What Makes a Good Trader?
On the Role of Quant Skills, Behavioral Biases and Intuition on Trader Performance

Brice Corgnet, Mark DeSantis, David Porter

Economic Science Institute & Argyros School of Business and Economics, Chapman University

Abstract

We study the determinants of individual trader performance by conducting a comprehensive analysis of a broad range of variables that have been studied separately in different strands of the literature (financial literacy, cognitive skills, behavioral biases and the theory of mind). We utilize an experimental trading environment that allows us to control information flows into the market and measure a large set of individual characteristics. We show that behavioral biases (such as overconfidence and the failure to understand random sampling) significantly explain trader performance whereas standard cognitive and theory of mind skills only have a marginal effect. These results support the recent effort to incorporate Behavioral Finance research findings into the financial training curriculum.

Keywords: Experimental asset markets, behavioral finance, cognitive ability, financial education.
JEL CODES: C92, G02.

Introduction

The cornerstone models of Finance build upon the assumption that a representative economic agent acts rationally (e.g. Markowitz, 1952; Sharpe, 1964; Samuelson, 1970). The rationality assumption, which requires individuals to have the capacity to correctly apply and carry out mathematical and statistical methods, has been challenged by Behavioral Finance scholars. In contrast to the representative agent model, studies have demonstrated the existence of a large degree of variability in individuals' ability to solve complex problems. When presented with such problems, most individuals tend to rely on simple heuristics instead of performing the requisite calculations (e.g. see Thaler, 1993, 2005; Barberis and Thaler, 2003; Sheffrin, 2007 for surveys).

The heterogeneity in individuals' cognitive capacities suggests that we may observe significant differences in their financial decisions. Broader access to the stock market coupled with the increasing complexity of the financial environment (e.g., large number of sophisticated financial instruments, interconnectedness of global markets, etc.) renders the understanding of the relationship between individuals' cognitive capacities and financial decisions both conceptually important and practically relevant.

The goal of our work is to provide an assessment of the skills that predict trader performance by analyzing a broad range of individual characteristics. These attributes, financial literacy, cognitive skills, behavioral biases and the theory of mind, have been studied in isolation in different strands of the literature with various types of data (archival, experimental and neuroimaging). Our methodological choice is to use an experimental asset market which allows us to control various aspects of the trading environment (see Bossaerts, 2009; Noussair and Tucker, 2014) as argued in Frydman et al. (2014):

> "*The advantage of experiments is that they give researchers a large degree of control over the trading and information environment, which can make it easier to tease theories apart.*"
>
> Frydman, Barberis, Camerer, Bossaerts and Rangel (2014), p. 907

Specifically, this environment enables us to manage the flow of information into the market so that the effect of cognitive skills is not confounded with that of insider trading.

The experimental methodology also allows us to collect a large set of individual measures for traders. Controlling for an extensive number of individual characteristics ensures the robustness of the effect of the hypothesized predictors. In this way we avoid a common criticism of the findings of the financial literacy literature, which have been shown to crucially depend on the absence of individual controls (e.g. Fernandes, Lynch and Netemeyer, 2014).

We conducted two related studies. In our first study, we invited participants to trade in experimental asset markets after which we collected a series of individual measures (financial literacy, IQ, behavioral biases, cognitive reflection, and self-monitoring) that have previously been found to correlate with trading behavior. We refine our analysis of the role of individual characteristics in trader performance with the second study. Indeed, we invited participants of the first study to undertake additional tests including a theory of mind test, a verbal intelligence test

and an assessment of overconfidence. Additional control variables, such as personality traits and risk attitudes, were also measured.

The results of our two studies lead to the same conclusion: behavioral biases such as overconfidence and the inability to understand random sampling explain trader earnings whereas standard cognitive and theory of mind skills do not. These findings contribute to the current discussion regarding the standard financial training curriculum (e.g. see Atkinson and Messy, 2013). Indeed, our results suggest that Behavioral Finance could play an important role in reshaping financial education programs to address individuals' biases and thus possibly mitigate their detrimental effect on trader performance.

What makes a good trader? Prior literature

Financial literacy and general cognitive ability

Policy makers have expressed concern regarding the general public's lack of understanding regarding basic finance topics (e.g. Greenspan, 2005; Mishkin, 2008; US Congress, 2010). The extensive research on financial education and financial literacy has attempted to identify specific concepts and skills that can enable better financial decisions, especially decisions related to retirement savings. Consequently, financial literacy has been referred to as the understanding of key financial concepts such as compound interest and the present value of money (Alba and Hutchinson, 1987). Financial literacy is also closely related to numeracy skills (see Fernandes, Lynch and Netemeyer, 2014). This literature has documented a positive relationship between financial literacy and sound financial decisions such as retirement savings (e.g. Adams and Rau, 2011) and household portfolio diversification (Von Gaudecker, 2015). A recent meta-analysis (Fernandes, Lynch and Netemeyer, 2014), however, shows that the effect of financial literacy and numeracy skills are drastically reduced upon the introduction of additional controls, such as personality traits, in the analysis. This implies that the assessment of the relationship between financial literacy or any individual characteristic and financial decisions should include a large set of control variables.

In addition to financial literacy and numeracy skills, general intelligence measures have been found to relate to stock market participation and successful investment decisions. Using a unique database of adult Finnish men, Grinblatt, Keloharju and Linnainmaa (2011) were able to study the relationship between market participation and IQ scores (as measured using the Finnish

Armed Forces Intelligence Assessment). According to Dutton and Lynn (2013), the Finnish IQ test, which they refer to as *Peruskoe*, assigns an important weight to the Raven progressive matrices test (Raven, 1941).[1] The authors report that high-IQ Finnish men were more likely to participate in the stock market than those with low IQ scores. This finding confirmed earlier studies suggesting a positive relationship between general cognitive ability and self-reported stock market participation (Kezdi and Willis, 2003; Benjamin, Brown, and Shapiro, 2006; Cole and Shastry, 2009; Christelis, Jappelli, and Padula, 2010). Grinblatt, Keloharju and Linnainmaa (2012) also showed, using the same Finnish men database, that the trades of high-IQ people outperformed those of low-IQ people. These high-IQ individuals exhibited better market timing than their low-IQ counterparts and were more likely to buy winning stocks and sell losing stocks. These findings illustrate that high-IQ people may have been able to mitigate behavioral biases such as the well-documented disposition effect (e.g. Odean, 1998; Chen et al. 2007). However, the authors leave to further research the study of the exact motives underlying the large returns of high-IQ traders:

> "*The source of high-IQ investors' stock-picking skill is unresolved. High-IQ investors may have better access to non-public information, they may be better at processing public or private information, or their greater immunity to behavioral biases may boost their returns*."
>
> Grinblatt, Keloharju and Linnainmaa (2012), p. 361

Behavioral biases

The works of Grinblatt, Keloharju and Linnainmaa suggest that the behavioral biases documented in the Behavioral Finance literature (Shleiffer, 2000; Thaler, 2005; Shefrin, 2007; Shiller, 2015) may help predict how well traders perform. Behavioral Finance has grown by demonstrating how the heuristics and biases identified by cognitive psychologists (e.g. Tversky and Kahneman, 1974) can distort financial decisions (e.g. see Thaler, 1993, 2005; Barberis and Thaler, 2003; Shefrin, 2007 for surveys). We focus our attention on behavioral biases that have been shown to correlate with trading behavior. This includes individuals' inability to understand random sampling as well as overconfidence.

[1] Other European countries' army-enrollment cognitive exams also place a strong emphasis on the Raven test.

Failure to understand random sampling

Individuals tend to mistakenly believe that they observe predictable patterns in randomly generated data. For example, the hot hand fallacy suggests that people expect a randomly generated outcome to be more likely to be observed in the future if it has been frequently observed in the past. This bias may explain why individuals, believing in the persistence of the fund manager's success, tend to invest in funds that have been successful in the past (Sirri and Tufano, 1998; Barber et al., 2005). Another example of an individual's failure to comprehend random sampling is the gambler's fallacy, which stresses that people expect small samples to closely reflect the probabilities of the random-generating device (e.g. Tversky and Kahneman, 1974). In the financial literature, this bias has been associated to the disposition effect, which suggests individuals sell winning stocks too soon and hold losing stocks too long. The disposition effect has been shown to lead to inefficient investments in the field (Odean, 1998; Chen et al. 2007) and in the lab (Kroll, Levy and Rapoport, 1988; Weber and Camerer, 1998; Huber, Kirchler and Stöckl, 2010).

Overconfidence

Another widely documented behavioral bias is overconfidence, which has been found to relate to excessive trading (Barber and Odean, 2000, 2001; Odean 1999), misreaction to news (Daniel, Hirshleifer, and Subrahmanyam, 1998, 2001; Hong and Stein, 1999; Shleiffer, 2000; Hirshleifer, 2001) and the formation of bubbles (Scheinkman and Xiong, 2003; Hong, Scheinkman and Xiong, 2006; Michailova and Schmidt, 2011). In addition, Biais et al. (2005) employed an experimental asset market with disperse information to show that overconfidence is negatively related to trader performance.

The literature in cognitive psychology has identified many more behavioral biases than the ones studied in Behavioral Finance (e.g. Kahneman, 2011). A common thread running through each of these biases is the individual's inability to refrain from using automatic responses and simple heuristics (Toplak, West and Stanovich, 2011). Considering a total of 15 different behavioral biases, Toplak, West and Stanovich (2011) show that individuals who are able to discard intuitive answers are typically more immune to behavioral biases.

Cognitive reflection and behavioral biases

Research in cognitive science has identified and validated a test (the CRT) that explains a person's ability to avoid common behavioral biases (Oechssler, Roider and Schmitz, 2009; Toplak, West and Stanovich, 2011, 2014). The CRT consists of questions which all have an appealing and intuitive, yet incorrect, answer. Upon reflection, one may disregard the intuitive answer in favor of the correct one. In the Experimental Finance literature CRT scores have been found to predict subjects' earnings in experimental asset markets with bubbles (Noussair, Tucker and Xu, 2014; Corgnet et al. 2015). The CRT questions are also very similar to the brainteasers that prospective traders are asked to solve during interviews with Wall Street companies (Crack, 2004; Zhou, 2008).[2] Thoma et al. (2015) show that a sample of 102 professional traders scored particularly high on the CRT and that CRT scores correlated positively with years of experience and salary.

These previous works illustrate the recent emergence of the field of Cognitive Finance, which we define as "the incorporation of theoretical concepts and tools of cognitive sciences (cognitive psychology and intelligence research) into the analysis of financial markets and financial decision-making."

Theory of mind and self-monitoring

Recent research has also investigated the role of trader intuition as an important determinant of trader performance. In particular, Bruguier, Quartz, and Bossaerts (2010) were able to identify a brain area (paracingulate cortex) that activates when insider trading is present in the market. The authors link this brain area to trader intuition and, more specifically, to people's capacity to infer others' intentions (often referred to as theory of mind, e.g. Frith and Frith, 1999). Their study showed that theory of mind skills as measured by, for example, the eye gaze test (Baron-Cohen et al., 1997) correlate with an individual's ability to predict price changes in experimental asset markets with insiders. The authors did not, however, study the relationship between trading behavior and theory of mind skills as they chose to focus on forecasting abilities:

[2] For example, Question 1.17 on page 15 of Crack (2004) is the same as the third question of the CRT, which we use in our current analysis (see Frederick, 2005).

> "*Of course, thinking about prices and forecasting them are integral to successful trading, but these two steps alone leave out the actual placing of orders. Trading intuition concerns not only assessment of what is going on in the market and prediction of future prices, but also submission of the right orders. Our study only considers the first two facets; future work should shed light on the third*."
>
> Bruguier, Quartz, and Bossaerts (2010), p. 1721

Our work seeks to address this third facet of successful trading by assessing the relationship between a trader's performance and his or her individual characteristics including theory of mind skills.

The work of Biais et al. (2005) is also related to the idea that the ability to read another person's intentions may affect one's trading behavior and account for trader performance. The authors focus on self-monitoring as a measure of people's disposition to attend social cues, and to adjust one's behavior to what is expected in social environments (e.g. Snyder and Gangestad, 1986). They conjectured that people who attain high scores on the self-monitoring scale would behave more strategically than others, as they would more accurately infer other traders' signals from asset prices. Ultimately, the authors posited that high self-monitors should earn higher trading profits, and they confirmed this intuition in a double auction trading experiment.

Study 1. A First Inquiry on Trader Performance and Cognitive Skills

The goal of our first study is to assess the relationship between traders' performance in an experimental asset market and their cognitive abilities. We first describe the experimental design and cognitive measures. We then discuss our regression results, which include a *cognitive factor* comprised of our four cognitive measures (Financial literacy, general intelligence, cognitive reflection, and sampling biases) determined via a principal components factor analysis.

Design

Asset markets

Our experimental asset market environment is similar to the experimental design of Plott and Sunder (1988, PS henceforth). We use the same parameters as in their original study (Market 9, Treatment C) regarding possible asset values and the number of market replications. The only notable difference with their original design is that our study uses a computerized instead of an

oral continuous double auction.[3] We used a computerized continuous double auction trading mechanism because it is widely used in stock market exchanges (Parsons et al. 2008).[4] Each experimental session consisted of 17 market periods during which participants could trade an experimental asset whose exact value was not know with certainty. Indeed, this asset could assume one of three possible values: 50, 240 or 490 francs. A franc was worth $0.001. At the beginning of each market period, every trader is informed of a possible value the asset cannot take. As half of the traders are given one clue (e.g. Not 50) and the other half are given the other possible clue (e.g. Not 240), the aggregate information available to all traders in the market is complete. PS argue that in a rational expectation equilibrium prices should reflect the true value of the asset (e.g. 490). In this paper, we focus on individual trading behavior rather than on the aggregation of information at the market level.[5] More specifically, we focus on the relationship between trader performance and individual characteristics.

Protocol

We recruited a total of 144 participants from a subject pool of more than 1,500 students at a major Western US University. We conducted a total of 12 sessions, each with 12 traders. In ten of the sessions, traders were endowed with 1,200 francs in cash. To ensure our results are not artifacts of this specific endowment structure, in the remaining two sessions we followed the PS approach by endowing each subject with a 25,000 franc loan that had to be repaid at the end of the each period. Before each session started, subjects completed a 10-minute training quiz regarding the random device (a spinning wheel) that was then used during the experiment to draw the actual value of the asset (either 50, 240 or 490 francs) at the end of each of the 17 markets. This training (see online Appendix O1, Instructions Part 1) consisted of having subjects predict the outcome of the spinning wheel over 10 trials. Each correct prediction was rewarded 25 cents, and each incorrect answer incurred a 10 cent penalty. Average earnings for the three-

[3] There were two other, minor differences between the designs. First, in 10 of the 12 sessions we endowed the participants with cash and shares in lieu of a loan that had to be repaid at the end of each market period (as in PS). Second, we used 5-minute periods instead of 7-minute periods as in the original design. However, because our trading mechanism was computerized, subjects could undertake at least as many trades as in the original 7-minute periods with oral auctions. The average (median) number of trades in PS was 13.5 (15.0) in Market 9 compared to 32.5 (28.0) in our study (*p-value* < 0.001).

[4] In continuous double auctions, traders can submit, at any time, offers to buy or sell the asset. Traders can also accept current market orders to buy or sell an asset.

[5] We leave the study of information aggregation at the market level to Corgnet, DeSantis and Porter (2015), which includes a detailed analysis of this topic.

hour experiments were equal to $46.45 including a $7 show-up fee. We summarize our experimental design in Table 1.

Table 1: Summary of our experimental design

Number of traders	*Number of markets* (market length in minutes) -Sessions-	*Endowment* Francs (Assets)	*Loan* Francs	*Asset values* Francs (Probabilities)	*Trading mechanism*
12	17 (5) - 12 -	1,200 (4) Used in Sessions 1-10	25,000 Used in Sessions 11-12	50, 240, 490 (0.35,0.45,0.20)	Computerized continuous double auction

Survey

At the end of each session, subjects completed a series of cognitive tests which have been shown to correlate with trading behavior. We also collected demographic information. The duration of the survey was 25 minutes. These tasks were computerized, and, as is common practice in the literature, the tests were not incentivized.

Financial literacy

We established our subjects' financial literacy using the test compiled and validated by Fernandes, Lynch and Netemeyer (2014) (see Appendix A). Subjects had 5 minutes to complete the test. We report a Cronbach alpha of 0.70 which is comparable to the 0.84 for Study 1 in Fernandes, Lynch and Netemeyer (2014). This test measures individuals' general financial knowledge (for example, regarding retirement savings) as well as their fundamental understanding of interest rate compounding and the time value of money.

General intelligence test

As a general measure of intelligence (Mackintosh, 2011), we used the Raven progressive matrices test (Raven, 1941). Specifically, we utilized the odd number of the last three series of matrices (Jaeggi et al. 2010) (see Appendix A). The duration of the test was 10 minutes. The number of matrices correctly solved in the Raven test is a conventional measure of cognitive ability. Measures of general intelligence are commonly related to working memory capacity, which refers to the short-term holding and manipulation of information (Conway, Kane and Engle, 2003). Stanovich (2009) argues, however, that general intelligence measures assess one's capacity to compute solutions to problems but fail to assess one's capacity to engage in reflection

which consists in discarding intuitive responses to initiate a deliberate thinking process. We thus measured cognitive reflection separately using the cognitive reflection test (CRT).

Cognitive reflection test

The original CRT consists of three questions which all have an appealing and intuitive, yet incorrect, answer. Upon reflection, one can disregard the intuitive answer and ascertain the correct one. Although basic cognitive abilities are required to answer the CRT questions correctly, an intelligent person may often rely on automatic or instinctive answers, failing to block intuitive processes by not engaging in reflection. It follows that CRT scores have been found to moderately and positively correlate with general measures of intelligence such as the SAT (r = 0.44; Frederick 2005), Wonderlic composite test (r = 0.43; Frederick 2005), Wechsler composite index (r = 0.32; Toplak, West and Stanovich, 2011), working memory (r = 0.32; Toplak, West and Stanovich, 2011) and Raven tests (r = 0.43; Corgnet, Espin and Hernan-Gonzalez, 2015). At the end of each experiment, subjects had 5 minutes to complete the CRT. We administered the extended (seven-question) version of the CRT in which the original three questions (Frederick, 2005) are augmented with four additional questions recently developed and validated by Toplak, West and Stanovich (2014) (see Appendix A for details). Our measure of cognitive reflection is given by the total number of correct answers (from 0 to 7). The Cronbach alpha reliability score for the extended CRT (0.69) is in line with that of Toplak, West and Stanovich (2014) who reported a reliability of 0.72.

A test to assess failures to understand random sampling

To measure an individual's failure to understand random sampling (as is the case, for example, in the hot hand or the gambler's fallacy) we develop a test that makes use of the data obtained from the experiment's training phase (see online Appendix O1, Instructions Part 1).

During the training phase, which took place before the market experiment, subjects were asked to predict the outcome of spinning a wheel, where each sector of the wheel represented the probability mass associated with each possible asset value in the market experiment (see Appendix B, Figure B.1). This random device (spinning wheel) was then used during the market experiment to determine the actual value of the asset. As in Market 9 of PS, the asset could assume one of the following three possible values 50, 240 and 490 with probabilities 35%, 45% and 20%. Subjects made a total of ten predictions. After each prediction, subjects spun the wheel

by clicking on the "Spin the Wheel" button and observed the outcome of the spin. An individual, who understands random sampling, would invariably predict (240) to be the most likely outcome, regardless of the history of spins. A larger number of non-240 predictions may indicate that the subject is less likely to understand that wheel spins are independent of each other and more likely to be a victim of what we refer to as sampling biases. For example, the participant may be subject to the gambler's fallacy or the hot hand fallacy (see Kahneman, 2011, for a review of other sampling biases, such as illusion of control or anchoring, that could lead a subject to make non-240 predictions). Subjects who are victims of the gambler's fallacy will typically switch from predicting 240 to another value (50 or 490) after observing a long series of 240 outcomes. By contrast, subjects who suffer from the hot hand fallacy will typically believe that 240 is more likely after observing a long series of 240 outcomes. We do not attempt to identify or quantify a specific bias. Rather we measure the degree to which the individual is subject to sampling biases in general. Thus, we consider a participant who predicted 240 more often to be less subject to sampling biases, and we define our sampling biases measure for a given subject as 10, which is the total number of predictions, minus the number of times the subject predicted 240.

Correlations between the different participant-level cognitive measures are included in Table 2. We observe that cognitive ability measures are positively and significantly correlated. There is a moderate to high correlation level between CRT and financial literacy, and both measures, unlike Raven scores, also significantly correlate (negatively) with sampling biases. CRT correlates more strongly with sampling biases than does financial literacy. The large correlation coefficient between CRT scores and sampling biases is consistent with research showing that CRT scores better predict an individual's ability to avoid commonly observed heuristics and biases (Toplak, West and Stanovich, 2011) than general intelligence measures.

Table 2. Correlation matrix for individual cognitive measures (*n* =144).

	CRT	Raven	Financial Literacy
Raven	0.264***	1	
Financial literacy	0.373****	0.290****	1
Sampling biases	-0.313****	-0.063	-0.183***

*p -value<.10, ** p-value<.05, *** p-value<.01, and **** p-value<.001

We also assessed participants' level of self-monitoring. Table 2 excludes the self-monitoring measure as it captures non-cognitive traits.

Self-monitoring

Following the work of Biais et al. (2005) we measure self-monitoring using the self-monitoring scale proposed by Snyder and Gangestad (1986) which attempts to measure individuals' capacity to attend social cues and adjust their behavior to social environments. Subjects have to answer whether each of 18 statements accurately describes their social behavior. For example, "*I can make impromptu speeches even on topics about which I have almost no information*." (see Appendix A for the details of the scale). We obtained a similar Cronbach alpha (0.69) as the one reported by Biais et al. (2005) (0.70). Subjects had 4 minutes to complete the test.

The self-monitoring scale captures non-cognitive traits and does not significantly correlate with the cognitive measures in our study (all |*p-values*| > 0.15). This is in line with Biais et al. (2005) who report a low negative correlation between IQ and self-monitoring (-0.11). Self-monitoring scores can thus be used as controls in our regression analysis without inducing collinearity issues.

Results

Online Appendix O2 includes figures displaying the evolution of asset prices across the 17 markets for each of the 12 sessions we conducted. To investigate the relationship between individual characteristics and trader earnings, we use panel regressions with random effects in which each subject is treated as a cross section observation (n = 144) and each market as a time observation (t = 17).[6,7] In each regression, we report robust standard errors and control for the type of endowment which was given to subjects using a dummy variable (Loan dummy). The regression coefficients associated to the Loan dummy should be negative because subjects earned less on average in those sessions ($34.19) than in the baseline sessions ($48.91) in which they were given a $1.2 endowment each period. We also control for the actual value of the asset

[6] Fixed effects cannot be used since we are assessing the effect of time-invariant regressors (such as Raven scores) on trader performance. Also, using the Breusch-Pagan Lagrange Multiplier test, we reject the hypothesis that random effects are not appropriate (*p-values* < 0.001 across all specifications used in the results section).

[7] In lieu of analyzing trader wealth by market, we could use average earnings across markets as our dependent variable. Despite substantially reducing the number of available observations, the use of average earnings yields results that are remarkably similar to those obtained via our panel data analysis (details available upon request).

in a given market (Asset Value). We expect regression coefficients associated to the Asset Value control to be positive because subjects earned more in markets in which the value of the asset was higher. Gender is controlled for by using a dummy that takes value one if the trader is a female and value zero otherwise (Gender dummy). Finally, we control for participants' self-monitoring scores in each of the regressions.

We assess the explanatory power of each of the cognitive variables previously described (CRT, Raven, financial literacy and sampling biases) (see Table 2). All individual measures are standardized so that one can directly compare the magnitude of the coefficients associated to each of these variables. We show that high CRT scores, and to a lesser extent a high degree of financial literacy, explain high trader earnings (see regression results in Table 3). Given that CRT and financial literacy are the only cognitive measures that significantly correlate with sampling biases (see Table 2), this suggests that avoiding sampling biases may be essential to trader success. This intuition is confirmed by our regression analysis as our measure of sampling biases significantly relates to trader earnings. This finding is in line with the fact that Wall Street job interview questions typically include problems that require the understanding of basic statistical principles (Crack, 2004; Zhou, 2008). These job interviews also include "insight" (brain teaser) problems that are very similar to the CRT questions (Frederick, 2005). Our findings are consistent with Thoma et al. (2015) who show that professional traders (n = 102) score remarkably high on the CRT (in the top 20% of the distribution of the original three-question CRT scores in Frederick, 2005, n = 3,428) and that CRT scores correlate positively with years of experience and salary. However, the correlation between traders' salary (average of $393,865) and CRT scores was not significant. As the authors acknowledge, this lack of significance may simply be due to the particularly low sample size (only 17 of the professional traders reported their salary in the survey).

General intelligence scores, as measured using the Raven test, affect trader earnings positively, although not significantly. Self-monitoring does not significantly affect earnings. This discrepancy with the Biais et al. (2005) results is likely due to the fact that they considered an

oral double auction environment in which the participants could see each other, which may have heightened the importance of social cues.[8]

In addition to our four cognitive measures we employed a principal components factor analysis to identify potential cognitive factors. This analysis produced one factor with an eigenvalue greater than one (1.78). We refer to this factor as the *cognitive factor* as it explains 44.6% of the total variance across measures and assigns loadings of 0.79, 0.73, 0.58 and -0.53 to the CRT, financial literacy, Raven and sampling biases variables, respectively. As noted in Table 3, the *cognitive factor* explains trader earnings at a 5% significance level similar to CRT scores and our sampling biases measure.

Table 3. Trader earnings as a function of individual measures

	Earnings (in $)				
Intercept	1.266****	1.262****	1.256****	1.252****	1.270****
	(0.072)	(0.071)	(0.071)	(0.074)	(0.071)
Cognitive measures					
CRT	**0.047****	–	–	–	–
	(0.021)				
Financial literacy	–	**0.034***	–	–	–
		(0.019)			
Raven	–	–	0.041	–	–
			(0.033)		
Sampling biases	–	–	–	**0.041****	–
				(0.019)	
Cognitive factor	–	–	–	–	**0.062****
					(0.026)
Self-monitoring	-0.005	-0.006	-0.009	-0.013	-0.008
	(0.022)	(0.022)	(0.020)	(0.023)	(0.023)
Gender dummy	-0.051	-0.050	-0.075	-0.077	-0.038
	(0.059)	(0.055)	(0.060)	(0.063)	(0.055)
Loan dummy	-0.872****	-0.858****	-0.883****	-0.857***	-0.869***
	(0.028)	(0.027)	(0.035)	(0.037)	(0.031)
Asset value	0.0004****	0.004****	0.004****	0.004****	0.004****
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	n = 2,244	n = 2,244	n = 2,244	n = 2,244	n = 2,244
Prob > χ^2	0.000	0.000	0.000	0.000	0.000
R^2	0.629	0.627	0.628	0.628	0.631

Estimation output using robust standard errors at the session level (in parentheses).
*p-value<.10, **p-value<.05, ***p-value<.01 and ****p-value<.001.

[8] In addition, traders in the Biais et al. (2005) experiments belonged to the same postgraduate studies classes (Masters and MBA students) and thus likely knew each other. This may also have amplified the importance of social cues.

In addition to individual earnings, we investigate the extent to which a subject's trading behavior was consistent with the true value of the asset. We define trading as being consistent whenever it involves the buying (selling) of the asset for a price below (above) V, where V (50, 240 or 490 francs in our experiment) is the true value of the asset. For each trader and for each market we compute the proportion of trades that are consistent with the true asset value. Although the proportion of consistent trades is positively correlated with individual earnings (ρ = 0.34), there are notable differences between the two measures. For example, some subjects may only execute trades that are consistent with the true value of the asset but fail to trade sufficiently to be a top earner.[9] We report the details of this analysis in Appendix C (see Table C.1).

In line with the trader earnings analysis, we show that CRT, financial literacy and sampling biases are the only measures that significantly explain the proportion of trades that are consistent with the true value of the asset. The Raven test also positively relates with the proportion of consistent trades although statistical significance is only marginal. We summarize our findings as follows.

Result 1. (Cognitive measures and trader performance)

i) Cognitive measures explain trader performance.

ii) Cognitive reflection and sampling biases explain trader performance better than financial literacy or the Raven test.

In Study 2, we refine our analysis of the drivers of trader performance.

[9] It follows that individual earnings are a noisy measure of consistent trading behavior.

Study 2. A Further Inquiry on the Determinants of Trader Performance: Trader Intuition, Behavioral Biases and Cognitive Skills

In our second study we collect additional measures related to standard cognitive skills, behavioral biases and the theory of mind. To do so, we invited the participants of the first study to a follow-up survey in which they completed a theory of mind test, a verbal intelligence test, an adding task and an assessment of overconfidence. We also measured additional controls such as personality traits and risk attitudes (see details in Study 2). The impact of these variables on trader performance is analyzed both individually as well as collectively (with the Study 1 measures) via a factor analysis.

Design

Participants

All of the subjects who participated in Study 1 were invited one month after the original study to complete a one-hour survey. As in Study 1, the survey's tests were not incentivized with the exception of the risk-elicitation and adding tasks. This survey offered a $12 show-up fee to participants. A majority (63.9%) of the individuals who participated in Study 1 also completed Study 2 (92 out of 144). Importantly, the subjects who attended the survey did not significantly differ from the subjects, who participated in Study 1 but did not return for the survey, with respect to the tests previously completed (all Wilcoxon rank sum tests produced p-values > 0.15 for Raven, CRT, financial literacy and sampling biases).

Study 2 included the following tests which were not part of our initial survey: Wonderlic verbal, adding skills, theory of mind, and overconfidence as well as a standard personality test and a standard risk-elicitation task. Also, as part of the Study 2 survey, our subjects took the CRT and the Raven test for the second time. With respect to these two tests, we utilize the data collected during Study 1 in our analysis. Nonetheless, our analyses are qualitatively unchanged if the measurements from Study 2 for these two tests are utilized instead of those from Study 1.[10]

[10] We take the first measure to be more accurate of cognitive skills as participants may have learned the solutions to a test after completing it the first time. We did not, however, find evidence of learning in our data (results available upon request).

Survey

We briefly present the tests used in the survey. Each is described in detail in Appendix A.

Wonderlic verbal test

We asked participants to complete the verbal section of the Wonderlic Personnel Test, which is commonly used by employers to assess the intellectual abilities of their recruits (Murphy, 1984). We constructed a score by computing the proportion of correct answers to the 24 verbal questions of the Wonderlic test. Subjects had 6 minutes to complete the test. This test has been shown to correlate with other measures of cognitive abilities including SAT and ACT scores (Frederick, 2005, reports correlation coefficients of 0.49 and 0.48 for the Wonderlic composite index -including the math and verbal parts of the tests- with SAT and ACT scores). Verbal skills have also been found to correlate with emotional intelligence which in turn correlates with theory of mind skills (see e.g. Mayer, Caruso and Salovey 1999; Ciarrochi, Chan and Caputi, 2000; Mayer et al. 2011).

Theory of mind

Following Bruguier, Quartz, and Bossaerts (2010) and De Martino et al. (2013), we also administered the eye gaze test (Baron-Cohen et al., 1997) to assess subjects' theory of mind skills (i.e, the capacity to infer other's intentions, see, for example, Frith and Frith, 1999). In this task, participants looked at images of people's eyes and had to choose one of four feelings that best described the mental state of the person whose eyes were shown. Our theory of mind score is defined as the number of correct answers to the 36 question, 10-minute test.

Adding skills

Following the approach of Dohmen and Falk (2006), we also assessed participants' adding skills by asking them to repeatedly sum five one-digit numbers for a duration of two minutes. Each correct answer was rewarded 10 cents. We constructed the adding skills variable as the number of correct answers in the two-minute task. This variable can also be interpreted as a proxy for working memory (Logie, Gilhooly and Wynn, 1994) which is considered to be an important dimension of general intelligence (Conway, Kane and Engle, 2003).

Overconfidence

We use an "above-average" measure of overconfidence in the spirit of Svenson (1981) and Odean (1998).[11] In particular, for each of the three previous tests as well as for the Raven test and the CRT, we asked participants to rank themselves as follows: "*Out of the last ten people that took this test, how would you rank yourself: First, Second, …, Tenth*." We then considered a subject to be overconfident (underconfident) [neither] for a specific test if the person ranked himself or herself better than (worse than) [the same as] his or her actual rank in the task (which was computed using the scores of all individuals who completed the test). We then constructed an overconfidence index between 0 and 5 by measuring the number of times a given person was classified as overconfident in the five tests (CRT, Raven, theory of mind, verbal Wonderlic and adding skills). The Cronbach alpha reliability coefficient of this measure is equal to 0.84. Our results are robust to using a binary classification where individuals would be categorized as overconfident only if they were overconfident in all five tests. Our results are also robust to developing an overconfidence measure for each of the five tests separately and then using these five measures in the analysis.

We also collected additional measures, which have been found to relate to trading behavior, personality traits and risk attitudes, and used them as controls in our regression analysis.

Personality traits

We administered the 44-item version of the Big Five personality test which was developed by John, Donahue and Kentle (1991) and John, Naumann and Soto (2008). The Cronbach alpha reliability scores for extraversion, agreeableness, conscientiousness, neuroticism and openness were 0.85, 0.80, 0.80, 0.85 and 0.80, respectively. We use personality traits as control variables because they have been shown to relate to financial decision making. For example, Brown and Taylor (2014) show that personality traits may affect household finance decisions identifying, for example, a positive relationship between openness and the probability of holding stocks. Also, Fernandes, Lynch and Netemeyer (2014) show that controlling for personality traits affects the magnitude and significance of the effect of financial literacy on financial decisions. Finally,

[11] Using survey data, Glaser and Weber (2003) showed that "above-average" overconfidence measures could explain excess trading whereas miscalibration tests of overconfidence (which assess the extent to which individuals overestimate the precision of their knowledge, e.g Lichtenstein, Fischhoff and Phillips, 1982) could not. Smith (2012) obtains a similar finding using experimental asset markets which are prone to bubbles. In Biais et al. (2005), overconfidence is measured using a miscalibration test.

personality traits have been found to correlate with several of the measures collected in our study. For example, openness has been found to correlate positively with Raven test scores (see DeYoung, 2011; Beauchamp, Cesarini and Johannesson, 2012), while both agreeableness and openness have been found to correlate positively with theory of mind skills (see Mayer et al. 2011).

Risk attitudes

Following the approach of Holt and Laury (2002), we elicited risk attitudes by asking subjects to make ten binary lottery choices. For each choice there exist two lotteries with one riskier than the other. We compute the number of safe choices as a measure of an individual's risk attitudes.[12] One lottery (out of 10) was randomly selected for each subject, and the results of this lottery were used to compute the subject's payment. Our objective was to control for risk attitudes as more risk tolerant traders may engage in trading strategies that involve greater risk and thus lead to higher returns. For example, more risk-tolerant traders may be more likely to trade (Fellner and Maciejovsky, 2007) or engage in risky speculative strategies. In addition, risk aversion has been found to correlate negatively with cognitive ability (Dohmen et al. 2010; Beauchamp, Cesarini and Johannesson, 2014).

Results

Individual measures

We reproduce the regression analyses of Study 1 by incorporating the additional control variables collected in Study 2 (i.e., risk attitudes and personality traits) and utilizing the sample of subjects who completed both Study 1 and Study 2. We obtain similar findings. Indeed, we report that CRT scores and sampling biases best explain individual trader earnings (see Appendix C, Table C.2).

We proceed by assessing the explanatory power of each of the newly collected measures (see Table 4). We find that Wonderlic verbal test scores have a positive effect on trader earnings, while overconfidence leads to lower earnings. The eye gaze test and adding skills relate positively, though not significantly, to trader earnings.

[12] The proportion of subjects inconsistently switching between the safer and the riskier option (12%) was similar to the proportion reported in Holt and Laury (2002) (about 10% of the cases). Our analysis is not qualitatively affected by removing these inconsistent subjects from the analysis. In the results section we present the results for all subjects, regardless of their consistency in the Holt and Laury risk attitudes elicitation task.

Table 4. Trader earnings as a function of individual measures

	Earnings (in $)			
Intercept	1.068**** (0.222)	0.966**** (0.226)	1.392**** (0.256)	1.011**** (0.222)
Study 2 measures				
Eye gaze test	0.011 (0.020)	–	–	–
Overconfidence	–	**-0.075**** (0.021)	–	–
Wonderlic verbal test	–	–	**0.077**** (0.030)	–
Adding skills	–	–	–	0.013 (0.025)
Self-monitoring	0.016 (0.033)	0.021 (0.031)	0.023 (0.031)	0.018 (0.033)
Risk aversion	0.005 (0.010)	-0.006 (0.011)	-0.005 (0.010)	0.006 (0.010)
Gender dummy	-0.056 (0.079)	-0.065 (0.074)	-0.033 (0.076)	-0.058 (0.081)
Loan dummy	-0.786**** (0.052)	-0.827**** (0.058)	-0.789**** (0.055)	-0.782**** (0.051)
Asset value	0.004**** (0.0002)	0.004**** (0.0002)	0.004**** (0.0002)	0.004**** (0.0002)
Personality traits (Big five)	ns	ns	ns	ns
Observations	n = 1,564	n = 1,564	n = 1,564	n = 1,564
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.614	0.621	0.616	0.614

Estimation output using robust standard errors at the session level (in parentheses).
*p-value<.10, **p-value<.05, ***p-value<.01 and ****p-value<.001.

In order to identify the distinct drivers of trader performance we proceed, similar to Study 1, by conducting a factor analysis.

Intuition and sophistication factors

Using the nine individual measures collected in Study 1 and Study 2 (see Table 5), we perform a principal components factor analysis. In Table 5, we describe the two main factors, which are characterized by the loadings associated to each of the variables.[13]

[13] A third factor, which does not explain individual earnings, had an eigenvalue only slightly higher than one. For the sake of clarity, we do not consider this factor.

Table 5. Factor loadings for Study 1 and Study 2 variables

Variable	*Loadings* (Major loadings in **bold**) Factor 1 *Intuition factor*	Factor 2 *Sophistication factor*
Financial literacy	0.001	**0.701**
Adding skills	**-0.811**	0.347
IQ Test (Raven)	0.333	**0.634**
Sampling biases	-0.100	0.274
Overconfidence	0.126	**-0.621**
CRT	-0.128	**0.744**
Eye gaze test	**0.753**	0.109
Wonderlic verbal test	**0.866**	0.140
Self-monitoring	0.172	-0.089
Eigenvalue	2.21	2.04
% of explained variance	24.6%	22.7%

The first factor primarily relates to theory of mind skills with major loadings for the eye gaze test and the Wonderlic verbal test. This factor also assigns a large negative loading to adding skills. This is not surprising in light of the large and significant negative correlation between adding skills and both the Eye Gaze and Wonderlic verbal tests (-0.429 and -0.609, see Table B.2 in Appendix B). Thus, the first factor may be interpreted as a measure of trader intuition or theory of mind skills where eye gaze test scores and verbal intelligence play an important role. The second factor assigns large weights to quantitative skills and behavioral biases. In particular, it assigns large loadings for CRT and overconfidence. It also assigns large weights to the IQ and financial literacy tests. Overall, this second factor assesses traders' sophistication as captured by their general level of intelligence (Raven), their knowledge of financial concepts and common financial calculations (Financial literacy) and their immunity to behavioral biases (Overconfidence and CRT). We will refer to Factor 1 as the *intuition factor* and to Factor 2 as the *sophistication factor*. In Table 6, we show that the *sophistication factor* significantly relates to trader earnings (p-value = 0.004) whereas the *intuition factor* does not (p-value = 0.427).

Table 6. Trader earnings as a function of the *intuition* and *sophistication factors*

	Earnings (in $)		
Intercept	1.164****	1.140****	1.209****
	(0.211)	(0.239)	(0.192)
Factors			
Intuition factor	0.035	–	0.032
	(0.044)		(0.031)
Sophistication factor	–	**0.080*** **	**0.079*** **
		(0.027)	(0.027)
Risk aversion	0.003	-0.003	-0.004
	(0.011)	(0.011)	(0.011)
Gender dummy	-0.065	-0.009	-0.014
	(0.088)	(0.066)	(0.069)
Loan dummy	-0.796****	-0.832****	-0.839****
	(0.051)	(0.058)	(0.058)
Asset value	0.004****	0.004****	0.003****
	(0.0002)	(0.0002)	(0.0003)
Personality traits (Big five)	ns	ns	ns
Observations	n = 1,479	n = 1,479	n = 1,479
Prob > χ^2	0.000	0.000	0.000
R^2	0.609	0.615	0.617

Estimation output using robust standard errors at the session level (in parentheses).
*p-value<.10, **p-value<.05, ***p-value<.01 and ****p-value<.001.

Similar to Study 1, our findings regarding trader earnings also hold when the proportion of trades consistent with the true value of the asset is analyzed (see Appendix C, Tables C.3 to C.5). We summarize the above Study 2 findings as follows.

Result 2. (Trader sophistication, intuition, and trader performance)

The sophistication factor significantly explains trader performance whereas the intuition factor does not.

Prior literature suggests quantitative skills, behavioral biases and theory mind of skills affect trading behavior. We thus complement our factor analysis by using these three categories to define separate factors. We define a *behavioral factor*, a *quant factor* and a *theory of mind factor* by performing a separate factor analysis on each of these dimensions.

Behavioral, quant and theory of mind factors

For the traders who completed the Study 2 survey, we have a total of nine variables that can be utilized to explain trader performance (see Table B.2 in Appendix B). Three variables are related

to standard quantitative skills: financial literacy, adding skills and IQ. None of these variables, however, are thought to capture traders' intuition or traders' ability to avoid common biases identified in the Behavioral Finance literature. To measure the extent to which a person suffers from behavioral biases we use our sampling biases test as well as our overconfidence measure. In addition, CRT scores have been shown to correlate negatively to 15 classic heuristics and biases (Toplak, West and Stanovich, 2011) and thus provide an additional related measure. Trader intuition, which has been linked to the individual's capacity to read other traders' intentions in market environments, has been related to theory of mind skills (Bruguier, Quartz, and Bossaerts, 2010) and self-monitoring (Biais et al. 2005). In turn, theory of mind skills have been shown to correlate with verbal intelligence (Mayer, Salovey and Caruso, 2008).

We thus classify our individual measures into three categories: quantitative skills (financial literacy, adding skills and Raven), behavioral biases (sampling biases, overconfidence and cognitive reflection) and theory of mind skills (measured via the Eye gaze, Wonderlic verbal and self-monitoring tests). From a statistical standpoint, these three categories would correspond to principal components factors if our individual measures were highly correlated within each category but not significantly correlated across categories. The actual correlation pattern is, however, more complex (see Table B.2 in Appendix B). As expected, individual measures within each category tend to be significantly correlated with a few exceptions such as the low correlation between Raven test scores and adding skills, and the low correlation between Wonderlic verbal test scores and the self-monitoring scale. We also observe significant correlations between measures across categories. For example, CRT scores exhibit a significant and positive correlation with other cognitive tests (Financial Literacy, Raven, and adding skills). This is not surprising given that CRT scores measure general cognitive ability in addition to cognitive reflection. Also, Wonderlic verbal test scores correlate positively with Raven scores confirming the positive relationship between verbal and non-verbal measures of intelligence (Ramsden, 2011). Surprisingly, Raven test scores, financial literacy and adding skills correlate (negatively) with overconfidence.

We proceed by performing a principal components factor analysis for each of the previously-defined categories of individual characteristics: quantitative skills, behavioral biases and theory of mind skills. Only one factor was retained for each grouping of variables.[14] In Table 7, we

[14] All other factors were associated with eigenvalues less than one.

show the factor loadings associated to each of the variables for each of the three factors. These factor loadings show that subjects with a high *quant factor* tend to perform well on the financial literacy test, adding skills task and the Raven test. Subjects, who have a high *behavioral factor*, are typically not affected by sampling biases and overconfidence and tend to have a high score on the CRT. Subjects with a high *theory of mind factor* perform well on the eye gaze and Wonderlic verbal tests. They also tend to have a high score on the self-monitoring scale.

Table 7. Factor loadings for the *quant*, *behavioral* and *theory of mind factors*

Variable	*Loadings*		
	Quant factor	*Behavioral factor*	*Theory of mind factor*
Financial literacy	0.828	_	_
Adding skills	0.498	_	_
IQ Test (Raven)	0.628	_	_
Sampling biases	_	-0.714	_
Overconfidence	_	-0.645	_
CRT	_	0.765	_
Eye gaze test	_	_	0.859
Wonderlic verbal test	_	_	0.836
Self-monitoring	_	_	0.295
Eigenvalue	1.33	1.51	1.52
% of explained variance	44.2%	50.3%	50.8%

In Table 8, we assess the explanatory power of the three factors. We show that the *behavioral factor* is the only factor that significantly explains trader earnings (p-value < 0.001). The *quant factor* and the *theory of mind factor* affect earnings positively but fail to reach statistical significance at 5% levels (p-value = 0.155 and p-value =0.092, respectively).

Table 8. Trader earnings as a function of *quant*, *behavioral* and *theory of mind factors*

	Earnings (in $)			
Intercept	1.113****	1.089****	1.183****	1.190****
	(0.209)	(0.260)	(0.217)	(0.215)
Factors				
Quant factor	0.043	–	–	0.016
	(0.030)			(0.031)
Behavioral factor	–	**0.093******	–	**0.085******
		(0.022)		(0.023)
Theory of mind factor	–	–	**0.043***	0.021
			(0.025)	(0.021)
Risk aversion	0.005	-0.009	0.003	-0.010
	(0.011)	(0.010)	(0.010)	(0.010)
Gender dummy	-0.036	-0.031	-0.054	-0.031
	(0.064)	(0.074)	(0.079)	(0.067)
Loan dummy	-0.815****	-0.823****	-0.791****	-0.831****
	(0.048)	(0.063)	(0.052)	(0.062)
Asset Value	0.004****	0.004****	0.004****	0.004****
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Personality traits (Big Five)	ns	ns	ns	ns
Observations	n = 1,479	n = 1,479	n = 1,479	n = 1,479
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.616	0.617	0.615	0.618

Estimation output using robust standard errors at the session level (in parentheses).
*p-value<.10, **p-value<.05, ***p-value<.01 and ****p-value<.001.

We illustrate the explanatory power of the *behavioral factor* in Figure 1. Participants whose *behavioral factor* score is in the top 20% of our sample outperform those in the top 20% of either the *theory of mind factor* or the *quant factor* (p-values <0.01). Also, the *behavioral factor* is the only factor for which the participants who are in the top 20% according to that factor ($38.05) significantly outperform those who are in the bottom 20% ($31.86) (p-value <0.001).

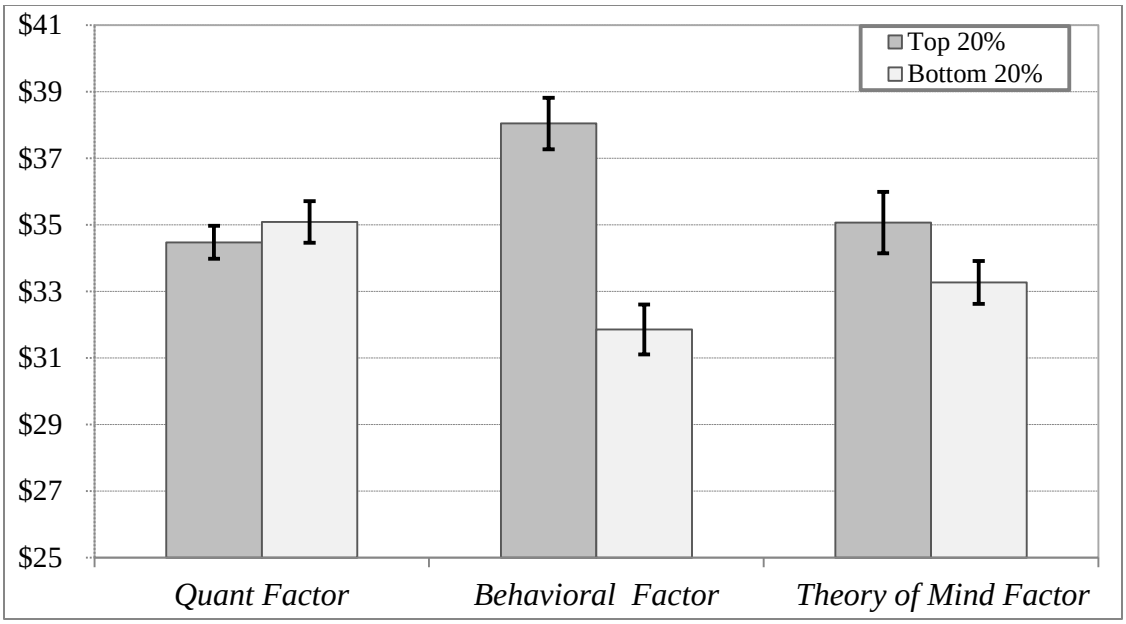

Figure 1. Average trader earnings (with 5% confidence intervals) for participants in the top 20% (bottom 20%) of each factor: *quant*, *behavioral* and *theory of mind*.

In Appendix C (Table C.6), we show that the *behavioral factor* continues to have a significant effect on trader earnings after controlling for the individual measures that we previously found to significantly correlate with earnings (Wonderlic verbal test, sampling biases, CRT and financial literacy). When both the *behavioral* and *sophistication factors* are included in the analysis (see Table C.6, last column), the *behavioral factor* continues to significantly explain trader earnings while the *sophistication factor* does not.

Finally, we show that the explanatory power of the *behavioral factor* extends to the analysis of the proportion of trades consistent with the true value of the asset (see Appendix C, Tables C.7 and C.8). Interestingly, although the *theory of mind factor* does not affect earnings significantly, it does impact an individual's ability to trade consistently with the true asset value (see Table C.7). That is, theory of mind skills can explain the ability of individuals to use asset prices, beyond their own private information, to infer others' information and thus the true value of the asset. This result is in line with the findings of Bruguier, Quartz and Bossaerts (2010) who show theory of mind skills to be a valid measure of trading intuition.

We summarize our findings regarding the explanatory power of the different factors as follows.

Result 3. (Behavioral biases and trader performance)

The behavioral biases factor is the only factor that significantly explains trader performance. Quantitative skills and theory of mind skills have only a marginal positive effect on trader performance.

Discussion

On the Role of Behavioral and Experimental Finance in Financial Education

Our studies show that people who are immune to commonly-known behavioral biases perform the best in experimental asset markets. Standard cognitive and theory of mind skills correlate positively but not significantly with trader performance. Financial Literacy also correlates positively with trader earnings though its statistical significance is only marginal.

Our findings echo recent research in Cognitive Psychology stressing the limitations of current cognitive tests (e.g. Raven) to assess rational thinking, which is defined as one's capacity to avoid behavioral biases (Stanovich, 2009). The author advocates the development of a rationality quotient (RQ) that would complement the commonly-measured IQ. To date, the best measure of RQ is provided by the extended CRT (Toplak, West and Stanovich, 2014) which plays a major role in the definition of our *behavioral factor*. Our finding regarding the predominant role of RQ as opposed to IQ in explaining trader performance is consistent with the well-known observation of Warren Buffet (Kilpatrick, 1994, p. 568):

"*You don't need to be a rocket scientist. Investing is not a game where the guy with the 160 IQ beats the guy with a 130 IQ. Rationality is essential.*"

Our results also support the recent move toward introducing Behavioral Finance findings in the standard Finance curriculum. For example, even though the CFA (Chartered Financial Analyst) curriculum emphasizes financial literacy, numeracy and computational ability, it has recently included a Behavioral Finance section.[15] Given the many limitations and challenges people face in undoing their own behavioral biases (e.g. Larrick, 2004), an important research topic is to gauge whether people can learn to avoid these biases the same way they learn financial concepts such as compounding and the time value of money. An interesting avenue for future research would be to design financial training programs that, in addition to alerting people to the negative financial consequences of behavioral biases, teach them how to avoid these biases.

[15] See http://www.businessinsider.com/cfa-level-3-behavioral-finance-2013-5
See http://www.cfainstitute.org/utility/pages/search_results.aspx?k=behavioral%20finance&s=All%20Sites

In that respect, we believe the experimental methodology could play a fundamental role by engaging people in experimental market environments that reproduce relevant aspects of real markets without endangering their own wealth. In addition, another issue with learning financial principles in real markets is the large number of factors affecting asset prices that blur the individual participant's responsibility in poor trader performance. Clear and unambiguous feedback on one's own trading performance is a very appealing feature of controlled market environments as a tool for financial education.[16] Ultimately, a Finance instructor using experimental markets could facilitate learning by showing the direct connection between behavioral biases and trader performance.

References

Adams, G. and B. Rau (2011) "Putting off Tomorrow to do What you Want Today: Planning For Retirement," American Psychologist 66(3), 180-192.

Alba, J. and J. Hutchinson (1987) "Dimensions of Consumer Expertise," Journal of Consumer Research 12(4), 411-454.

Atkinson, A. and F. Messy (2013), "Promoting Financial Inclusion Through Financial Education: OECD/INFE Evidence, Policies and Practice," OECD Working Papers on Finance, Insurance and Private Pensions, No. 34, OECD Publishing, Paris.

Barber, B., and T. Odean (2000) "Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," Journal of Finance 55, 773-806.

Barber, B. and T. Odean (2001) "Boys Will be Boys: Gender, Overconfidence, and Common Stock Investment," Quarterly Journal of Economics 116(1), 261-292.

Barber, B., Odean, T. and L. Zheng (2005) "Out of Sight, out of Mind: The Effects of Expenses on Mutual Fund Flows," Journal of Business 78 (6), 2095-2120.

Barberis, N. and R. Thaler (2003). "A Survey of Behavioral Finance," Handbook of the Economics of Finance, North-Holland.

Baron-Cohen, S., Jolliffe, T., Mortimore, C. and M. Robertson (1997) "Another Advanced test of Theory of Mind: Evidence From Very High Functioning Adults With Autism or Asperger Syndrome," Journal of Child Psychology and Psychiatry 38, 813-822.

[16] The computer software used for these experiments is open source and available for free. It can be run on virtually any browser and any electronic device connected to the internet.

Beauchamp, J., Cesarini, D., and M. Johannesson (2015) “The Psychometric Properties of Measures of Economic Risk Preferences,” Working paper, New York University, New York.

Benjamin, D., Brown S., and J. Shapiro, (2013) “Who is Behavioral? Cognitive Ability and Anomalous Preferences,” Working paper, Harvard University.

Biais, B., Hilton, D., Mazurier, K. and S. Pouget (2005) “Judgmental Overconfidence, Self-Monitoring and Trading Performance in an Experimental Financial Market,” The Review of Economic Studies 72(2), 287-312.

Bossaerts, P. (2009) “What Decision Neuroscience Teaches us About Financial Decision Making,” Annual Review of Financial Economics 1, 383-404.

Brown, S. and K. Taylor (2014) “Household Finances and the ‘Big Five’ Personality traits," Journal of Economic Psychology 45(C), 197-212.

Bruguier, A., Quartz, S. and P. Bossaerts (2010) “Exploring the Nature of ‘Trader Intuition’,” Journal of Finance 65, 1703-1723.

Chen, G., Kim, K., Nofsinger, J. and O. Rui (2007) “Trading Performance, Disposition Effect, Overconfidence, Representativeness Bias, and Experience of Emerging Market Investors,” Journal of Behavioral Decision Making 20(4), 425-51.

Christelis, D., Tullio, J. and M. Padula (2010) “Cognitive Abilities and Portfolio Choice,” European Economic Review 54, 18-38.

Ciarrochi, J., Chan, A., and P. Caputi (2000) “A Critical Evaluation of the Emotional Intelligence Concept,” Personality and Individual Differences 28, 539-561.

Cole, S. and G. Shastry (2009) “Smart Money: The Effect of Education, Cognitive Ability, and Financial Literacy on Financial Market Participation,” Working paper, Harvard Business School, 09-071.

Conway, A., Kane, M. and R. Engle (2003) “Working Memory Capacity and its Relation to General Intelligence,” Trends in Cognitive Sciences 7(12), 547-52.

Corgnet, B., Espín, A. and R. Hernan-Gonzalez (2015) “The Cognitive Basis of Social Behavior: Cognitive Reflection Overrides Antisocial but not Always Prosocial Motives,” Economic Science Institute working papers, 15-04.

Corgnet, B., Hernan-Gonzalez, R, Kujal, P. and D. Porter (2014) “The Effect of Earned Versus House Money on Price Bubble Formation in Experimental Asset Markets,” Review of Finance 19, 1455-1488.

Corgnet, B., DeSantis, M. and D. Porter (2015) "On the Cognitive Foundations of Information Aggregation in Asset Markets: Reflective Learning & Market Efficiency," Economic Science Institute working papers, 15-15.

Crack, T. (2004) "Heard on the Street: Quantitative Questions from Wall Street Job Interviews," Dunedin, New Zealand.

Daniel, K., Hirshleifer, D., and A. Subrahmanyam (1998) "Investor Psychology and Security Market Under- and Overreactions," Journal of Finance 53, 1839-1885.

Daniel, K., Hirshleifer, D., and A. Subrahmanyam (2001) "Overconfidence, Arbitrage and Equilibrium Asset Pricing," Journal of Finance 56, 921-965.

De Martino, B., O'Doherty, J., Debajyoti, R., Bossaerts, P. and C. Camerer (2013) "In the Mind of The Market: Theory of Mind Biases Value Computation During Financial Bubbles," Neuron 79, 1222-1231.

DeYoung, C. (2011) "Intelligence and Personality," The Cambridge Handbook of Intelligence, Chapter 35, 711-737.

Dohmen, T. and A. Falk (2006) "Performance Pay and Multidimensional Sorting: Productivity, Preferences, and Gender," American Economic Review 10, 556-590.

Dohmen, T., Falk, A., Huffman, D. and U. Sunde (2010) "Are Risk Aversion and Impatience Related to Cognitive Ability?," American Economic Review 100(3),1238-60.

Dutton, E. and R. Lynn (2013) "A Negative Flynn Effect in Finland, 1997-2009," Intelligence 41(6), 817-820.

Fellner, G. and B. Maciejovsky (2007) "Risk Attitude and Market Behavior: Evidence From Experimental Asset Markets," Journal of Economic Psychology 28(3), 338-350.

Fernandes, D., Lynch, J. and R. Netemeyer (2014) "Financial Literacy, Financial Education, and Downstream Financial Behaviors," Management Science 60(8), 1861-1883.

Frederick, S. (2005) "Cognitive Reflection and Decision Making," Journal of Economic Perspectives 19(4), 25-42.

Frith, C. and U. Frith (1999) "Interacting Minds—A Biological Basis," Science 286, 1692-1695.

Frydman, C., Barberis, N., Camerer, C., Bossaerts, P. and A. Rangel (2014) "Using Neural Data to Test a Theory of Investor Behavior: An Application to Realization Utility," Journal of Finance 69 (2), 907-946.

Gaudecker, H. (2015) “How Does Household Portfolio Diversification Vary with Financial Literacy and Financial Advice?” Journal of Finance 70(2), 489-507.

Glaser, M. and M. Weber (2003) “Overconfidence and Trading Volume” Working paper, University of Mannheim.

Greenspan, A. (2005) “The Importance of Financial Education Today,” Social Education 69(2), 64-66.

Grinblatt, M., Keloharju, M. and J. Linnainmaa (2011) “IQ and Stock Market Participation,” Journal of Finance 66, 2121-2164.

Grinblatt, M., Keloharju, M. and J. Linnainmaa (2012) “IQ, Trading Behavior, and Performance,” Journal of Financial Economics 104(2), 339-362.

Hirshleifer, D. (2001) “Investor Psychology and Asset Pricing,” Journal of Finance 56, 1533-1597.

Holt, C. and S. Laury (2002) “Risk Aversion and Incentive Effects,” American Economic Review 92(5),1644-1655.

Hong, H. and J. Stein (1999) “A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets,” Journal of Finance 54, 2143-2184.

Hong, H., Scheinkman, J., and W. Xiong (2006) “Asset Float and Speculative Bubbles,” Journal of Finance 61, 1073-1117.

Huber, J., Kirchler, M., and T. Stockl (2010) “The Hot Hand Belief and the Gambler’s Fallacy in Investment Decisions Under Risk,” Theory and Decision 68(4), 445-462.

Jaeggi, S., Studer-Luethi, B., Buschkuehl, M., Su, Y., Jonides, J. and W. Perrig (2010) “The Relationship Between N-Back Performance and Matrix Reasoning – Implications for Training and Transfer,” Intelligence 38(6), 625-635.

John, O., Donahue, E. and R. Kentle (1991) “The Big Five Inventory--Versions 4a and 54,” Berkeley, CA: University of California, Berkeley, Institute of Personality and Social Research.

John, O., Naumann, L. and C. Soto (2008) “Paradigm Shift to the Integrative Big Five Trait Taxonomy: History, Measurement, And Conceptual Issues,” In O. John, R. Robins, and L. Pervin (Eds.), Handbook of Personality: Theory and Research, 3, 114-158. New York, NY: Guilford Press.

Kahneman, D. (2011) “Thinking Fast and Slow,” New York: Farrar, Straus and Giroux.

Kezdi, G., and R. Willis (2003) "Who Becomes a Stockholder? Expectations, Subjective Uncertainty, and Asset Allocation," Retirement Research Center Working paper, University of Michigan.

Kilpatrick, A. (1994) "Of Permanent Value: The Story of Warren Buffett," Birmingham, AL: AKPE.

Kroll, Y., Levy, H. and A. Rapoport (1988) "Experimental Tests of the Separation Theorem and the Capital Asset Pricing Model," American Economic Review 500-519.

Larrick, R. (2004) "Debiasing," Chapter 16 in Koehler DJ, Harvey N (eds.). Blackwell Handbook of Judgment and Decision Making. Blackwell publishing Ltd.

Lichtenstein, S., Fischhoff, B. and L. Phillips (1982) "Calibration of Probabilities: The State of the Art to 1980," in H. Jungermann and G. deZeew (eds.) Decision Making and Change in Human Affairs (Amsterdam: D. Rede).

Logie, R., Gilhooly, K., and V. Wynn (1994) "Counting on Working Memory in Arithmetic Problem Solving," Memory & Cognition 22, 395-410.

Mackintosh, N. (2011) "History of Theories and Measurement of Intelligence," The Cambridge Handbook of Intelligence, Chapter 1, 3-19.

Markowitz, H. (1952) "Portfolio Selection," Journal of Finance 7, 77-91.

Mayer, J., Caruso, D. and P. Salovey (1999) "Emotional intelligence meets traditional standards for an intelligence," Intelligence 27, 267-298.

Mayer, J., Salovey , P. and D. Caruso (2008) "Emotional Intelligence: New Ability or Eclectic Traits?" American Psychologist 63, 503-517.

Mayer, J., Salovey, P., Caruso, D. and L. Cherkasskiy (2011) "Emotional Intelligence," The Cambridge Handbook of Intelligence, Chapter 26, 711-737.

Michailova, J. and U. Schmidt (2011) "Overconfidence and Bubbles in Experimental Asset Markets," Kiel Working Papers 1729, Kiel Institute for the World Economy.

Mishkin, F. (2008) "The Importance of Economic Education and Financial Literacy," Presentation, Third National Summit on Economic Financial Literacy, February 27, Board of Governors of the Federal Reserve System, Washington, DC.
http://www.federalreserve.gov/newsevents/speech/mishkin20080227a.htm

Murphy, K. (1984) "The Wonderlic Personnel Test," Test Critiques, 769-775. Keyser, D. J and Sweetland, R. C authors. Kansas City MO: Test Corporation of America.

Noussair, C. and S. Tucker (2014) “A Collection of Surveys on Market Experiments,” Journal of Economic Surveys 27(3), 395-397.

Noussair, C., Steven J. and Y. Xu (2014) “A Futures Market Reduces Bubbles But Allows Greater Profit for More Sophisticated Traders,” SSRN Working Paper.

Odean, T. (1998) “Are Investors Reluctant to Realize Their Losses?” Journal of Finance 53(3), 1175-1789.

Odean, T. (1999) “Do Investors Trade Too Much?,” American Economic Review 89, 1279-1298.

Oechssler, J., Roider, A. and P. Schmitz (2009) “Cognitive Abilities and Behavioral Biases,” Journal of Economic Behavior & Organization 72(1), 147-152.

Parsons, S., Marcinkiewicz M., Niu, J. and S. Phelps (2008) “Everything you Wanted to Know About Double Auctions, but Were Afraid to (bid or) ask,” Working Paper, Department of Computer and Information Science, Brooklyn College.

Plott, C. and S. Sunder (1988) “Rational Expectations and the Aggregation of Diverse Information in Laboratory Security Markets,” Econometrica 56, 1085-1118.

Ramsden, S., Richardson, F., Josse, G., Thomas, M., Ellis, C., Shakeshaft, C., Seghier, M. and C. Price (2011) “Verbal and Nonverbal Intelligence Changes in the Teenage Brain,” Nature 479 (7371), 113-116

Raven, J. (1941) “Standardization of Progressive Matrices,” British Journal of Medical Psychology 19(1), 137-150.

Samuelson, P. (1970) “The Fundamental Approximation Theorem of Portfolio Analysis in terms of Means, Variances, and Higher Moments,” Review of Economic Studies 37(4), 537-42.

Scheinkman, J. and W. Xiong (2003) “Overconfidence and Speculative Bubbles,” Journal of Political Economy 111, 1183-1219.

Sharpe, W. (1964) “Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk,” Journal of Finance 19(3), 425-442

Shefrin, H. (2007) “Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing,” New York: Oxford University Press

Shiller, R. (2015) “Irrational Exuberance,” 3rd edition Princeton, NJ: Princeton University Press.

Shleifer, A. (2000) “Clarendon Lectures: Inefficient Markets,” Oxford University Press.

Sirri, E. and P. Tufano (1998) “Costly Search and Mutual Fund Flows,” Journal of Finance 53, 1589-1622.

Smith, N. (2012) “Private Information and Overconfidence in Experimental Asset Markets,” ICES Working Paper.

Snyder, M. and S. Gangestad (1986) “On the Nature of Self-Monitoring: Matters of Assessment, Matters of Validity,” Journal of Personality and Social Psychology 51:125-139.

Stanovich, K. (2009) “What Intelligence Tests Miss: The Psychology of Rational Thought,” Yale University Press.

Svenson, O. (1981) “Are we all Less Risky and More Skillful Than our Fellow Drivers?,” Acta Psychologica 47, 143-148.

Thaler, R. H. (1993) “Advances in Behavioral Finance,” New York: Russell Sage Foundation.

Thaler, R.H. (2005) “Advances in Behavioral Finance,” Volume II, Princeton: Princeton University Press.

Thoma, V., White, E., Panigrahi, A., Strowger, V. and I. Anderson (2015) “Good Thinking or Gut Feeling? Cognitive Reflection and Intuition in Traders, Bankers and Financial Non-Experts,” PLoS One 10(4).

Toplak, M., West, R., and K. Stanovich (2011) “The Cognitive Reflection Test as a Predictor of Performance on Heuristics and Biases Tasks,” Memory & Cognition 39, 1275-1289.

Toplak, M., West, R., and K. Stanovich (2014) “Assessing Miserly Information Processing: An Expansion of the Cognitive Reflection Test,” Thinking & Reasoning 20(2), 147-168.

Tversky, A. and D. Kahneman (1974) “Judgment under Uncertainty: Heuristics and Biases,” Science 185, 1124-1131.

US Congress (2010) Dodd–Frank Wall Street Reform and Consumer Protection Act, HR 4173.ENR, 111th Cong., 2nd sess. Accessed May 31, 2013.
http://www.gpo.gov/fdsys/pkg/ BILLS-111hr4173enr/pdf/BILLS-111hr4173enr.pdf

Weber, M. and C. Camerer (1998) “The Disposition Effect in Securities Trading: An Experimental Analysis,” Journal of Economic Behavior & Organization 33(2), 167-184.

Zhou, X. (2008) “A Practical Guide to Quantitative Finance Interviews,” CreateSpace Independent Publishing Platform; 14th edition.

Appendices

Appendix A. Survey Description

Descriptive statistics for the variables used in the Study 1 and Study 2 surveys are shown below:

Study 1: Survey variables

Financial literacy

The scale was taken from Fernandes, Lynch and Netemeyer (2014).

1) Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy:

- more than today with the money in this account
- exactly the same as today with the money in this account
- *less than today with the money in this account*
- Don't know
- Refuse to answer

2) Do you think that the following statement is true or false? “Bonds are normally riskier than stocks.”

- True
- *False*
- Don't know
- Refuse to answer

3) Considering a long time period (for example 10 or 20 years), which asset described below normally gives the highest return?

- savings accounts
- *stocks*
- bonds
- Don't know
- Refuse to answer

4) Normally, which asset described below displays the highest fluctuations over time?

- savings accounts
- *stocks*
- bonds
- Don't know
- Refuse to answer

5) When an investor spreads his money among different assets, does the risk of losing a lot of money:

- increase
- *decrease*
- stay the same
- Don't know
- Refuse to answer

6) Do you think that the following statement is true or false? “If you were to invest $1000 in a stock mutual fund, it would be possible to have less than $1000 when you withdraw your money.”

- *True*
- False
- Don't know
- Refuse to answer

7) Do you think that the following statement is true or false? “A stock mutual fund combines the money of many investors to buy a variety of stocks.”

- *True*
- False
- Don't know
- Refuse to answer

8) Do you think that the following statement is true or false? “After age 70 1/2, you have to withdraw at least some money from your 401(k) plan or IRA.”

- ❍ *True*
- ❍ False
- ❍ It depends on the type of IRA and/or 401(k) plan
- ❍ Don't know
- ❍ Refuse to answer

9) Do you think that the following statement is true or false? “A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less.”

- ❍ *True*
- ❍ False
- ❍ Don't know
- ❍ Refuse to answer

10) Suppose you had $100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have on this account in total?

- ❍ *More than $200*
- ❍ Exactly $200
- ❍ Less than $200
- ❍ Don't know
- ❍ Refuse to answer

11) Which of the following statements is correct?

- ❍ Once one invests in a mutual fund, one cannot withdraw the money in the first year
- ❍ *Mutual funds can invest in several assets, for example invest in both stocks and bonds*
- ❍ Mutual funds pay a guaranteed rate of return which depends on their past performance
- ❍ None of the above
- ❍ Don't know
- ❍ Refuse to answer

12) Which of the following statements is correct? If somebody buys a bond of firm B:

- ❍ He owns a part of firm B
- ❍ *He has lent money to firm B*
- ❍ He is liable for firm B's debts
- ❍ None of the above
- ❍ Don't know
- ❍ Refuse to answer

13) Suppose you owe $3,000 on your credit card. You pay a minimum payment of $30 each month. At an Annual Percentage Rate of 12% (or 1% per month), how many years would it take to eliminate your credit card debt if you made no additional new charges?

- ❍ less than 5 years
- ❍ between 5 and 10 years
- ❍ between 10 and 15 years
- ❍ n*ever*
- ❍ Don't know
- ❍ Refuse to answer

Table A.1. Distribution of financial literacy scores (Study 1)

Financial literacy score	0	1	2	3	4	5	6	7	8	9	10	11	12	13	Mean	Standard Deviation
% of subjects	1.39	3.47	4.17	4.17	9.03	12.50	16.67	14.58	10.42	11.11	6.94	2.78	2.08	0.69	6.42	2.69

Extended cognitive reflection test (CRT):

Taken from Frederick (2005):

(1) A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost? ____ cents
[Correct answer: 5 cents; intuitive answer: 10 cents]

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? ____ minutes
[Correct answer: 5 minutes; intuitive answer: 100 minutes]

(3) 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? ____ days
[Correct answer: 47 days; intuitive answer: 24 days]

Taken from Toplack et al. (2014):

(4) If John can drink one barrel of water in 6 days, and Mary can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together? _____ days
[correct answer: 4 days; intuitive answer: 9]

(5) Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class? _____ students
[correct answer: 29 students; intuitive answer: 30]

(6) A man buys a pig for $60, sells it for $70, buys it back for $80, and sells it finally for $90. How much has he made? _____ dollars
[correct answer: $20; intuitive answer: $10]

(7) Simon decided to invest $8,000 in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Simon, from July 17 to October 17, the stocks he had purchased went up 75%. At this point, Simon has: a. broken even in the stock market, b. is ahead of where he began, c. has lost money
[correct answer: c; intuitive response: b]

Table A.2. Distribution of CRT scores (Study 1)

CRT score	% of subjects
0	12.50
1	20.14
2	21.53
3	15.97
4	11.81
5	8.33
6	3.47
7	6.25
Mean	2.65
Standard Deviation	1.95

Sampling biases

Table A.3. Distribution of sampling biases scores (Study 1)

Sampling biases score	0	1	2	3	4	5	6	7	8	9	10	Mean	Standard Deviation
% of subjects	12.12	5.30	9.09	9.85	18.18	16.67	15.91	8.33	2.27	2.27	0.00	4.02	2.32

Raven Test

The following is an example of a Raven question:

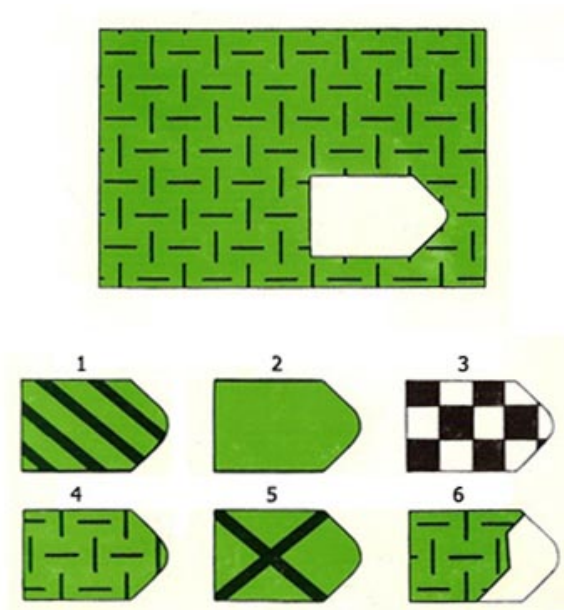

Figure A.1: Example of a Raven Test question

Table A.4. Distribution of Raven scores (Study 1)

Raven score	0	1	2-3	4	5-7	8	9	10	11	12	13	14	15	16	17	18	Mean	Standard Deviation
% of subjects	0.00	0.69	0.00	1.39	0.00	0.69	1.39	2.78	10.42	11.11	15.97	11.11	15.97	13.89	13.19	1.39	13.74	2.69

Self-monitoring scale

This scale is taken from Snyder and Gangestad (1986) and it was used by Biais et al. (2005).

For each of the following questions, we code 1 if the answer reflects self-monitoring, and 0 otherwise. Our measure of the degree to which the participant is a self-monitor is the percentage of answers coded with a 1.

Answer each Question by TRUE or FALSE:

I find it hard to imitate the behavior of other people.
At parties and social gatherings, I do not attempt to do or say things that others will like
I can only argue for ideas, which I already believe.
I can make impromptu speeches even on topics about which I have almost no information.
I guess I put on a show to impress or entertain others.
I would probably make a good actor.
In a group of people I am rarely the center of attention.
In different situations and with different people, I often act like very different persons.
I am not particularly good at making other people like me.
I'm not always the person I appear to be.
I would not change my opinions (or the way I do things) in order to please someone or win their favor.
I have considered being an entertainer.
I have never been good at games like charades or improvisations.
I have trouble changing my behavior to suit different people and different situations.
At a party I let others keep the jokes and stories going.
I feel a bit awkward in public and do not show up quite as well as I should.

I can look anyone in the eyes and tell a lie with a straight face.
I may deceive people by being friendly when I really dislike them.

Table A.5. Distribution of self-monitoring scores (Study 1)

Self-monitoring score	0-4	5	6	7	8	9	10	11	12	13	14	15	16	Mean	Standard Deviation
% of subjects	0.00	1.39	4.86	6.25	10.42	6.94	15.28	10.42	11.11	14.58	6.25	10.42	2.08	10.93	2.75

Study 2: Survey variables

Eye gaze test

This is an example of the 36 questions in the test of Baron-Cohen (1997):

Figure A.2: Example of an eye gaze test question

Table A.6. Distribution of eye gaze test scores (Study 2)

Eye gaze score	0-5	6	7-13	14	15-16	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	Mean	Stand. Dev.
% of subjects	0.00	1.08	0.00	1.08	0.00	2.15	5.38	2.15	5.38	0.00	4.30	5.38	6.45	10.78	12.90	8.60	8.60	11.83	4.30	5.38	1.08	3.23	26.31	4.64

Wonderlic verbal test

	PRESENT	**RESENT**
A.	SIMILAR	
B.	CONTRADICTORY	
C.	NOT RELATED	

Figure A.3: Example of Wonderlic verbal test question.

Table A.7. Distribution of Wonderlic verbal scores (Study 2)

Wonderlic verbal score	0	1-2	3	4-13	14	15	16	17	18	19	20	21	22	23	Mean	Standard Deviation
% of subjects	4.30	0.00	1.08	0.00	1.08	3.23	2.15	3.23	17.20	23.66	15.05	12.90	9.68	6.45	18.48	4.70

Overconfidence

Table A.8. Distribution of overconfidence scores (Study 2)

Overconfidence score	0	1	2	3	4	5	Mean	Standard Deviation
% of subjects	7.53	12.90	21.51	21.51	27.96	8.60	2.75	1.41

Adding skills

The instructions for this task were as follows. Instructions:

This task consists in adding five one-digit numbers. During a period of 2 minutes you can solve as many problems as you want to. An example of the sum problem is displayed below. Next to the display, there is an input box and an O.K. button. You will have to enter the result into the box (only integer numbers are allowed) and then click on the O.K. button. For each sum problem that you solve correctly, you will receive 10 cents. If you enter a wrong result and click O.K., a message 'Last answer was not correct.' will be displayed. You will be informed about the number of problems you have solved correctly (on the right hand side of the screen). The time remaining in seconds will be displayed in the upper left corner of the screen.

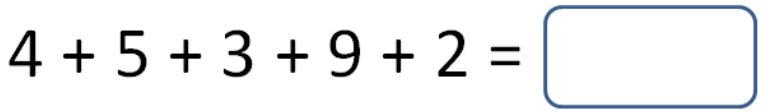

Figure A.4: Example of Adding Task question.

Table A.9. Distribution of adding scores (Study 2)

Adding skills score	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	29	30	32	37	40	45	Mean	Stand. Dev.
% of subjects	*1.08*	*4.3*	*3.23*	*3.23*	*3.23*	*6.45*	*10.75*	*11.83*	*5.38*	*7.53*	*2.15*	*6.45*	*5.38*	*6.45*	*2.15*	*4.3*	*2.15*	*1.08*	*3.23*	*1.08*	*1.08*	*1.08*	2.15	3.23	1.08	17.57	7.74

Personality traits

The Big Five Inventory (John, Donahue and Kentle , 1991 and John, Naumann and Soto, 2008).

Table A.10. Big five traits descriptive statistics (Study 2)

Variable	α	Mean	Std. Dev.
Openness	.80	35.5	10.7
Conscientiousness	.80	30.6	8.3
Extraversion	.85	26.0	8.1
Agreeableness	.80	32.3	8.5
Neuroticism	.85	21.6	7.6

Risk attitudes

The risk elicitation task was taken from Holt and Laury (2002). The instructions were as follows.
In this part of the experiment you will be asked to make a series of choices in decision problems. How much you receive will depend partly on chance and partly on the choices you make. The decision problems are not designed to test you. What we want to know is what choices you would make in them. The only right answer is what you really would choose. For each line in the table on the right, please state whether you prefer option A or option B. Notice that there are a total of 10 lines in the table but just one line will be randomly selected for payment. Each line is equally likely to be chosen, so you should pay equal attention to the choice you make in every line. At the end of the experiment, a number between 1 and 10 will be randomly selected by the computer. This number determines which line is going to be paid. Your earnings for the selected line depend on which option you chose in that line: option A or option B. To determine your earnings, Then, a second number between 1 and 10 will be randomly selected by the computer. This number is then compared with the numbers in the line and option selected (see the table below):
* If you selected option A and the second number shows up in the upper row you earn $2.00. If the number shows up in the upper row you earn $1.60.

* If you selected option B and the second number shows up in the lower row you earn $3.85. If the number shows up in the lower row you earn $0.10.

Table A.11. The ten binary lottery choices (Holt and Laury, 2002).

Line	OPTION A	OPTION B
1	1/10 of $2.00, 9/10 of $1.60	1/10 of $3.85, 9/10 of $0.10
2	2/10 of $2.00, 8/10 of $1.60	2/10 of $3.85, 8/10 of $0.10
3	3/10 of $2.00, 7/10 of $1.60	3/10 of $3.85, 7/10 of $0.10
4	4/10 of $2.00, 6/10 of $1.60	4/10 of $3.85, 6/10 of $0.10
5	5/10 of $2.00, 5/10 of $1.60	5/10 of $3.85, 5/10 of $0.10
6	6/10 of $2.00, 4/10 of $1.60	6/10 of $3.85, 4/10 of $0.10
7	7/10 of $2.00, 3/10 of $1.60	7/10 of $3.85, 3/10 of $0.10
8	8/10 of $2.00, 2/10 of $1.60	8/10 of $3.85, 2/10 of $0.10
9	9/10 of $2.00, 1/10 of $1.60	9/10 of $3.85, 1/10 of $0.10
10	10/10 of $2.00, 0/10 of $1.60	10/10 of $3.85, 0/10 of $0.10

Table A.12. Number of sage choices in the Holt and Laury task (Study 2)

Number of sage choices	0	1	2	3	4	5	6	7	8	9	10	Mean	Standard Deviation
% of subjects	6.45	1.08	2.15	3.23	19.35	17.20	25.81	18.28	2.15	1.08	3.23	5.20	2.20

Appendix B. Additional Figures and Tables

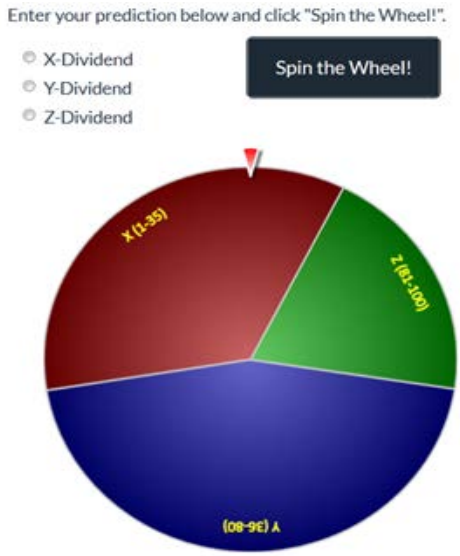

Figure B.1. The random device used to determine the actual value of the asset (50, 240 or 490) at the end of each market. Following PS instructions, we refer to 50, 240 and 490 as X-Dividend, Y-Dividend and Z-Dividend.

	Quant skills			*Behavioral biases*			*Theory of Mind*		
	Financial literacy (Study 1)	Adding skills (Study 2)	IQ test Raven (Study 1 & 2)	Sampling biases (Study 1)	Overconfidence (Study 2)	CRT (Study 1 & 2)	Eye gaze test (Study 2)	Wonderlic verbal test (Study 2)	Self-monitoring (Study 1)
Financial literacy	1								
Adding skills	**0.214****	1							
IQ test (Raven)	**0.262****	-0.023	1						
Sampling biases	0.107	0.129	-0.038	1					
Overconfidence	**-0.206****	**-0.327*****	**-0.263****	**-0.189***	1				
CRT	**0.469******	**0.267****	**0.241****	**-0.317*****	**-0.228****	1			
Eye gaze test	0.030	**-0.429******	**0.230****	0.051	-0.097	-0.042	1		
Wonderlic verbal test	0.106	**-0.609******	**0.272*****	0.032	0.036	0.026	**0.492******	1	
Self-monitoring	0.043	-0.079	-0.068	0.113	0.010	-0.060	0.131	0.050	1

*p -value<.10, ** p-value<.05, *** p-value<.01, and **** p-value<.001

Table B.2. Correlation matrix including Study 1 & Study 2 measures (*n* =92).

Appendix C. Analysis of Trading Behavior

All regression estimates use robust standard errors level (in parentheses). Statistical significance is represented as follows: *p-value<.10, **p-value<.05, ***p-value<.01, and ****p-value<.001.

To ensure that subjects' consistent trading behavior is not solely due to the prior information they received at the beginning of the period, we control for the proportion of trades which were consistent with their prior information (see Plott and Sunder, 1988). This ensures that any variable predicting a high level of trading consistency is linked to the capacity of a person to use asset prices (beyond their own private information) to infer others' information and thus the true value of the asset.

Study 1

Table C.1. Proportion of consistent trades as a function of individual cognitive measures

	Proportion of trades consistent with the asset's true value				
Intercept	0.513****	0.511****	0.507****	0.501****	0.515****
	(0.039)	(0.038)	(0.038)	(0.039)	(0.038)
Cognitive measures					
CRT	**0.032*** **	–	–	–	–
	(0.011)				
Financial literacy	–	**0.022** **	–	–	–
		(0.010)			
Raven	–	–	0.013	–	–
			(0.009)		
Sampling biases	–	–	–	**-0.032** **	–
				(0.014)	
Cognitive factor	–	–	–	–	**-0.039**** **
					(0.011)
Proportion of trades consistent with prior information	0.239****	0.238****	0.237****	0.235****	0.238****
	(0.049)	(0.050)	(0.050)	(0.051)	(0.049)
Self-monitoring	0.006	0.005	0.003	-0.001	0.004
	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)
Gender dummy	0.054***	0.054**	0.036*	0.037**	0.061****
	(0.018)	(0.022)	(0.021)	(0.019)	(0.016)
Loan dummy	-0.024**	-0.015	-0.026***	-0.013	-0.021**
	(0.010)	(0.012)	(0.010)	(0.012)	(0.010)
Asset value	-0.0001**	-0.0001**	-0.0001**	-0.0001**	-0.0001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market	0.0002	0.0003	0.0003	0.0003	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	n = 2,067	n = 2,067	n = 2,067	n = 2,067	n = 2,067
Prob > χ^2	0.000	0.000	0.000	0.000	0.000
R^2	0.089	0.085	0.082	0.089	0.092

Study 2

Table C.2. Trader earnings as a function of Study 1 individual measures and Study 2 controls

	Earnings (in $)			
Intercept	1.119**** (0.237)	1.066**** (0.224)	1.122**** (0.188)	1.035**** (0.245)
Study 1 measures				
CRT	**0.056**** (0.023)	–	–	–
Financial literacy	–	0.020 (0.017)	–	–
Raven	–	–	0.041 (0.031)	–
Sampling biases	–	–	–	**0.048**** (0.020)
Self-monitoring	0.025 (0.030)	0.019 (0.033)	0.021 (0.030)	0.008 (0.034)
Risk aversion	-0.0001 (0.010)	0.005 (0.010)	0.003 (0.010)	-0.0003 (0.009)
Gender dummy	-0.016 (0.073)	-0.043 (0.075)	-0.039 (0.064)	-0.058 (0.081)
Loan dummy	-0.804**** (0.051)	-0.784**** (0.051)	-0.819**** (0.052)	-0.783**** (0.060)
Asset value	0.004**** (0.0002)	0.004**** (0.0002)	0.004**** (0.0002)	0.004**** (0.0002)
Personality traits (Big five)	ns	ns	ns	ns
Observations	n = 1,564	n = 1,564	n = 1,564	n = 1,564
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.617	0.614	0.616	0.612

Table C.3. Proportion of consistent trades as a function of Study 1 individual measures and Study 2 controls

	Proportion of trades consistent with the asset's true value			
Intercept	0.481****	0.458****	0.452****	0.416****
	(0.122)	(0.106)	(0.092)	(0.039)
Study 1 measures				
CRT	**0.039****	–	–	–
	(0.016)			
Financial literacy	–	**0.022****	–	–
		(0.011)		
Raven	–	–	0.010	–
			(0.012)	
Sampling biases	–	–	–	**-0.040******
				(0.011)
Proportion of trades consistent with prior information	0.270****	0.270****	0.266****	0.239***
	(0.046)	(0.047)	(0.048)	(0.047)
Self-monitoring	0.020	0.018	0.017	0.008
	(0.013)	(0.014)	(0.013)	(0.016)
Risk aversion	0.002	0.005	0.002	0.002
	(0.006)	(0.006)	(0.006)	(0.006)
Gender dummy	0.050	0.034	0.050	0.024
	(0.033)	(0.031)	(0.033)	(0.030)
Loan dummy	-0.006	-0.006	-0.001	0.016
	(0.022)	(0.022)	(0.020)	(0.019)
Asset value	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Market	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Personality traits (Big five)	ns	ns	ns	ns
Observations	n = 1,451	n = 1,451	n = 1,451	n = 1,451
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.111	0.105	0.103	0.103

Table C.4. Proportion of consistent trades as a function of Study 2 individual measures

	Proportion of trades consistent with the asset's true value			
Intercept	0.450****	0.405****	0.565****	0.452****
	(0.093)	(0.096)	(0.134)	(0.092)
Study 2 measures				
Eye gaze test	0.010	–	–	–
	(0.010)			
Overconfidence	–	**-0.028*** **	–	–
		(0.009)		
Wonderlic verbal test	–	–	**0.031** **	–
			(0.015)	
Adding skills	–	–	–	0.010
				(0.012)
Proportion of trades consistent with prior information	0.265****	0.264****	0.265****	0.266****
	(0.048)	(0.047)	(0.048)	(0.048)
Self-monitoring	0.015	0.017	0.018	0.017
	(0.014)	(0.014)	(0.013)	(0.013)
Risk aversion	0.005	0.000	0.003	0.005
	(0.005)	(0.006)	(0.006)	(0.005)
Gender dummy	0.019	0.017	0.030	0.025
	(0.031)	(0.030)	(0.031)	(0.031)
Loan dummy	0.007	-0.008	0.007	-0.001
	(0.020)	(0.021)	(0.019)	(0.020)
Asset value	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Market	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Personality traits (Big five)	ns	ns	ns	ns
Observations	n = 1,451	n = 1,451	n = 1,451	n = 1,451
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.103	0.109	0.104	0.103

Table C.5. Proportion of consistent trades as a function of the *intuition* and *sophistication factors*

	Proportion of trades consistent with the asset's true value		
Intercept	0.445****	0.483****	0.496****
	(0.102)	(0.122)	(0.126)
Factors			
Intuition factor	0.005	–	0.004
	(0.019)		(0.015)
Sophistication factor	–	**0.042******	**0.042******
		(0.010)	(0.010)
Proportion of trades consistent with prior information	0.242****	0.245****	0.244****
	(0.047)	(0.045)	(0.045)
Risk aversion	0.006	0.002	0.002
	(0.005)	(0.006)	(0.006)
Gender dummy	0.021	0.050*	0.050*
	(0.034)	(0.027)	(0.026)
Loan dummy	0.008	-0.015	-0.015
	(0.019)	(0.021)	(0.021)
Asset value	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)
Market	-0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)
Personality traits (Big five)	ns	ns	ns
Observations	n = 1,386	n = 1,386	n = 1,386
Prob > χ^2	0.000	0.000	0.000
R^2	0.090	0.101	0.101

Table C.6. Trader earnings as a function of *behavioral* and *sophistication factors* as well Study 2 individual measures

	Earnings ($)				
Intercept	1.062****	1.107****	1.020****	1.268****	1.122****
	(0.264)	(0.256)	(0.264)	(0.266)	(0.235)
Behavioral factor	**0.116******	**0.116******	**0.062****	**0.088******	**0.087******
	(0.030)	(0.042)	(0.027)	(0.024)	(0.023)
CRT	-0.032	–	–	–	–
	(0.033)				
Sampling biases	–	0.028	–	–	–
		(0.037)			
Overconfidence	–	–	-0.044	–	–
			(0.028)		
Wonderlic verbal test	–	–	–	0.042	–
				(0.030)	
Sophistication factor	–	–	–	–	0.018
					(0.033)
Risk aversion	-0.009	-0.009	-0.010	-0.010	-0.008
	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
Gender dummy	-0.047	-0.024	-0.049	-0.023	-0.022
	(0.082)	(0.069)	(0.080)	(0.074)	(0.064)
Loan dummy	-0.820****	-0.834****	-0.837****	-0.825****	-0.832****
	(0.066)	(0.063)	(0.066)	(0.065)	(0.061)
Asset value	0.004****	0.004****	0.004****	0.004****	0.004****
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Personality traits (Big five)	ns	ns	ns	ns	ns
Observations	n = 1,479	n = 1,479	n = 1,479	n = 1,479	n = 1,479
Prob > χ^2	0.000	0.000	0.000	0.000	0.000
R^2	0.619	0.618	0.619	0.618	0.618

Table C.7. Proportion of consistent trades as a function of the *quant*, *behavioral* and *theory of mind factors*

	Proportion of trades consistent with the asset's true value			
Intercept	0.448****	0.450****	0.502****	0.506****
	(0.105)	(0.121)	(0.105)	(0.114)
Factors				
Quant factor	**0.016***	–	–	0.0004
	(0.009)			(0.010)
Behavioral factor	–	**0.055******	–	**0.053******
		(0.010)		(0.011)
Theory of mind factor	–	–	**0.025****	**0.017***
			(0.011)	(0.009)
Proportion of trades consistent with prior information	0.267****	0.241****	0.265****	0.240****
	(0.048)	(0.044)	(0.048)	(0.045)
Risk aversion	0.006	-0.002	0.004	-0.003
	(0.005)	(0.006)	(0.006)	(0.006)
Gender dummy	0.029	0.041	0.022	0.039
	(0.029)	(0.026)	(0.031)	(0.026)
Loan dummy	-0.005	-0.010	0.004	-0.010
	(0.018)	(0.022)	(0.018)	(0.022)
Asset value	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Market	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Personality traits (Big five)	ns	ns	ns	ns
Observations	n = 1,451	n = 1,451	n = 1,451	n = 1,451
Prob > χ^2	0.000	0.000	0.000	0.000
R^2	0.102	0.102	0.110	0.110

Table C.8. Proportion of consistent trades as a function of the *behavioral* and *sophistication factors* as well as Study 2 individual measures

	Proportion of trades consistent with the asset's true value				
Intercept	0.443****	0.444****	0.452****	0.500****	0.453****
	(0.128)	(0.121)	(0.129)	(0.130)	(0.122)
Behavioral factor	**0.061**** **	**0.048**** **	**0.056**** **	**0.053**** **	**0.054**** **
	(0.020)	(0.016)	(0.016)	(0.011)	(0.011)
CRT	-0.009	–	–	–	–
	(0.026)				
Sampling biases	–	0.008	–	–	–
		(0.016)			
Overconfidence	–	–	0.001	–	–
			(0.016)		
Wonderlic verbal test	–	–	–	0.012	–
				(0.017)	
Sophistication factor	–	–	–	–	0.001
					(0.010)
Proportion of trades consistent with prior information	0.267****	0.240****	0.241****	0.241****	0.241****
	(0.048)	(0.048)	(0.044)	(0.045)	(0.045)
Risk aversion	0.006	-0.002	-0.002	-0.002	-0.002
	(0.005)	(0.007)	(0.006)	(0.006)	(0.007)
Gender dummy	0.036	0.039	0.041	0.043*	0.041
	(0.035)	(0.027)	(0.030)	(0.026)	(0.026)
Loan dummy	-0.009	-0.007	-0.010	-0.010	-0.010
	(0.024)	(0.025)	(0.021)	(0.021)	(0.021)
Asset value	-0.0002**	-0.0002**	-0.0002**	-0.0002**	-0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Market	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Personality traits (Big five)	ns	ns	ns	ns	ns
Observations	n = 1,386	n = 1,386	n = 1,386	n = 1,386	n = 1,386
Prob > χ^2	0.000	0.000	0.000	0.000	0.000
R^2	0.110	0.110	0.110	0.110	0.110

Online Appendix

Appendix O1 (instructions) and O2 (asset prices charts). (click here)