disease? (one chance in 12 or one chance in 37); (ii) Suppose you have a close

friend who has a lump in her breast and must have a mammogram. Of 100 women like her, 10 of them actually have a malignant tumor and 90 of them do not. Of the 10 women who actually have a tumor, the mammogram indicates correctly that nine of them have a tumor and indicates incorrectly that one of them does not. Of the 90 women who do not have a tumor, the mammogram indicates correctly that 81 of them do not have a tumor and indicates incorrectly that nine of them do have a tumor. The table below summarizes all of this information. Imagine that your friend tests positive (as if she had a tumor), what is the likelihood that she actually has a tumor?; (iii) Imagine that you are taking a class and your chances of being asked a question in class are 1% during the first week of class and double each week thereafter (i.e., you would have a 2% chance in Week 2, a 4% chance in Week 3, an 8% chance in Week 4). What is the probability that you will be asked a question in class during Week 7?; (iv) Suppose that 1 out of every 10,000 doctors in a certain region is infected with the SARS virus; in the same region, 20 out of every 100 people in a particular at-risk population also are infected with the virus. A test for the virus gives a positive result in 99% of those who are infected and in 1% of those who are not infected. A randomly selected doctor and a randomly selected person in the at-risk population in this region both test positive for the disease. Who is more likely to actually have the disease? (Both, doctor, or at-risk person).

[20] The dual process theory may be traced back to *The Principles of Psychology* of William James (1890).

[21] For example, Ottaviani and Vandone (2011) shows the link between impulsivity and personal indebtedness of finance professionals.

[22] Dohmen et al. (2018) note (p. 117) that the causality between cognitive abilities and risk preferences could also go in the reverse direction since risk attitudes play a role in the individual choices (education, etc.) potentially influencing the accumulation of cognitive skills.

[23] We only deal with research on risk preferences in financial decisions. The psychology literature points out that higher cognitive abilities tend to reduce the likelihood of undesirable real-world risky behavior, such as smoking, drinking alcohol, or committing crime.

[24] Tulsky et al. (2003) provide a historical overview of the factors that influence the Wechsler scale.

[25] Chapman et al. (2018) highlight a result on loss aversion that appears to be more prevalent in individuals with high cognitive abilities. Higher loss aversion among high-ability people has also been found in previous research (e.g., Frederick, 2005), so that it is one of the empirical regularities documented and discussed by Dohmen et al. (2018). However, in his meta-analysis, Lilleholt (2019) does not find clear evidence about the effect of cognitive abilities on loss aversion.

[26] That is, the self-reported degree of agreement with the statement "I am good at math" on an 11-point Likert scale.

[27] However, Potrafke (2019) recently finds from new macro data, a positive correlation between risk aversion and IQ at country level, that is, a higher risk aversion in countries with high IQ populations than in countries with low IQ populations.

[28] On a methodological point of view, Dave et al. (2010) argue that when evaluating risk preferences, simpler tasks should be preferred for subjects who exhibit low cognitive skills while more complex tasks should be favored only for high-ability subjects.

[29] Burks et al. (2009), Dave et al. (2010), Taylor (2016), Chapman et al. (2018) and Bruns et al. (2022) also observe more inconsistent choices among low-ability subjects.

[30] More specifically, looking both at laboratory and real-world evidence and relying on both studies of behavior in risky situations by psychologists and psychiatrists and studies on economic decision-making by economists, Dohmen et al. (2018, p. 120) conclude that "Cognitive ability tends to be positively correlated with avoidance of harmful risky situations and to be negatively correlated with risk aversion in advantageous situations".

[31] Such a relationship between high cognitive ability and low impatience had been documented by the meta-analysis of Shamosh and Gray (2008). Note, however, that in their replication of Frederick (2005), Campitelli and Labollita (2010) find no correlation between CRT scores and answers to (hypothetical) intertemporal choices.

[32] Tversky and Kahneman's (1981, p. 453) original vignette reads as follows: "Imagine that the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimate of the consequences of the programs are as follows:Problem 1: If Program A is adopted, 200 people will be saved. If Program B is adopted, there is 1/3 probability that 600 people will be saved, and 2/3 probability that no people will be saved. Which of the two programs would you favor?Problem 2: If Program C is adopted 400 people will die. If Program D is adopted there is 1/3 probability that nobody will die, and 2/3 probability that 600 people will die. Which of the two programs would you favor?".They found that 72% of the respondents favor Program A at Problem 1 while

only 22% select Program C at Problem 2, a clear instance of framing effect since both problems are similar, except that the first one is framed in terms of gains (number of people saved), while the second is (equivalently) framed in terms of losses (number of people dead).

[33] The 18-item Need for Cognition Scale is based on self-assessment on 18 items such as "I would prefer complex to simple problems" or "Thinking is not my idea of fun" (Cacioppo et al., 1984).

[34] More generally, Peters et al. (2006) find that better numeracy (independently of higher general intelligence) allows people to retrieve and use appropriate numerical principles, thus improving decision-making.

[35] Similar results, also based on the CRT as measure of cognitive ability, are reported by Duttle (2016), though significant effects are found only for two types of overconfidence (overprecision and overplacement), not for the third type (overestimation).

[36] Since they get conclusive results for the assessment problems where there are unambiguous correct answers but not for the endowment effect, Hoppe and Kusterer (2011, p. 100) conjecture that the impact of cognitive abilities on biases may only concerns problems where analytical skills are helpful to find the correct answer. This conjecture could be confirmed by the fact that cognitive abilities seem also to have no effect on the sunk-cost fallacy (Haita-Falah, 2017) where again there is no direct problem of computation.

[37] Note, however, that Oechssler et al. (2009) found no influence of cognitive abilities (measured by the CRT) on anchoring.

[38] See, however, Mather et al. (2012) for more mitigated results.

[39] Again, things are complicated by the potentially confounding impact of age on financial literacy (Gamble et al., 2015).

[40] Some studies confirm correlations between cognitive abilities and financial outcomes. However, some of these studies (e.g., Agarwal et al., 2009; Korniotis & Kumar, 2011) that depict declining financial outcomes among the older population (using age as a proxy for cognitive abilities) may be neglecting confounding effects such as birth cohort effects. Other studies focus on the role of education (e.g., Cole et al., 2014). For a survey of the literature focused on the effect of age on cognitive abilities and financial decision, see Korniotis and Kumar (2010).

[41] The mistake in using credit cards, called by the authors "balance transfer mistake", appears when people transfer their entire credit card balance from an existing account to a new card and choose to use the new card for new purchases while the optimal strategy is to continue to use the old card during a certain period. The mistake in home loan application, called "rate-changing mistakes", appears when a loan applicant is penalized by being charged a higher Annual Percentage Rate (APR) because of a high difference between her own home price estimate and the bank's estimate.

[42] In the case of education, some research concludes that exam results (especially results at mathematics tests) are significantly correlated to standard measures of intelligence. However, academic achievements are linked to both fluid and crystallized intelligence and it is almost impossible to disentangle the two types of intelligence. The link between usual measures of cognitive abilities such as IQ and educational success deals with a question of double causation: higher IQ may be a cause of educational success but it is also a consequence, since people with higher IQ stay longer in education.

[43] In Europe, the launch of the GDPR 2016/679 (General Data Protection Regulation) makes availability of individual data even more difficult.

[44] In a companion paper also based on Estonian data, Vaarmets et al. (2019) show that stock market investors are more educated and have better academic achievements than non-investors.

[45] Note that earlier laboratory studies have been conducted on the beauty-contest game, named after John Maynard Keynes' metaphor of the newspaper beauty contest for analyzing investor decision-making in financial markets. In the modern experimental version of the game, each of N players picks a number between 0 and 100, the winner being the player closest to some fraction p (e.g., $p = 2/3$ or $1/2$) of the average. The only Nash equilibrium of the game implies every player choosing zero, and zero is the (weakly) dominant strategy in the two-person version of the game (Nagel, 1995; Grosskopf & Nagel, 2008). Burnham et al. (2009) and Brañas-Garza et al. (2012) find that higher cognitive abilities are associated with lower entries in beauty-contest games, hence leading to behavior closer to the Nash equilibrium.

[46] The "Hit 15" is a game played against a computer in which each player must add 1, 2, or 3 on each turn. The winner is the first to hit 15, the subject being the starting player. See Section 1 (Figure 4) for details about the winning strategy.

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Not applicable.

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APPENDIX

TABLE A1 Aggregate comparison of CRT results of the Campitelli and Gerrans (2014) and Azevedo et al. (2023) studies.

	Data from Campitelli and Gerrans (2014)			Data from Azevedo et al. (2023)		
Number of men	**1067**			**21385**		
Number of women	**952**			**22589**		
Panel A: CRT item 1						
	Correct	**Intuitive**	**Other**	**Correct**	**Intuitive**	**Other**
Men	23.62%	71.04%	5.34%	35.45%	56.88%	7.87%
Women	17.86%	76.26%	5.88%	28.50%	62.34%	9.17%
Difference	5.76%	−5.22%	−0.54%	6.95%	−5.66%	−1.29%
t-test	3.18	−2.65	−0.53	15.63	−12.07	−4.80
p-value	0.001	0.008	0.591	0.000	0.000	0.000
Panel B: CRT item 2						
	Correct	**Intuitive**	**Other**	**Correct**	**Intuitive**	**Other**
Men	43.11%	35.99%	20.90%	53.51%	27.37%	19.12%
Women	29.41%	45.80%	24.79%	40.68%	37.10%	22.22%
Difference	13.70%	−9.81%	−3.89%	12.83%	−9.73%	−3.10%
t-test	6.37	−4.48	−2.08	26.94	−21.79	−8.02
p-value	0.000	0.000	0.037	0.000	0.000	0.000
Panel C: CRT item 3						
	Correct	**Intuitive**	**Other**	**Correct**	**Intuitive**	**Other**
Men	43.86%	39.93%	16.21%	39.64%	41.45%	18.91%
Women	28.47%	54.41%	17.12%	27.04%	51.41%	21.55%
Difference	15.39%	−14.49%	−0.91%	12.60%	−9.96%	−2.64%
t-test	7.16	−6.51	−0.55	28.04	−20.92	−6.88
p-value	0.001	0.008	0.584	0.000	0.000	0.000
Panel D: CRT aggregate						
	Correct	**Intuitive**	**Other**	**Correct**	**Intuitive**	**Other**
Men	1.11	1.47	0.42	1.29	1.25	0.46
Women	0.76	1.76	0.48	0.96	1.51	0.53
Difference	0.35	−0.30	−0.05	0.32	−0.25	−0.07
t-test	7.49	−6.45	−1.75	31.04	−25.87	−9.89
p-value	0.000	0.000	0.008	0.000	0.000	0.000

Note: The left (right) part of the Table gives the results for the Campitelli and Gerrans (2014) study (respectively, for the Azevedo et al., 2023 study). The first three Panels compare the percentages of answers among men and women for each of the three CRT items. The *t*-test row gives the critical value of the test (comparison of proportions for Panels 1–3, standard Student test for Panel 4). The *p*-value row provides the *p*-value of the test.

TABLE A2 Stochastic dominance (order 1) test of CRT scores in the Campitelli and Gerrans (2014) and Azevedo et al. (2023) studies.

Panel A: Data from Campitelli and Gerrans (2014)							
Number of men	**1067**			**Number of women**	**952**		
Correct answers	**Men**	**Women**	**Percentage of men**	**Percentage of women**	**CDF of men**	**CDF of women**	**Difference**
0	434	518	40.67%	54.41%	40.67%	54.41%	−13.74%
1	252	221	23.62%	23.21%	64.29%	77.63%	−13.33%
2	215	139	20.15%	14.60%	84.44%	92.23%	−7.78%
3	166	74	15.56%	7.77%	100%	100%	0%
Total	1067	952	100%	100%			
Panel B: Data from Azevedo et al. (2023)							
Number of men	**21385**			**Number of women**	**22589**		
Correct answers	**Men**	**Women**	**Percentage of men**	**Percentage of women**	**CDF of men**	**CDF of women**	**Difference**
0	7073	10228	33.07%	45.28%	33.07%	45.28%	−12.20%
1	5487	5860	25.66%	25.94%	58.73%	71.22%	−12.49%
2	4461	3628	20.86%	16.06%	79.59%	87.28%	−7.69%
3	4364	2873	20.41%	12.72%	100%	100%	0%
Total	21385	22589	100%	100%			

Note: Panel A (Panel B) gives the result of the first-order stochastic dominance test for the Campitelli and Gerrans (2014) study (respectively, for the Azevedo et al., 2023 study). The last column shows the difference between men and women CDFs' for each number of correct answers. In the two studies, all differences are negative or 0 (when CDFs equal 1), showing the first-order stochastic dominance of the distribution of scores.

TABLE A3 Similarity indices of CRT scores in the Campitelli and Gerrans (2014) and Azevedo et al. (2023) studies.

	Data from Campitelli and Gerrans (2014)					Data from Azevedo et al. (2023)				
Number of men			**1067**						**21385**	
Number of women			**952**						**22589**	
Panel A: Correct answers										
Number of correct answers	**Men**	**Women**	**% of men**	**% of women**	**Absolute difference (%)**	**Men**	**Women**	**% of men**	**% of women**	**Absolute difference (%)**
0	434	518	40.67%	54.41%	13.74%	7073	10228	33.07%	45.28%	12.20%
1	252	221	23.62%	23.21%	0.40%	5487	5860	25.66%	25.94%	0.28%
2	215	139	20.15%	14.60%	5.55%	4461	3628	20.86%	16.06%	4.80%
3	166	74	15.56%	7.77%	7.78%	4364	2873	20.41%	12.72%	7.69%
Average difference	0.35					0.32				
Index of similarity	0.86					0.88				
Panel B: Intuitive answers										
Number of correct answers	**Men**	**Women**	**% of men**	**% of women**	**Absolute difference (%)**	**Men**	**Women**	**% of men**	**% of women**	**Absolute difference (%)**
0	227	139	21.27%	14.60%	6.67%	6331	4743	29.60%	21.00%	8.61%
1	321	214	30.08%	22.48%	7.61%	6113	6016	28.59%	26.63%	1.95%
2	310	331	29.05%	34.77%	5.72%	6098	7432	28.52%	32.90%	4.39%
3	209	268	19.59%	28.15%	8.56%	2843	4398	13.29%	19.47%	6.18%
Average difference	−0.30					−0.25				
Index of similarity	0.86					0.89				

(Continues)

TABLE A3 (Continued)

Panel C: Others Number of correct answers	Men	Women	% of men	% of women	Absolute difference (%)	Men	Women	% of men	% of women	Absolute difference (%)
0	710	596	66.54%	62.81%	3.94%	14052	13738	65.71%	60.82%	4.89%
1	274	274	25.68%	28.78%	3.10%	5390	6360	25.20%	28.16%	2.95%
2	70	65	6.56%	6.83%	0.27%	1403	1875	6.56%	8.30%	1.74%
3	13	17	1.22%	1.79%	0.57%	540	616	2.53%	2.73%	0.20%
Average difference	−0.05					−0.07				
Index of similarity	0.96					0.95				

Note: The left (right) part of the Table gives the results for the Campitelli and Gerrans (2014) study (respectively, for the Azevedo et al., 2023 study). The three Panels detail the calculation of the similarity index for the three types of answers. The value of the similarity index is defined in Equation (1). The columns "Men" and "Women" detail the number of men and women for each score level.

The similarity index (Nelson, 2016) used in the Table below is defined as

$$S = 1 - \frac{1}{2}\sum_{i=0}^{i=3}\left|p_i^w - p_i^m\right| \quad (1)$$

where p_i^w (p_i^m) is the proportion of women (men) obtaining i correct answers. The interpretation of Ottaviani (2011) is simple. If the number of men and women was the same in the sample, S would measure the proportion of couples that can be matched with the same score.