Cognitive Finance

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Abstract. We review the field of cognitive finance, which uses experimental methods to study the impact of individual cognitive skills on financial decision-making and market outcomes. The overview shows that cognitive skills play a central role in accounting for sound financial decisions and sustaining market efficiency. We conclude that finance is a cognitive science.

1. Behavioral and Cognitive Finance

The emergence of behavioral finance has transformed finance by recognizing 'that economic agents are human' (Pollard, Ringstrom, and Gonzales, 2017). Behavioral finance incorporates well-known biases identified in psychology into the analysis, thus relaxing the standard assumption of perfectly rational investors (Barber and Odean, 2001; Shefrin, 2002).

Yet, behavioral finance goes beyond incorporating psychological biases into finance models. According to Thaler (2015), behavioral finance is finance but "done with strong injections of good psychology *and other social sciences*" (emphasis added). More recently, Lo (2017) has also endorsed this more interdisciplinary approach by stating: "We need to piece together insights from multiple disciplines to get the full panoramic picture of how financial markets work and why they fail." However, this interdisciplinary approach risks having finance scholars cherry-pick the bits and pieces from other social sciences that support their argument (Shefrin, 2002, 2009; Duxbury, 2015).

To alleviate such cherry-picking, Hirshleifer (2015) emphasizes the need to study deviations from rationality *causally*. An appealing approach to achieve this goal is experimental finance. By having complete control of the environment, experimental finance allows us to study causal relations between individual behavior and market outcomes (Frydman et al., 2014). Corgnet, DeSantis, and Porter (2018) go one step further by stressing the need to study individual cognition to understand financial decisions and their impact on markets. They refer to this approach as ‘cognitive finance.’

This chapter showcases studies that establish a link between individual cognitive skills and financial decision-making (Section 2) and between cognitive skills and market outcomes (Section 3). Section 2 shows that cognitive skills are essential to explain financial decisions such as stock market participation, stock picking, and trading performance. Section 3 shows that individual cognitive skills foster market efficiency, but that markets populated by cognitively sophisticated traders are not informationally efficient when the cognitive sophistication of participants is not common knowledge. We conclude in Section 4 by describing future avenues of research in cognitive finance. Appendix A lists all of the papers cited that measure cognitive ability and the test used to measure such ability.

2. Cognitive Traders

2.1. Cognitive ability tests

This section reviews the most prominent cognitive ability measures used in the cognitive finance literature (see Appendix A for a summary of the measures used). Measuring cognitive ability dates back to the work of Binet and Simon (1905), who developed a series of tests to assess children’s mental ability. Intelligence tests have not changed substantially since that time (Mackintosh, 2011). For example, standard intelligence tests such as the Raven test (Raven, 1936; 2000) primarily build on the early work of Binet and Simon. In the Raven test, subjects must find a pattern that logically follows a sequence. To do so, they need to hold in memory the various patterns and mentally simulate potential solutions. The ability to retain information in one’s memory and use it to solve problems is referred to as working memory and is a critical feature of standard intelligence tests (IQ tests) (Mackintosh, 2011).

Yet, standard intelligence tests do not measure all cognitive skills a successful financial decision-maker must possess. For example, standard intelligence tests do not measure the ability to inhibit impulses, which is one of the three executive functions in cognitive psychology (Diamond, 2013). Inhibitory control is commonly assessed using the Stroop task (Stroop, 1935), which shows subjects the name of colors (e.g., red) printed in a color that might not match the word (e.g., green) and asks them to say the written word aloud. Subjects who score high on inhibitory control are not distracted by the printed color and can quickly say the written word. Such ability is closely related to cognitive reflection, which captures subjects' capacity to avoid impulses and engage in more reflective reasoning (Stanovich, 2009). The most common measure of cognitive reflection is the Cognitive Reflection Test (CRT, henceforth). The CRT consists of three questions with an intuitive yet incorrect answer which can only be disregarded by engaging in reflection (Frederick, 2005). These types of questions are very similar to the brain teasers used in Wall Street job interviews (Crack, 2004; Zhou, 2008), so it is not surprising that professional traders score exceptionally high on the CRT (Thoma et al. 2015).

Another important skill in finance is the ability to reason backward (e.g., Chari and Kehoe, 1990; Riedel, 2009). Because this is a cognitively demanding task, the experimental finance literature has used it as a relevant dimension of cognition (e.g., Cueva and Rustichini, 2015; Bosch-Rosa, Meissner and Bosch-Domenech, 2018). The most common tool to measure backward induction ability is the race-to-X game. In this game, two players sequentially place integers into a common pot, and the first one to reach a value of X wins. Of course, the integers that players can choose are smaller than the target value X, resulting in a game that is solvable through backward induction.[1] A drawback of the race-to-X game is that it can be excessively complicated depending on the parameters chosen (e.g., Bosch-Rosa and Meissner, 2020). Additionally, one should consider that the race-to-X game is a "Eureka!" type of game. Once people find the solution, they will perfectly solve all following repetitions. Therefore, a sound procedure

[1] Take as an example the race-to-60. If subjects can only pick values between 1 and 10, then the first mover can always win by starting at 5 and then, after the other players' choice, pushing the pot to the values 16, 27, 38, 49, and finally 60. The idea of such a strategy is to obtain a value that is 11 units away from the target, which guarantees that the counterpart cannot reach the target before you do.

is to have subjects play against computers that pick random numbers and evaluate their backward induction ability relying only on the results of the first rounds.

Finally, Corgnet, DeSantis, and Porter (2018) show that assessing the informational content of market signals, which is a necessary skill for successful trading, requires cognitive skills that go beyond the standard computational ability needed in intelligence and backward induction tests. To uncover the fundamental value of an asset, it is not enough to correctly compute the fundamental value using market signals, traders must also evaluate how informative these signals are. For example, suppose a market is populated by noise traders who submit orders at random. In such a case, traders will have to differentiate between informative and uninformative signals to update their information correctly. Such differentiation requires traders to infer the intentions of other market participants and to understand that noise traders have no strategic intention and are solely driven by unpredictable impulses. The ability to infer the mental state of others is referred to as theory of mind, and it can be measured using the eye gaze test (Baron-Cohen et al. 2001). In this test, subjects are presented with a series of photographs showing a person's eyes and are asked to identify the feeling that best describes the pictured person. This test is widely used in social cognition studies and has been shown to predict social understanding skills (McDonald, Flanagan, Rollins and Kinch, 2013).

2.2. Risk-taking and cognitive ability

From measuring an asset's beta to diversifying a portfolio, risk is at the center of most financial decisions. Nonetheless, the correlation between risk attitudes and cognitive ability is far from being well-understood (Dohmen, Falk, Huffman, and Sunde, 2018; Lillehot, 2019).

Burks, Carpenter, Goette, and Rustichini (2009) found a negative correlation between cognitive ability and risk aversion using a sample of trainees from a large US trucking company. Risk aversion was measured using a multiple price list and cognitive ability using Raven matrices. Dohmen, Falk, Huffman, and Sunde (2010) also found a negative correlation surveying a large representative sample of the German population. Cognitive ability was measured using a symbol-digit correspondence test, similar to the Raven test, and a word fluency task, which asked subjects to list as many animals as possible in 90 seconds. Risk aversion was measured through multiple price lists containing different combinations of lotteries and safe payments. Using a similar risk elicitation task, Benjamin, Brown, and Shapiro (2013) reported a negative correlation between the risk aversion of a sample of Chilean high school students and their college entrance examination scores. In this same line, Deck, and Salar (2015) and Deck, Salar, and Sheremeta (2021) showed that cognitive load, induced using various techniques such as a number memorization task or time pressure, led to higher levels of risk aversion.

However, Andersson, Holm, Tyran, and Wengström (2016, 2020) claimed that the negative correlation between cognitive ability and risk-taking found in the literature is spurious and most likely driven by the design of the multiple price list task. Because low ability subjects are more likely to make random errors, and because most multiple price lists have more risk-averse choices than risk-seeking alternatives, such designs overestimate the correlation between low cognitive ability and risk aversion. Jagelka (2020) estimates that cognitive ability may promote risk aversion using a structural model to correct the effect of random errors.

Moving to the laboratory, Taylor (2013) did not find any correlation between subjects' risk attitudes and cognitive ability when choices were incentivized. However, he found a negative correlation when risky choices were hypothetical. In Taylor (2013), risk was measured using multiple price lists, and cognitive ability was measured using the CRT. Bosch-Rosa, Meissner, and Bosch-Domenech (2018) found no correlation between their different measures of cognitive ability (a measure of strategic sophistication based on guessing games (Nagel, 1995), the CRT, and a race-to-60 task) and risk aversion (measured using a multiple price list).[2] In Amador et al. (2021), the authors measured subjects' cognitive ability using the 7-item CRT from Capraro, Corgnet, Espin, and Hernan-Gonzalez (2017), the maximum number of four-digit summations that subjects can do in 60 seconds, and the Remote Associates Test. The latter test measures subjects'

[2] Nonetheless, Bosch-Rosa, Meissner and Bosch-Domenech (2018) found a significant and negative correlation between the risk aversion of traders and the size of asset market bubbles.

creative ability as one has to find a word (e.g., spider) that relates to apparently unconnected terms (e.g., widow, bite). Amador et al. (2021) showed that none of their measures of cognitive ability correlated with risk preferences. Furthermore, using structural models, Amador et al. (2021) showed that the multiple price lists designs artificially increased the negative correlation between cognitive ability and risk aversion, thus confirming the results of Andersson, Holm, Tyran, and Wengström (2016, 2020).

2.3. Bayes rule and cognitive ability

Beyond risk attitudes, financial decision-making relies on the risk assessments of traders. In the case of the rational decision-maker considered in classical finance models, such estimates are based on probability calculations and the use of Bayes' rule. However, behavioral finance research has shown that financial decision-makers often fail to use Bayes' rule, relying instead on heuristics and biases (e.g., Tversky and Kahneman, 1974; Shleifer, 2000; Barber and Odean, 2001; Shefrin, 2002; Thaler, 2005; Shiller, 2015). Such heuristics can explain many biases, like the gambler's fallacy, the hot hand fallacy, and base rate neglect. However, recent work has shown that cognitive skills can help decision-makers avoid such biases (e.g., Cokely and Kelley, 2009; Campitelli and Labollita, 2010; Oechssler, Roider and Schmitz, 2009; Lesage, Navarrette and De Neys, 2013).

The negative relationship between heuristic-driven behavioral biases and cognitive ability follows directly from the computational skills required to make Bayesian calculations (Lesage, Navarrete, and De Neys, 2013). Lesage, Navarrete, and De Neys (2013) made this point by showing that university and secondary school students performed worse on a Bayesian reasoning task under cognitive load. The cognitive load was induced by having subjects memorize a pattern of dots while undertaking the Bayesian task. Sirota, Juanchich, and Hagmayer (2014) reported that standard intelligence scores, measured with a Raven test, correlated positively with performance on Bayesian reasoning tasks. However, the correlation coefficient was moderate ($\rho = 0.31$). Toplak, West, and Stanovich (2011) also reported a small positive ($\rho = 0.24$) correlation between subject's intelligence test scores (using the Wechsler Abbreviated Scale of Intelligence, Wechsler,1999) and their performance on a list of 15 heuristics and biases tasks (such as the gambler's fallacy and the conjunction fallacy). However, they report that such correlation was substantially higher ($\rho = 0.42$) when cognitive ability was measured using the CRT instead of the Wechsler intelligence test.

In the experimental finance literature, Corgnet, DeSantis, and Porter (2018) have shown that traders who possess high levels of cognitive reflection are more likely to update their prior beliefs about the value of an asset. As a result, high cognitive reflection traders are less likely to exhibit conservatism. Conservatism is a common behavioral bias characterized by insufficient updating of prior beliefs in the face of new information (Phillips and Edwards, 1966; Edwards 1968; Beach and Braun, 1994). These findings are consistent with Oechssler, Roider and Schmitz (2009) and Hoppe and Kusterer (2011), who showed a negative relationship between cognitive reflection and the conservatism bias in Bayesian reasoning tasks. Interestingly, Corgnet, DeSantis and Porter (2018) found that intelligence scores, as measured with the Raven test, did not explain conservatism. Again, this result suggests that cognitive reflection is more likely to grant immunity from behavioral biases than standard intelligence.

2.4. Financial literacy and cognitive ability

Once investors have assessed risk, they will have to manage it and engage in diversification strategies. To do so, investors will need financial knowledge. Financial knowledge is often measured using financial literacy scales that typically include questions related to interest rate compounding, time value of money, and the main characteristics of financial assets such as bonds and stocks (see Fernandes, Lynch and Netemeyer, 2014). Investors who possess high financial literacy have been shown to hold more diversified portfolios and to outperform those who score low (Gaudecker, 2015). Financial literacy also positively relates to stock market participation (Van Rooij, Lusardi and Alessie, 2011) and higher levels of wealth (Behrman et al. 2012; Van Rooij, Lusardi and Alessie, 2012; Jappelli and Padula, 2013) (see Beshears et al. 2018 for a review of this literature). Because financial literacy is highly correlated with numeracy (see Fernandes, Lynch and Netemeyer, 2014), it is also closely related to cognitive ability. In a recent experiment, Muñoz-Murillo, Álvarez-Franco, and Restrepo-Tobón (2020) show that even after controlling for several confounds such as risk aversion and patience, CRT scores correlated positively with financial literacy scores ($\rho = 0.32$).

2.5. Trading performance and cognitive ability

The first studies on the relationship between cognitive ability and financial performance were based on archival data from household savings accounts (see Gomes, Haliassos, and Ramadorai, 2020 for a review). Using Finnish data, Grinblatt, Keloharju, and Linnainmaa (2011) found that higher cognitive ability was related to higher participation rates in the stock market. Gerardi, Goette, and Meier (2013) also found that people with higher numerical ability were less likely to default on their mortgages. Agarwal et al. (2009) have shown that people with higher cognitive ability, as proxied by age, make fewer financial mistakes related to decisions regarding mortgages, loans, and credit lines. Other studies have shown that investors with higher cognitive ability obtain higher risk-adjusted returns (Christelis, Jappelli, and Oadula, 2010; Grinblatt, Keloharju, and Linnainmaa, 2012; Agarwal and Mazumder 2013; Barber and Odean, 2013). However, these findings were subject to potential confounds. As noted in Grinblatt, Keloharju, and Linnainmaa (2012): “High-IQ investors may have better access to non-public information, may be better at processing information, or their greater immunity to behavioral biases may boost their returns.”

Several laboratory studies have attempted to alleviate such confounds. Breaban and Noussair (2015), Corgnet, Hernán-González, Kujal, and Porter (2015) as well as Corgnet, Hernán-González, and Kujal (2020) reported a positive correlation between cognitive ability and earnings in experimental markets. In all cases, subjects’ earnings were positively (and significantly) correlated with their CRT scores. Cueva and Rustichini (2015) found similar results using a measure of cognitive ability based on a race-to-15 game, a Raven test, and a weighted average of both scores. These initial results have been confirmed in subsequent studies (e.g., Noussair, Tucker, and Xu, 2016; Ahrens, Bosch-Rosa, and Roulund, 2019; Shestakova, Powel, and Gladyrev, 2019) using either the Raven test or the CRT as measures of cognitive ability. More recently, Miklánek and Zajíček (2020) showed that CRT explains participants' earnings after controlling for risk attitudes (measured as in Dohmen, Falk, Huffman, and Sunde, 2010,), one's propensity to speculate (Janssen, Füllbrunn, and Weitzel, 2018), the willingness to compete, and overconfidence.

Corgnet, DeSantis, and Porter (2018) went one step further by studying the characteristics that explain traders' performance in an experimental market with public and private information (Plott and Sunder, 1988). To do so, they distinguished between three different skills: fluid intelligence (Raven test), cognitive reflection (CRT), and theory of mind (eye gaze test). They showed that higher cognitive ability, measured either with the Raven test or the CRT, resulted in higher payoffs. Furthermore, the authors reported a positive interaction between theory of mind skills and cognitive reflection in explaining traders' earnings. That is, traders needed both theory of mind skills and cognitive reflection to uncover the fundamental value of the asset and trade advantageously. A high level of cognitive reflection led traders to learn actively from market orders, while theory of mind skills helped them separate information from noise. The findings of Corgnet, DeSantis, and Porter (2018) echo those of Corgnet, Deck, DeSantis and Porter (2018), who studied the behavior of traders in a market in which extra pieces of information could be bought. In their paper, Corgnet, Deck, DeSantis and Porter show that traders with high theory of mind skills gained an informational advantage by acquiring private information when others did not and that those subjects who possessed higher theory of mind skills and higher CRT scores obtained higher earnings.

In the same vein, Hefti, Heinke, and Schneider (2018) argued that two dimensions could explain trading success in an experimental asset market. The first one relates to the computational ability of traders and the second one to their theory of mind skills. The authors claimed that traders could not be successful unless they possessed both high computational and theory of mind skills.[3] To test their hypothesis, Hefti, Heinke, and

[3] Note that Corgnet, Hernán-González, and Kujal (2020) do not find evidence for a positive effect of theory of mind skills on traders' performance in a bubbles market, although they report a positive effect for CRT. However, this study has less power than Hefti, Heinke, and Schneider (2018).

Schneider (2018) conducted market sessions where they measured the computational ability of subjects using the Raven test, mathematical and logical problems, and a variation of the race-to-X game.[4] Theory of mind ability was measured using the eye gaze test and the Heider-Simmel test (see Bruguier, Quartz, and Bossaerts, 2010). Their results showed that subjects who possessed both abilities were the ones that obtained the highest profits. An interesting result of Hefti, Heinke, and Schneider (2018) was that subjects who scored low in computational ability and high in theory of mind ability, referred to as semiotic traders, performed worse than those who scored low in both dimensions. The explanation is that semiotic traders are inclined to follow trends that are not justified by an increase in fundamentals, which results in a tendency to ride bubbles. This tendency to ride bubbles was also observed in traders who possess high theory of mind skills in De Martino et al. (2013).

3. Cognitive Markets

3.1. Asset market bubbles and cognitive ability

An important area of research in experimental finance revolves around the formation of asset market bubbles. Because fundamental values are not observable "in the wild," asset market experiments are an ideal environment to study the formation and dynamics of asset market bubbles.

The most popular experimental setup to study bubbles was pioneered by Smith, Suchanek, and Williams (1988) (SSW, henceforth). In it, traders are endowed with cash and shares which they can trade for a finite number of periods (usually 15). The shares hold value because they pay a stochastic dividend from a known distribution at the end of each period. This means that the fundamental value of the asset can be calculated, and any sustained sequence of prices above it can be cataloged as an asset bubble. Despite the apparent simplicity of SSW markets, they consistently produce bubbles (see Palan, 2013; Powell and Shestakova, 2016 for surveys).

[4] The game they used is the Game of Nim (see McKinney and Van Huyck, 2007).

A robust result in the SSW literature is the strong correlation between the magnitude of bubbles and traders' cognitive ability. Huber and Kirchler (2012) and Kirchler, Huber, and Stockl (2012) were the first to point in this direction by showing that modifying the framing of the SSW instructions to facilitate backward induction calculations resulted in smaller asset market bubbles. These results were confirmed in Cheung, Hedegaard, and Palan (2014), who showed that training participants to compute the asset's fundamental value could lower bubbles.[5] Furthermore, Cueva and Rustuchini (2015) reported that markets populated with high cognitive ability participants exhibited lower levels of volatility.

Building on these results, Bosch-Rosa, Meissner, and Bosch-Domenech (2018) showed that only markets populated by low cognitive ability traders produced bubbles. To do so, they ran an experiment that took place on two different dates. On the first date, subjects were invited to participate in a battery of cognitive ability tasks that measured three critical dimensions: cognitive reflection, strategic sophistication, and backward induction ability. To measure each dimension, subjects answered the CRT questions, two versions of the ⅔ beauty contest game (Nagel, 1995; Bosch-Rosa and Meissner, 2020), and twelve rounds of the race-to-60 game. The authors then ranked subjects based on their cognitive ability and re-invited subjects to sessions composed only of high or low cognitive ability traders. The results were clear. In the low-ability sessions, bubbles and crashes were observed, whereas, in the high-ability sessions, market prices perfectly tracked the asset's fundamental value. Another interesting result from Bosch-Rosa, Meissner, and Bosch-Domenech (2018) was that common knowledge of high cognitive ability played no role. In high-ability sessions, market prices tracked the asset's fundamental value whether subjects' (high) cognitive ability was announced publicly or not.

Akiyama, Hanaki, and Ishikawa (2017) emphasized that bubbles in SSW markets are not exclusively driven by the lack of subjects' cognitive ability, but that strategic uncertainty also plays a prominent role. To test this hypothesis, they designed two types of markets, one with six human traders (control) and one with one human and five computerized traders that bought and sold the asset at its fundamental value (treatment). Importantly,

[5] However, this effect was only observed when all traders were told that other market participants were also trained.

traders knew the types of traders that were present in their market. To measure the effect of strategic uncertainty in markets, the authors compared traders' price forecasts in both types of sessions. Because there was no strategic uncertainty in treatment sessions, any deviation in price forecasts from fundamental value was interpreted as resulting from the bounded rationality of the human trader. They could then compare the difference in price forecasts between treatment and control sessions to assess the extent to which strategic uncertainty explained the deviation of forecasts from fundamentals. The results showed that strategic uncertainty accounted for half of the initial price forecast deviation from fundamentals, whereas bounded rationality explained the other half. Moreover, Akiyama, Hanaki, and Ishikawa (2017) categorized subjects based on their CRT score and showed that strategic uncertainty had a larger effect on those with a perfect CRT score, while not affecting those with low scores.

More recently, Kocher, Lucks, and Schindler (2019) studied the effects of self-control in SSW markets. Self-control is a crucial cognitive skill in financial markets (Lo, Repin, and Steenberger, 2005) that relates to standard cognitive ability, and more specifically, to cognitive reflection and inhibitory control (Da Silva et al. 2018). In Kocher, Lucks, and Schindler (2019), subjects took part in a Stroop task before markets started. In the "tough" sessions, subjects had to complete a complicated version of the Stroop task in which many of the instances were incongruent, that is, the printed color and the color name differed. Subjects completed an easy version of the Stroop task in the placebo sessions, so self-control was not impacted. This design allowed the authors to causally study the effects of ego-depletion and self-control in asset markets. Their results showed that markets composed of subjects treated with the "tough" Stroop task generated larger bubbles than the "placebo" markets. Moreover, the authors showed that, while cognitive ability could explain subjects' profits in the placebo sessions, it lost explanatory power in the markets in which self-control was depleted.

3.2. Market efficiency and cognitive ability

Thus far, we have considered experimental markets à la SSW in which there was no private information to be aggregated into prices. To study the informational efficiency of markets, we need to use markets with private information (Plott and Sunder, 1982, 1988). Until the recent advent of behavioral finance (Shefrin, 2002; Barberis and Thaler, 2005), the informational efficiency hypothesis formalized by Fama (1970) had been hardly challenged. This was most likely because, as recognized by Fama (Fama, 1991), the efficient market hypothesis cannot be tested using archival data. Experimental markets provide a solution to this impasse by allowing experimenters to design markets in which we can control the asset's fundamental value and evaluate the extent to which private information is aggregated into prices.

The work of Plott and Sunder (1982) provided early evidence that insider information effectively disseminated in line with the strong-form informational efficiency of Fama (1970). Even more remarkable, Plott and Sunder (1988) reported that dispersed private information could be successfully aggregated even without a complete set of contingent claims in the market. Despite these encouraging experimental results, economic theorists have long recognized that strong-form efficiency requires restrictive conditions in the form of computational capacity “far beyond what is realistic” (Radner, 1982).

To shed light on the role of cognitive sophistication, Corgnet, DeSantis and Porter (2021) assessed whether markets populated with traders possessing high cognitive skills, as measured with CRT, exhibited higher informational efficiency. To that end, they recruited participants who scored in the top 20% on CRT scores using data from a prior survey. These participants scored an average of 2.65 on the three-question CRT, which placed them above the samples reported in Frederick (2005) from MIT (2.18), Princeton (1.63), and Harvard (1.43), and on par with the score of professional traders (2.59) (see Thoma et al. 2015). Corgnet, DeSantis and Porter (2021) then showed that mispricing was substantially lower in markets populated by cognitively sophisticated traders than in markets in which participants were recruited randomly from the database (with an average CRT of 1.23, which is a typical score for a university population). This first result established that the cognitive skills of traders impacted the informational efficiency of markets in line with the conjecture of Radner (1982). However, even in markets populated by sophisticated traders, private information was not fully incorporated into prices. More specifically, asset prices were not equal to those predicted by a fully revealing rational expectation equilibrium. Instead, they were in line with the prediction of the Walrasian equilibrium, according to which traders use their private information to trade but do not update their beliefs using the information contained in asset prices. This equilibrium is at odds with the aggregation of private information.

Guesnerie (2005) emphasizes that both high levels of trader cognitive sophistication and common knowledge of rationality are needed to achieve a rational expectations equilibrium that sustains informational efficiency. To test this idea, Corgnet, DeSantis and Porter (2021) conducted a treatment in which they recruited participants who scored in the top 20% on the CRT and told them that all participants in the market were recruited in this way. This manipulation ensured common knowledge of cognitive sophistication between market participants. They showed that markets populated by sophisticated traders with common knowledge of sophistication resulted in higher levels of informational efficiency. Furthermore, in these markets, all private information was aggregated in line with rational expectations. The need for common knowledge of cognitive sophistication to achieve efficient markets in Corgnet, DeSantis and Porter (2021) might appear at odds with the result of Bosch-Rosa, Meissner and Bosch-Domènech (2018). However, common knowledge of rationality is likely to be more relevant in a market with private information than in an SSW market. In the presence of private information, lack of common knowledge of rationality means that a market order can reflect either a person's level of rationality or their private signal. It is this uncertainty that blurs the informative content of market orders and hampers informational efficiency. Furthermore, in SSW markets, even if there is no common knowledge of rationality, traders can confidently infer that the other participants are behaving rationally after observing a series of prices at the fundamental value.

Finally, Corgnet, DeSantis and Porter (2020) put forth that the structure of private information is key to understanding the impact of cognitive sophistication on informational efficiency. Using agent-based simulations and experiments, they showed that, in markets in which information was highly concentrated in the hands of a few competing insiders, the dissemination of private information was robust to the presence of cognitively unsophisticated traders. In contrast, when private information was highly fragmented, information aggregation was substantially hampered by the presence of unsophisticated traders (Corgnet, DeSantis, and Porter, 2021). The authors emphasized that the structure of information, dispersed or fragmented, impacts how cognitively demanding it is for a trader to uncover private information from asset prices.

4. Discussion

Four decades ago, economists firmly believed in the efficient market hypothesis (Jensen, 1978; Malkiel, 1989). In such a paradigm, markets reflect all private information so that financial decisions do not require any specific skill. By challenging the efficient market hypothesis, behavioral finance opened the way for studying cognition in financial markets. Cognitive finance then took on the challenge of demonstrating the causal link between individual skills and market outcomes. By doing so, this literature has established direct evidence that behavioral biases matter in financial markets, thus responding to Thaler's (2015) call that: "Nothing would help the cause of behavioral economics more than to show that behavioral biases matter in financial markets."

The first results in the cognitive finance literature are clear. Cognitive skills help explain financial performance and the efficiency of markets, especially when coupled with common knowledge of rationality.

The next generation of cognitive finance research will likely go beyond the classical SSW and Plott and Sunder (1982, 1988) setups to consider more complex financial assets (Bossaerts et al. 2020) and more complex institutions (e.g., Halim, Riyanto and Roy, 2019; Corgnet, DeSantis and Porter, 2020). As complexity increases in financial markets, there will be a need to assess how these new institutions fare in terms of efficiency when traders suffer from cognitive limitations. The lab is an ideal place to make such comparisons as it allows to vary both the characteristics of the institution and the cognitive sophistication of its participants. A pioneering work in that direction is the experimental study of Pouget (2007) who compared the efficiency of a Call Market with a Walrasian tâtonnement mechanism in a market with asymmetric information. In it, the author showed that Walrasian tâtonnement leads to a higher level of efficiency because it facilitates learning: "Cognitive simplicity enables agents to learn faster (…)" (Pouget, 2007, p. 299).

This research agenda echoes what Bolton and Ockenfels (2012) refer to as “behavioral economic engineering,” whose aim is to study how actual behavior interacts with the institutional design.

As complexity increases in financial markets, we conjecture that cognitive skills will become increasingly relevant in explaining financial performance and market outcomes. At the same time, the increasing complexity of markets might trigger the replacement of human traders by algorithms (Biais and Foucault, 2014; Foucault, Hombert and Roşu, 2016), thus questioning the role of human cognition in understanding financial decision-making.

However, it is difficult to imagine a scenario in which unsupervised algorithms take over financial markets. In a novel experimental design, Asparouhova et al. (2020) showed that human traders who could use algorithms did not delegate all their trading to robots. Furthermore, traders who alternated human and algorithmic trading earned the most. Therefore, it is difficult to imagine that financial professionals, and more importantly, society, would allow algorithms to control the organization and regulation of markets. Furthermore, a market dominated by algorithms (homo algoritmus), similar to a market dominated by homo economicus, could enter the paradoxical state of not producing any trades (Grossman and Stiglitz, 1980). Humans are thus likely to continue to play a central role in markets so that finance will continue to be a *cognitive science*.

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Appendix A

Table 1. List of articles using cognitive ability measures.

Authors	Measure(s)
Agarwal, S., Driscoll, J. C., Gabaix, X. and Laibson, D. (2009).	• Age as proxy of IQ
Agarwal, S. and Mazumder, B. (2013).	• Armed Forces Qualifying Test (AFQT) score
Ahrens, S. Bosch-Rosa, C., Roulund, R., (2019).	• Cognitive Reflection Test (CRT)
Akiyama, E., Hanaki, N. and Ishikawa, R. (2017).	• Cognitive Reflection Test (CRT)
Amador-Hidalgo, L., P. Brañas-Garza, A. M. Espín, T. García-Muñoz, and A. Hernández-Román (2021).	• Toplak et al. (2014) expansion of the Cognitive Reflection Test • Four-digit summations • Remote Associates Test
Andersson, O., Holm, H.J., Tyran, J.R. and Wengström, E., (2016).	• Variation of Raven Progressive Matrices • Cognitive Reflection Test
Andersson, O., Holm, H. J., Tyran, J. R., and E. Wengström (2020).	• Variation of Raven Progressive Matrices • Cognitive Reflection Test
Benjamin, D. J., Brown, S. A., and J. M. Shapiro (2013).	• National Standardized Test (math and verbal)
Bosch-Rosa, C., Meissner, T., and Bosch-Domènech, A. (2018).	• Cognitive Reflection Test • Two-player beauty contest • Beauty Contest • Race-to-60 game
Bosch-Rosa, C. and Meissner, T., (2020).	• Race-to-60 game • Two-player beauty contest • Beauty Contest • Raven Progressive Matrices
Breaban, A. and Noussair, C.N. (2015).	• Cognitive Reflection Test
Bruguier, A.J., Quartz, S.R. and Bossaerts, P., (2010).	• Heider Movie • Financial Market Prediction Task • Eye Gaze Test • Standard Mathematics and Logic Questions
Burks, S. V., J. P. Carpenter, L. Goette, and A. Rustichini. (2009).	• Raven Progressive Matrices
Campitelli, G. and M. Labollita (2010).	• Cognitive Reflection Test
Capraro, V., Corgnet, B., Espín, A. M. and Hernán-González, R. (2017).	• Toplak et al. (2014) expansion of the Cognitive Reflection Test
Christelis, D., Jappelli, T., and Padula, M. (2010).	• Ability to Perform Calculations • Executive Function Test (word fluency) • Memory Indicator

Cokely, E. T. and C. M. Kelley (2009).	• Working Memory Span • Cognitive Reflection Test • Ability to Transform Probabilities
Corgnet, B., Deck, C., DeSantis, M., and Porter, D. (2018).	• Toplak et al. (2014) expansion of the Cognitive Reflection Test • Eye Gaze Test
Corgnet, B., DeSantis, M., and Porter, D. (2018).	• Toplak et al. (2014) expansion of the Cognitive Reflection Test • Eye Gaze Test
Corgnet, B., DeSantis, M., and Porter, D. (2021).	• Eye Gaze Test • Toplak et al. (2014) expansion of the Cognitive Reflection Test • Financial Literacy Test • Raven Progressive Matrices • Self-Monitoring Test
Corgnet, B., Hernán-González, R., Kujal, P. and Porter, D., (2015).	• Cognitive Reflection Test
Corgnet, B., Hernán-González, R., and Kujal, P. (2020).	• Eye Gaze Test • Toplak et al. (2014) expansion of the Cognitive Reflection Test
Cueva, C., and A. Rustichini (2015).	• Raven Progressive Matrices • Race to 15
Da Silva, S., Da Costa Jr, N., Matsushita, R., Vieira, C., Correa, A. and De Faveri, D., (2018)	• Toplak et al. (2014) expansion of the Cognitive Reflection Test
Deck, C., Salar, J. and R. Sheremeta (2021).	• Toplak et al. (2014) expansion of the Cognitive Reflection Test • Primi et al. (2016) expansion of the Cognitive Reflection Test
De Martino, B., O'Doherty, J. P., Ray, D., Bossaerts, P., and Camerer, C. (2013).	• Eye Gaze Test
Dohmen, T., Falk, A., Huffman, D., & Sunde, U. (2010).	• Executive Function Test (word fluency) • Symbol-digit correspondence task
Gerardi, K., Goette, L., and Meier, S. (2013).	• Basic Mathematical Skills • Reaction Time to Mathematical Questions • Executive Function Test (word fluency) • Economic Literacy Questions

Grinblatt, M., Keloharju, M. and J. Linnainmaa (2011).	• Finnish Armed Forces (FAF) Intelligence Assessment
Grinblatt, M., Keloharju, M. and J. Linnainmaa (2012).	• Finnish Armed Forces (FAF) Intelligence Assessment
Hefti, A., Heinke, S., and Schneider, F. (2018).	• Eye Gaze Test • Heider-Simmel Test • Mathematical and Logical Problems • Raven Progressive Matrices • Game of Nim
Hoppe, Eva I., and David J. Kusterer, (2011).	• Cognitive Reflection Test
Jagelka, T. (2020).	• Grades • Numeracy Test • Self-reported skills: oral
Janssen, D.J., Füllbrunn, S. and Weitzel, U., (2019).	• Cognitive Reflection Test
Kocher, M. G., Lucks, K. E., & Schindler, D. (2019).	• Cognitive Reflection Test • Stroop task
Lesage, E, G. Navarrete, and W. De Neys. (2013)	• Cognitive Reflection Test
Miklánek, T., & Zajíček, M. (2020).	• Cognitive Reflection Test • 12 logic problems
Muñoz-Murillo, M., Álvarez-Franco, P. B., and Restrepo-Tobón, D. A. (2020).	• Cognitive Reflection Test
Oechssler, J., Roider, A. and P. Schmitz. 2009.	• Cognitive Reflection Test
Noussair, C.N., Tucker, S. and Y. Xu. (2016).	• Cognitive Reflection Test
Shestakova, N, Powell,O, Gladyrev, D. (2019).	• Cognitive Reflection Test • Time taken to answer all instructions control questions correctly
Sirota, M., M. Juanchich, and Y. Hagmayer (2014).	• Raven Progressive Matrices
Taylor, M.P. (2013).	• Cognitive Reflection Test • 6 numeracy questions
Thoma, V, White, E., Panigrahi, A., Strowger, V., and I. Anderson (2015).	• Cognitive Reflection Test