Federal Reserve Bank of New York
Staff Reports

Trading by Professional Traders: An Experiment

Marco Cipriani
Roberta De Filippis
Antonio Guarino
Ryan Kendall

Staff Report No. 939
August 2020

Trading by Professional Traders: An Experiment
Marco Cipriani, Roberta De Filippis, Antonio Guarino, and Ryan Kendall
Federal Reserve Bank of New York Staff Reports, no. 939
August 2020
JEL classification: C93, G11, G14

Abstract

We examine how professional traders behave in two financial market experiments; we contrast professional traders' behavior to that of undergraduate students, the typical experimental subject pool. In our first experiment, both sets of participants trade an asset over multiple periods after receiving private information about its value. Second, participants play the Guessing Game. Finally, they play a novel, individual-level version of the Guessing Game and we collect data on their cognitive abilities, risk preferences, and confidence levels. We find three differences between traders and students: Traders do not generate the price bubbles observed in previous studies with student subjects; traders aggregate private information better; and traders show higher levels of strategic sophistication in the Guessing Game. Rather than reflecting differences in cognitive abilities or other individual characteristics, these results point to the impact of traders' on-the-job learning and traders' beliefs about their peers' strategic sophistication.

Key words: bubbles, experiments, financial markets, information aggregation, professional traders, strategic sophistication

---

Cipriani: Federal Reserve Bank of New York (email: marco.cipriani@ny.frb.org). De Filippis, Guarino, Kendall: University College London (emails: roberta.filippis.10@ucl.ac.uk, a.guarino@ucl.ac.uk, ryan.kendall@ucl.ac.uk). The authors received research assistance from Antonella Buccione, Andrea Giacometti, and Seungmoon Park. This project was registered under the unique AEA RCT ID# AEARCTR-0003853.

To view the authors' disclosure statements, visit
https://www.newyorkfed.org/research/staff_reports/sr939.html.

1 Introduction

Experimental studies of financial markets have complemented empirical work using field data from real-world markets since at least the 1980s (e.g., Plott and Sunder, 1982; Friedman et al., 1984; Smith et al., 1988). An important question is to what extent the behavior of undergraduate students in the laboratory is representative of the choices made by professional traders.

In this paper, we address this issue by running a series of laboratory market experiments with a sample of professional traders and portfolio managers working in the city of London (UK).[1] As a control, we repeat the same experiment with the standard experimental subjects, namely, undergraduate students. Studying the behavior of professional traders can help us to make progress in understanding financial markets. There are several reasons to conjecture that traders may behave differently from students. They might have different levels of strategic sophistication or might entertain different beliefs about other subjects. Furthermore, they might be different in individual-level traits in terms of cognitive abilities and behavioral biases. Some of these differences may be due to selection, others to training.[2]

We focus on three classical strands of the experimental finance literature: the literature on "bubbles" in markets (started by Smith et al., 1988); the literature on private information aggregation (started by Plott and Sunder, 1988); and the literature on "guessing games" (also known as p-beauty contest games) (started by Nagel, 1995). Often, with undergraduate subjects, these experiments document substantial deviations from equilibrium predictions. First, in market experiments, subjects rarely trade at the equilibrium price; instead, they typically overprice the asset, a phenomenon often referred to as bubbles (see Palan, 2013, for a survey), which is only corrected at the end of the experiment (when the bubble bursts). Second, in experiments with private information, the information aggregation is sometime incomplete (see Sunder, 1992, for a survey and Corgnet et al., 2015, for a recent study). Third, in the celebrated Guessing Game, subjects choose numbers far from the Nash equilibrium, reflecting either limited depth of reasoning or low beliefs about others' depth of reasoning (see Agranov et al., 2012, and Agranov et al., 2015 for recent

[1] In the taxonomy of Harrison and List (2004), our study is an artefactual field experiment.

[2] For instance, in a series of papers, Haigh and List have compared students and professional futures and options traders in terms of myopic loss aversion (Haigh and List, 2005), the Allais paradox (List and Haigh, 2005) and investment under uncertainty and the options model (List and Haigh, 2010).

studies).

We run three experiments. Our experimental design, while borrowing from past studies, presents several novelties. In our first experiment, the "Trading Game," subjects trade an asset that earns dividends over multiple periods in a continuous double auction. Our experimental asset market innovates with respect to the standard setup by introducing private information about the asset's fundamental value. Our study essentially combines elements of the classic bubble experiments with elements of the experiments on information aggregation (started by Plott and Sunder, 1988). To the best of our knowledge, ours is the first study in which the problem of private information aggregation is studied in a multi-period set up, rather than in a market in which the asset lives for only one period.[3] Finally, there are gains from trade in our economy, as in Plott and Sunder (1982), Friedman et al. (1984) and Cason and Friedman (1997).

In our second experiment, the Guessing Game (Nagel, 1995), each subject chooses one number and the winner is the subject whose number is closest to a fraction (2/3 in our case) of the average. Although this is not a financial market in a strict sense, subjects earn money by outguessing the others. This is a common feature of financial markets where traders have to think about "where the market goes" to make a profit. As Keynes (1937/2018, p. 99) writes, *"[t]he actual, private object of the most skilled investment to-day is 'to beat the gun', as the Americans so well express it, to outwit the crowd,and to pass the bad, or depreciating, half-crown to the other fellow."*[4] A voluminous literature has shown that student subjects choose numbers far away from the Nash equilibrium. This may be due either to subjects' limited depth of reasoning or to beliefs about other subjects' level of reasoning. In order to disentangle these two explanations, we complement this celebrated experiment with a novel, individual-level version of the Guessing Game, in which strategic considerations do not matter (only subjects' understanding of the game does). In this "Individual Guessing Game," we ask each subject to choose 8 numbers and then we pay them if a randomly selected number among them is equal to 2/3 of the average. Comparing the results

[3]Studies on herd behavior in sequential trading like Cipriani and Guarino (2005; 2009) consider multiple periods; nevertheless, subjects receive information on the asset value which is revealed at the end of the sequence. That framework is, therefore, equivalent to a double auction with one period only (e.g., Plott and Sunder, 1982; 1988).

[4]The sentence suggests a connection between our Trading Game and Guessing Game, as someone who profitably rides a bubble also passes the overpriced asset ("the half-crown") to others.

of the Guessing Game to those of the Individual Guessing Game we are able to separate subjects' ability to solve the game from subjects' beliefs about the others' strategies.

Finally, after subjects complete these experiments, they execute a series of individual-level tasks measuring cognitive abilities (Raven IQ Test and Cognitive Reflection Test) as well as tasks to elicit risk aversion and overconfidence.

The results of our study are easy to summarize:

1. Professional traders do not produce the classic bubble pattern observed with students; instead, they trade at prices that track the fundamental value rather closely.

2. Professional traders aggregate private information better than students.

3. Professional traders choose numbers significantly closer to the Nash Equilibrium than students. This is driven, at least partially, by the fact that traders believe that their peers are strategically sophisticated, whereas students do not.

These remarkable differences are not due to traders' superior cognitive abilities (e.g., arising from selection into the banking and finance industry). In fact, we find that students perform as well as traders in the Cognitive Reflection Test and slightly better in the Raven's IQ Test. Moreover, traders are as confident as students (indeed, neither group is overconfident), hence overconfidence cannot explain our results. Finally, since traders show less risk aversion than students, risk preferences cannot explain why students engage in bubble behavior whereas traders do not. Taken together, these results imply that the differences between traders and students we observe in our financial market experiments may be due to on-the-job learning, including learning about the strategic sophistication of one's peers.

There are only a few experimental papers using professionals, and no experiments on financial market bubbles using exclusively professional traders. The seminal paper by Smith et al. (1988) include one session with "professional and business people."[5] King et al. (1993) include one session with "over-the-counter" traders. Bubbles are observed in both experiments. It is important to notice that in both papers there is only one session with professionals. Moreover, subjects in the

[5]This session, "Experiment 10," was interrupted for 10 minutes because of a technical issue.

professional session of Smith et al. (1988) are professionals in general, not professional traders, and the 6 trader subjects in King et al.'s (1993) professional session play together with experimenters (3 out of 9 subjects). Finally, a recent paper by Weitzel et al. (2020) uses financial professionals in a market experiment. They observe bubbles with both students and financial professionals, although with financial professionals bubbles are less pronounced. It is important to remark that the subjects in Weitzel et al. (2020) are also financial professionals in general, and are not necessarily directly involved in trading or investing as in our experiment. Financial professionals in general do not necessarily have trading experience and may trade very differently from professional traders.

In terms of information aggregation, there are two related papers using financial professionals. Alevy et al. (2007) run an experiment on informational cascades (based on the model of Bickchandani et al., 1992 - that is, not a financial market experiment). They find that financial professionals rely on their private information to a greater extent than student subjects do, and, as a result, fewer cascades form in the laboratory. Cipriani and Guarino (2009) use financial professionals to study herd behavior in a sequential trading financial market (based on Glosten and Milgrom, 1985). They find that information aggregation by financial professionals is similar to that of previous work with student subjects (Cipriani and Guarino, 2005).

Finally, we are not aware of Guessing Game experiments with financial professionals. Within the class of dominance solvable games (to which the Guessing Game belongs), experiments by Palacios-Huerta and Volij (2009) and Levitt et al. (2011) study the behavior of professional chess players in the Centipede Game and in the Race to 100 Game.

The rest of the paper is organized as follows. Section 2 describes the games used in the experiment along with equilibrium predictions. Section 3 provides details about our subject pool. Section 4 presents our main results pertaining to different behavior in the market games. Section 4.3 compares traders and students in terms of individual-level traits (e.g. cognitive abilities). Section 5 concludes and Section 6 contains the instructions and additional material referred to throughout the paper.

2 The Experiment

In our experiment, subjects participate in i) the Trading Game; ii) the Guessing Game; iii) the Individual Guessing Game; iv) individual-level tasks aimed to infer their cognitive abilities, risk preferences, and confidence.[6]

2.1 The Trading Game

We first provide a simple model of the Trading Game and then describe the procedures that we use to implement it in the laboratory.

2.1.1 Setup

We consider a market with a continuum of traders who trade a risky asset. Time is discrete and indexed by $t = 1, 2, .., 10$. The numeraire is cash. Traders are risk neutral and do not discount the future.

At each period t, the asset yields dividends d_t equal to 50 or 150 with equal probability. Dividends are independently distributed over time. The asset has no residual value after period 10.

The realization of the dividends is unknown to traders. In each period t, however, they receive noisy private information about the value of the current dividend d_t in the form of a symmetric binary signal with precision 0.75. In particular, each trader i receives a signal s_t^i distributed as $\Pr(s_t^i = 0|d_t = 50) = \Pr(s_t^i = 1|d_t = 150) = 0.75$. Conditional on the dividend value, signals are independently distributed. Note that the signal is only informative about the dividend in the current period, not about future dividends.

At the beginning of the period, half of the traders are selected to pay a fee of 50 for each asset held in their portfolio at the end of the period. Whether a trader has to pay a fee in a given period is independent of whether they had to pay it in previous periods.

In period $t = 1$, each trader has an endowment of 3 assets and $7,000$ of cash. After trading in

[6] Subjects also answered a series of questionnaires administered to infer non-cognitive abilities (Big-5, Locus of Control, Grit, Self-Monitoring). We do not describe them here since they are not relevant for this analysis.

period t and receiving the dividend, the portfolio of cash and assets carries over to period $t + 1$.

2.1.2 Equilibrium Prediction

In the Rational Expectations Equilibrium (REE) of the model, the price is equal to the asset's fundamental value (i.e., the expected value of current and future dividends). At each period t, private signals are perfectly aggregated by the price. Moreover, in each period, all traders who have to pay a fee for holding the asset at the end of the period sell it to those who do not pay the fee, thereby realizing all the gains from trades.

In particular, in period 1, demand and supply clear the market for a price of 950 when $d_1 = 50$ and for a price of 1050 when $d_1 = 150$ (see Figure 6.1 in Appendix): the equilibrium price is equal to the sum of the expected value of dividends in all subsequent nine periods ($100 * 9 = 900$) and the realized dividend in period 1 (50 or 150). The same logic applies to any subsequent period. Equilibrium prices are reported in Table 1. Note that the equilibrium price of the asset is weakly decreasing over time: between time t and time t+1, it decreases by 100 (when the dividend is either 150 or 50 in both periods t and t+1), or by 200 (when the dividend is 150 in period t and 50 in period t+1), or it remains constant (when the dividend is 50 in period t and 150 in period t+1).

Period (t)	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$	$t=7$	$t=8$	$t=9$	$t=10$
$d_t = 50$	950	850	750	650	550	450	350	250	150	50
$d_t = 150$	1050	950	850	750	650	550	450	350	250	150

Table 1: REE by period and dividend realization

2.1.3 Trading in the laboratory

In the experiment, we have 8 subjects acting as traders. At the beginning of period 1, each subject receives an endowment of 3 assets and $7,000$ Experimental Currency Units (ECU).

Subjects receive a private signal at the beginning of each period. Specifically, when the dividend is equal to 150, 6 subjects observe a "blue ball" and 2 subjects a "red ball;" when the dividend is equal to 50, 6 subjects observe a "red ball" and 2 subjects a "blue ball." This signal structure guarantees that, in each period, private signals jointly reveal the dividend even if the number of subjects is finite.[7] At the beginning of each period, subjects also learn whether they are fee-paying or non-fee-paying subjects for that period.

In each period, subjects trade for 150 seconds in a double-auction market. They post offers to sell or buy one asset. To post a sell offer, a subject enters the minimum price they are willing to accept and clicks on a sell button. The offer appears immediately on everyone's screen, in a column labeled "Sell Offers" (the identity of the subject making the offer is not revealed). Similarly, to post a buy offer, a subject enters the maximum price they are willing to pay and clicks on a buy button. A trade is automatically executed whenever the lowest sell offer (ask) is lower than the highest buy offer (bid).[8] Subjects can also buy or sell by clicking on a "BUY" or on a "SELL" button, which automatically accept the best outstanding sell or buy offer.

Each subject can post a maximum number of sell offers equal to the number of assets held in his portfolio; moreover, the sum of all the outstanding buy offers cannot exceed the cash held in his portfolio. At any time, a subject can withdraw outstanding buy or sell offers that have not already been executed by clicking a button labeled "Cancel." A subject's screen displays their current portfolio of cash and assets, the list of past trades (with their own executed trades highlighted), all the outstanding bid and ask prices, and the time left before the end of the period (see sections 6.13 and 6.14 for instructions and decision screen shots).

At the end of each period, subjects are informed about the dividend's realization and their end-of-period portfolio. Changes in the portfolio between 2 periods are due to the dividends earned, the fee payments, and the profits or losses from trading. The portfolio at the end of a period carries over to the next period. After one period ends, trading in the following period starts, according to the same rules, until all ten periods are completed.

---

[7] Other signal structures (for instance, i.i.d. signals with precision 0.75), even if informative, may not deliver the same result.

[8] In other words, if a subject wanted, for instance, to buy at the prevailing (i.e., the lowest) ask, they could simply enter a price equal to or greater than that price, and the trade would be immediately executed (at the outstanding price).

2.2 The Guessing Game

After the Trading Game, subjects play the standard Guessing Game (GG - Nagel, 1995). Each subject chooses one number in [0,100]. Subjects are asked to guess a number as close as possible to a "target" number, defined as 2/3 of the average of the 8 numbers entered by all the subjects (2/3 is a standard target, used in Nagel's original paper too). The subject whose number is closest to the target number earns £5; the others earn nothing. In the case of a tie, the amount is equally split. The decision screen shot is in Section 6.6.

The only Nash equilibrium of the game is all subjects choosing 0. The most common interpretative framework for behavior in the guessing game is level-k theory. A subject who chooses randomly in [0,100] is said to be a level-0 subject. A subject who believes that all other subjects are level-0 and best responds on the basis of this belief, is said to be a level-1 subject. Since a level-1 subject believes that other subjects choose, on average, 50, their best response is to choose 31.8.[9] If a subject believes that all others subjects are level-1 and best responds accordingly, they choose 21.2 and are said to be a level-2 subject. In general, a level-k subject is one who best responds to the belief that others are level-(k-1) subjects. When k tends to infinity, the best response converges to the Nash equilibrium action.

2.3 The Individual Guessing Game

After this standard GG, we ask subjects to take part in a modified, individual-level version of the GG. In this Individual Guessing Game (IGG), each subject chooses 8 numbers and the target number is 2/3 times the average of these 8 numbers. One of the subject's 8 chosen numbers is randomly selected for payment and, if it equals the target number, the subject earns £5. The decision screen shot is in Section 6.7.

As we explained above, according to level-k theory, subjects with higher levels of strategic reasoning choose lower numbers in the GG. However, for any choice in the GG between 1 and 50, one cannot disentangle a subject's level of reasoning from the subject's *belief* about other subjects' levels of reasoning. For instance, suppose a subject chooses 31.8 and is, therefore, classified as a

[9]This number slightly differs from 33.3 since the average takes the subject's own guess into account.

level-1 subject. This choice could be because the subject lacks the *ability* to reason past level 1; or it could be because, although the subject does have such an ability, they *believe* that other subjects are level-0 subjects.

Our novel IGG disentangles one own's ability and their belief about the ability of others. In particular, in the IGG, the only 8 numbers that guarantees earning £5 are all zeros. A subject who enters this answer has the ability to reason to an arbitrarily high level. Therefore, using the example above, if a subject chooses 31.8 in the GG and correctly answers the IGG, they show a high level of strategic thinking ability but a low-level belief about the strategic sophistication of their peers.

2.4 Individual-level tasks

We use individual-level tasks to collect data on cognitive abilities, risk preferences, and confidence.[10]

2.4.1 Risk Preferences - Bomb Risk Elicitation Task (BRET)

To measure risk preferences, we employ the "Bomb Risk Elicitation Task" (BRET, Crosetto and Filippin, 2013). In the BRET, subjects are shown a screen with 100 boxes and are asked to choose to "open a number of boxes" (between 1 and 99). Each box contains 20 pence; therefore, earnings increase linearly with the number of boxes chosen. Among the boxes, however, there is one that, if chosen, makes the subject lose all their earnings (in the original version by Crosetto and Filippin (2013) this box was described as a box containing a bomb; we used a more neutral description).[11]

Since all boxes appear the same, the decision about the number of boxes is a decision under risk. A risk-neutral subject collects 50 boxes. A risk-averse subject collects less than 50 boxes and a risk-loving one more than 50. The more boxes a subjects collects the higher their degree of risk-seeking preference. BRET is the only task described in Section 2.4 that is incentivized.

[10]We also collect data on other non-cognitive traits not discussed in this paper.

[11]For a comparison of different risk elicitation methods, see Crosetto and Filippin (2016).

2.4.2 Cognitive Ability - Raven's matrices (IQ)

Our first test of cognitive ability is the Raven's (1941) progressive matrices test (perhaps, the most well-known IQ test). We selected 18 of the most difficult Raven's matrices, available in Raven's Advanced Progressive Matrices (Raven, 1990). We did this to avoid a ceiling effect on the scores (which we did, as the highest score recorded was 15 out of 18). A subject's IQ score is the number of correct answers within a 10-minute period.

2.4.3 Cognitive Ability - Cognitive Reflection Test (CRT)

Our second test of cognitive ability is the Cognitive Reflection Test (Frederick, 2005). The test is designed to measure a subject's tendency to override an incorrect impulsive response and engage in further reflection that leads to the correct answer. For instance, one question is the following: "A bat and a ball cost £1.10 in total. The bat costs one pound more than the ball. How much does the ball cost?" An answer of 5 pence is correct while an answer of 10 pence suggests a lack of reflection.

We use the extended 7-question version of the CRT (Toplak, West, and Stanovich, 2014). A subject's CRT score is the number of correct answers within a 5-minute period.

2.4.4 Confidence

After the Raven test and after the CRT, we present subjects with an 8-row table, in which each row reads: "What is the percent chance that X of the 7 other participants had more correct answers than you did?" (for X = {0,1,...7}). In other words, we elicit the entire distribution of beliefs about the subject's ranking for each of these two cognitive ability tests. Given the subject's answers, for each test, we compute the expected number of outperforming subjects. The difference between the actual and expected numbers is our confidence measure for the subject. A positive number indicates that the subject is over-confident (because they expected to be outperformed by fewer subjects than was the case); a negative number indicates that the subject is under-confident; and a score of 0 means that the subject is not biased. As we said, for each subject, we have this measure for both the Raven and the CRT test. We average these measures to get the composite measure of confidence, which we use in Section 4.3.

3 Experimental Subjects

We ran the experiment in the Experimental Laboratory for Finance and Economics (ELFE) in the Centre for Finance at the Department of Economics at UCL.

We ran two treatments, the "Trader Treatment" and the "Student Treatment." The two treatments differ in the pool of subjects. In the Trader Treatment, the subjects are traders and portfolio managers working in London (UK). In the Student Treatment, subjects are UCL undergraduate students from all disciplines; we use the Student Treatment as our control treatment.

Each treatment consists of 7 sessions; in each session, 8 subjects perform the tasks described above. Overall, our sample includes 56 professional traders and 56 undergraduate students. Subjects had no previous experience with this experiment and participate in one session only. Each session lasted approximately 2 hours.

The subject pool for the Trader Treatment consists of: 30 traders, 4 proprietary traders, 4 sales-traders, 12 portfolio managers, and 6 belonging to other categories (e.g., trading strategists or sales with management of virtual portfolios).[12] Subjects work in a variety of financial markets, such as equity, equity derivatives, FX, fixed income, and commodities. Thirty-two subjects are employed by an investment bank, 12 by an investment fund and the others by other types of institutions (or chose not to report). Traders' age ranges between 22 and 48 years, with a mean of 32 years and a standard deviation of 6.17 years. Their average job tenure is 9.25 years, with a range between 1.5 and 21 years (standard deviation: 5.42 years). Three subjects have an MPhil or Ph.D., 30 a Master degree, 4 an MBA, 19 a Bachelor degree. Thirty subjects studied economics or finance, 8 mathematics or physics, 8 engineering or computer science, and the remaining have a degree in other disciplines or did not declare it.

In our Student treatment, we use UCL undergraduate students from all disciplines. We chose

[12]In our call for subjects, we wrote that "we need participants who are either traders or portfolio managers or who have had such roles in the past. You are also eligible if you do not have the formal title of trader or portfolio managers, but you perform activities that are closely related to that of a trader or portfolio manager (e.g., sales-trader or sales on the trading floor)". The call for subjects is in Section 6.12.

the the gender composition of the undergraduate subject pool to match that of traders: in the Trader treatment, 48 subjects are male (86%); in the Student treatment, 44 subjects are male (79%).

At the end of the experiment, subjects are paid based on their choices in the Trading Game, the GG, the IGG, and the BRET. In the Trading Game, we convert ECU into British Pounds according to different exchange rates for the different treatments: for traders, we exchange experimental ECUs into British Pounds at the exchange rate of £2.50 = 100 ECU whereas, for students, we exchange them at the exchange rate £0.25 = 100 ECU. In the Trading Game, traders earned an average of £234.93 (approximately equal to $306), with a standard deviation of £40.53, a minimum of £121, and a maximum of £401.33; students earned an average of £23.35 (approximately equal to $30.45), with a standard deviation of £6.06, a minimum of £7.84, and a maximum of £42.50.[13]

4 Results

We now describe the results of the experiment, starting with the Trading Game. We use professional traders in our experiment because of their expertise in trading and investing.[14] Our conjecture is that traders will trade at a price closer to the equilibrium predictions than will students (e.g., traders will show a lower level of mispricing). This is our alternative hypothesis which we test against the null hypothesis that there is no difference between the Student Treatment and the Trader Treatment. Throughout the paper, we use non-parametric tests run at the session level; that is, for each test, we use 7 observations for the Trader Treatment and 7 observations for the Student Treatment.

[13]Traders earned an average total of £240.34 (approximately equal to $313), with a standard deviation of £41.27, a minimum of £121, and a maximum of £406.40. Students earned an average total of £29.43 (approximately equal to $38), with a standard deviation of £8.65, a minimum of £10.94, and a maximum of £49.81.

[14]The behavior of professionals in laboratory experiments is surveyed by Fréchette (2015).

4.1 The Trading Game

4.1.1 Bubbles

Figure 1 shows the price path in the two treatments and contrasts it with the fundamental value of the asset, that is, the sum of current and future expected dividends (which, as we explained in Section 2, coincides with the REE).

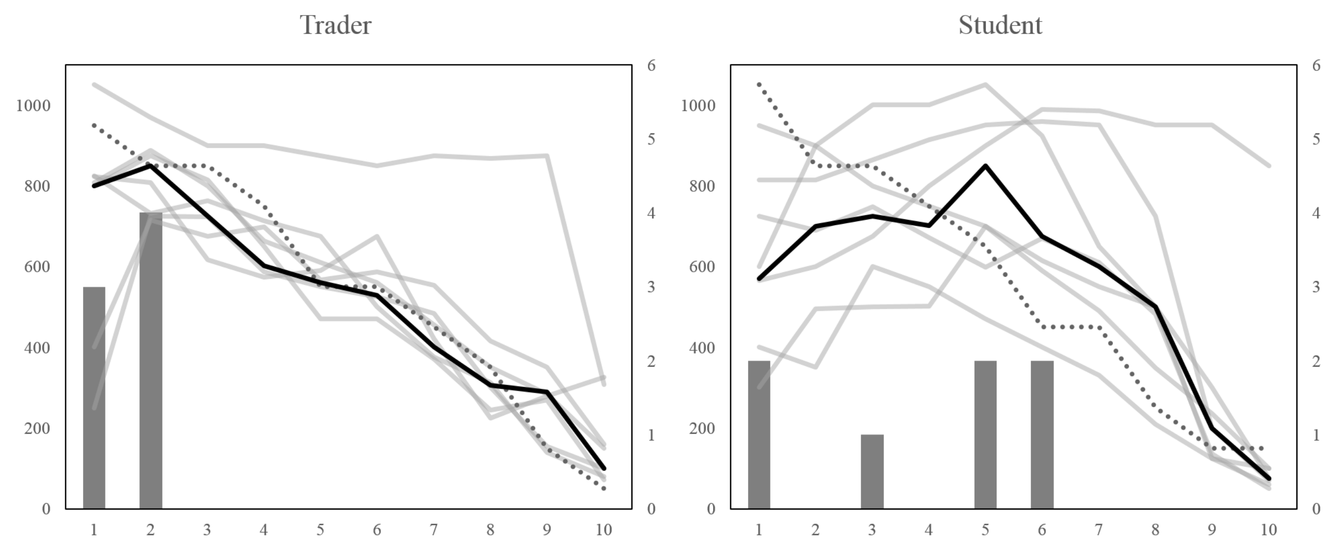


Figure 1: FV (dotted line), median trading prices by session (gray lines), median trading price by group (black line), and peak-price period (gray bars) for both treatments.

In each graph, the dotted line represents the declining fundamental value (FV). Recall from Table 1 that the FV is weakly decreasing over time and is not necessarily the same across sessions: the dotted line represents the median across the seven realized FVs. Each gray line is the median trading price of each period in a given session. Finally, the black line is the median trading price of each period across all sessions.

The difference between the two treatments is striking. In the Trader Treatment, the median price hovers around the fundamental value. In the Student treatment, in contrast, we observe the classic bubble behavior observed in previous experimental studies: at the beginning of the experiment, the price is lower than the fundamental value, then it increases above the fundamental value (the bubble), and only at the end of the experiment does it converge to the fundamental value.[15]

To quantify the mispricing, we use the Relative Absolute Deviation (RAD) measure commonly used in the experimental bubble literature. In each period of each session, we compute the absolute difference between that period's observed average price and the FV. The average of these absolute differences across all ten periods of a session divided by the average FV of the session is the session's RAD measure. Intuitively, the RAD captures the percentage difference, across all periods, between the average mean prices per period and the average FV. The 14 RAD measures (one for each session of each treatment) are in Table 2. The average RAD in the Trader Treatment is 22.5%, whereas the average RAD in the Student Treatment is almost twice as large, 39.2%. Testing the null hypothesis of no difference across groups against the alternative hypothesis that the Trader Treatment will has lower levels of mispricing, we reject the null at the p-value= 0.049 level (one-sided Mann-Whitney U-test).

	1	2	3	4	5	6	7	Avg.
Trader sessions	.241	.280	.206	.534	.060	.134	.124	.225
Student sessions	.457	.411	.343	.756	.393	.239	.146	.392
p-value								0.049

Table 2: RAD by session

Table 3 displays the average RAD across sessions, computed for each period and each treatment.[16]

Period (t)	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$	$t=7$	$t=8$	$t=9$	$t=10$
Traders	28%	14%	14%	12%	15%	21%	24%	30%	70%	112%
Students	38%	28%	17%	20%	27%	60%	62%	112%	100%	107%
p-value	0.104	0.036	0.451	0.191	0.130	0.013	0.019	0.006	0.690	0.841

Table 3: Relative absolute deviations (average) by period and group. We report p-values for one-sided Mann-Whitney U tests for differences between traders and students.

In periods 6, 7, and 8, traders had significantly lower RADs than students, with one-sided Mann-Whitney U tests p-values of 0.013, 0.019 and 0.006. These are the periods when the students create a bubble whereas the traders trade at price close to the FV.

[15]The figures look similar using means rather than medians (see Section 6.2).

[16]The RAD is a measure of percentage deviation. As shown in the table, the RAD increases over the periods, due to the fact that subjects' pricing errors remains roughly constant.

In Figure 1, for each period, we also report (in dark-gray bars) the number of sessions (on the vertical axis on the right) in which the median trading price reached the highest level in that period. For the Trader treatment, all seven sessions had their peak price in the first two periods, consistent with the fact that fundamental value is weakly declining;[17] in contrast, in the Student Treatment, in four sessions out of seven the peak is reached in periods 5 or 6, consistent with the fact in this treatment we observe bubbles. This measure is different across treatments with a p-value= 0.049 level (one-sided Mann-Whitney U-test).[18]

Figure 2 displays the median deviation between price and FV across periods and treatments. Specifically, for every trade, we compute the difference between its price and the actual FV of the asset in that period. Figure 2 reports the median of these differences. As the figure shows, the Student Treatment follows the classic bubble pattern (the price is below the FV in the early periods, above the FV in the middle periods, and ends close to the FV at the end of the experiment), whereas the Trader Treatment does not.

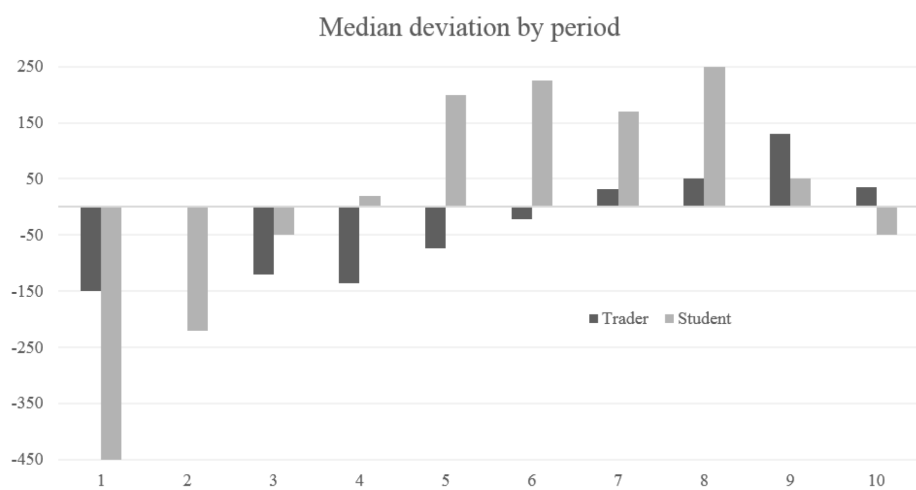


Figure 2: Difference between median price and FV by period

As a final observation, note that in the Student Treatment there is substantial heterogeneity across sessions. In contrast, in the Trader Treatment, behavior in six sessions is very homogeneous;

[17]In our study, if $d_1 = 50$ and $d_2 = 150$, then the theory predicts that the price in periods 1 and 2 should both be 950. An experimental market with these dividend realizations would align with the theory if it had a peak price at either period 1 or 2. For any other dividend realization, the theoretically predicted peak price is unique at period 1.

[18]The periods with the highest median price for the 7 sessions in the Trader Treatment are $\{1, 1, 1, 2, 2, 2, 2\}$. For the Student Treatment, the periods are $\{1, 1, 3, 5, 5, 6, 6\}$. The null of the test is that the set of periods has the same central tendency. is the same.

one session is an outlier, with traders unable to track the fundamental value. Importantly, not even this session shows the standard bubble pattern we observe in the Student Treatment and in previous experiments. Indeed, in the first round subjects trade at prices higher than the FV (whereas in typical bubble experiments the price is lower than the FV); moreover, the price remains higher than the FV even in the last round (whereas in typical bubble experiments the price crashes and becomes close to the FV).

Finally, in the REE, all assets are held by subjects who are not required to pay a fee thus realizing all gains from trade. In the experiment, since the fee is paid at the end of the period, subjects have the opportunity to gain from trade. If, instead, they do not trade or trade without accounting for the fee, then, on average, 50% of assets are held by non-fee-paying subjects. In the Student Treatment, only 56% of assets are held (at the end of the period) by non-fee-paying subjects. If we restrict the analysis to the last 3 periods, allocative efficiency is only marginally better, with 62% of assets held by non-fee-paying subjects. In the Trader Treatment, the frequencies are 57% for all periods and 62% for the last 3 periods. Essentially, even in the Trader Treatment, allocative efficiency seems to have been sacrificed to other aspects of the market environment. At least within the period of time they were allowed to trade, both students and traders did not manage to realize all the gains from trade.

4.1.2 Information Aggregation

As we explained in Section 2, at the beginning of each period, subjects receive information about the current period's dividend. The question we want to answer is whether (or to what extent) this information is used in the experiment.

Recall that in the REE, private information is fully aggregated. The change of price between t and t+1 depends on two components: the fact that between time t and time t-1 time-t dividend is paid out (and therefore should not be reflected in time t+1 price); and the fact that the t+1 price reflects the t+1-dividend's realization. In particular, as shown in Table 1, moving from period t to period $t+1$, three situations can occur: $d_t = 150$ and $d_{t+1} = 50$, in which case the REE price drops by 200; $d_t = 150$ and $d_{t+1} = 150$ or $d_t = 50$ and $d_{t+1} = 50$, in which case the REE price drops by 100; and $d_t = 50$ and $d_{t+1} = 150$, in which case the REE price remains constant. These three cases are labeled HL, {HH, LL}, and LH in Figure 3 below.

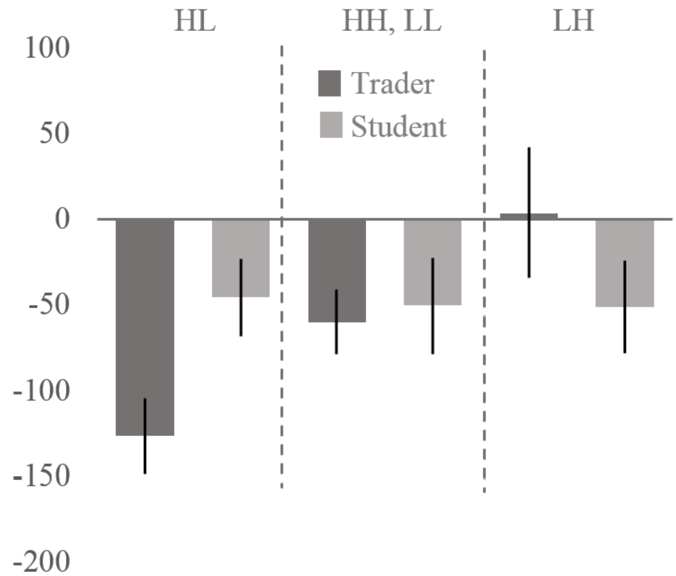


Figure 3: Average price change by state. In states HL, {HH, LL}, and LH the REE predicts a price change of -200, -100, and 0, respectively. Standard errors are reported for each bar.

Figure 3 shows the price change from one period to the next, averaged for the three cases described above, in the two treatments. In the Trader Treatment the average price changes are -127, -60, and 4 versus a theoretical counterpart of -200, -100 and 0. The Spearman's rank correlation coefficient between REE and observed price changes across all rounds and sessions is 0.39, which is significantly different from zero (p-value = 0.001).[19] This is quite different from the Student Treatment, in which the average price changes are -46, -51 and -51, respectively. The Spearman's rank correlation coefficient for this treatment is 0.01, which is not significantly different from zero (p-value = 0.914).[20] Whereas in the Trader Treatment price changes are correlated with the REE prices changes, in the Student Treatment they are not: that is, traders aggregate private information better than students do. This can also be seen in Table 4, where we report the distance between REE and observed price changes for each session and for both treatments. Specifically,

[19]We conduct a t-test testing the null hypothesis that there is zero correlation between the price changes observed and the theoretical predictions. The alternative hypothesis is that this correlation is greater than zero.

[20]The Pearson's correlation coefficients for the Trader and Student treatments are 0.34 and -0.01, respectively. T-tests for the null hypothesis of zero correlation against the alternative hypotheses of correlation different from zero are significant at the 0.007 and 0.908 level, respectively.

in each period from 2 to 10, we compute the absolute difference between the average price change and the REE one. We then average this error across all 9 periods in that session. This provides a session-level measure for how well the actual price change matched the theoretically predicted price change. In the Trader Treatment, the average distance is 81.1, whereas in the Student Treatment it is 121.8. The difference is statistically significant (one-sided Mann-Whitney U test p-value = 0.011).

Session	1	2	3	4	5	6	7	Avg.
Trader Treatment	92.4	91.9	81.1	109.0	41.0	89.3	63.3	81.1
Student Treatment	158.4	135.0	112.8	151.5	115.0	108.4	71.4	121.8
p-value								0.011

Table 4: Average absolute difference between price change and predicted FV change by session.

Note that (the lack of) information aggregation is a separate issue from (the absence of) bubbles. In particular, students might have engaged in bubble behavior and still made use of their signals: in this case, the change in price from one period to the next would still be related to dividends' realizations. Similarly, traders could have failed to use private information, while still keeping the price around the fundamental value: this would have entailed, for instance, reducing the price by 100 (the unconditional expected change) each period.

4.2 Guessing Games

We now turn to the analysis of subject's behavior in the Guessing Games. We start with the standard GG and then we move to the individual decision making version of it (IGG).

4.2.1 Guessing Game

Figure 4 shows the distribution functions of subjects' choices in the GG by treatment. As one can see in Figure 4, there is a much larger mass of subjects choosing numbers lower than 15 in the Trader Treatment than in the Student Treatment.

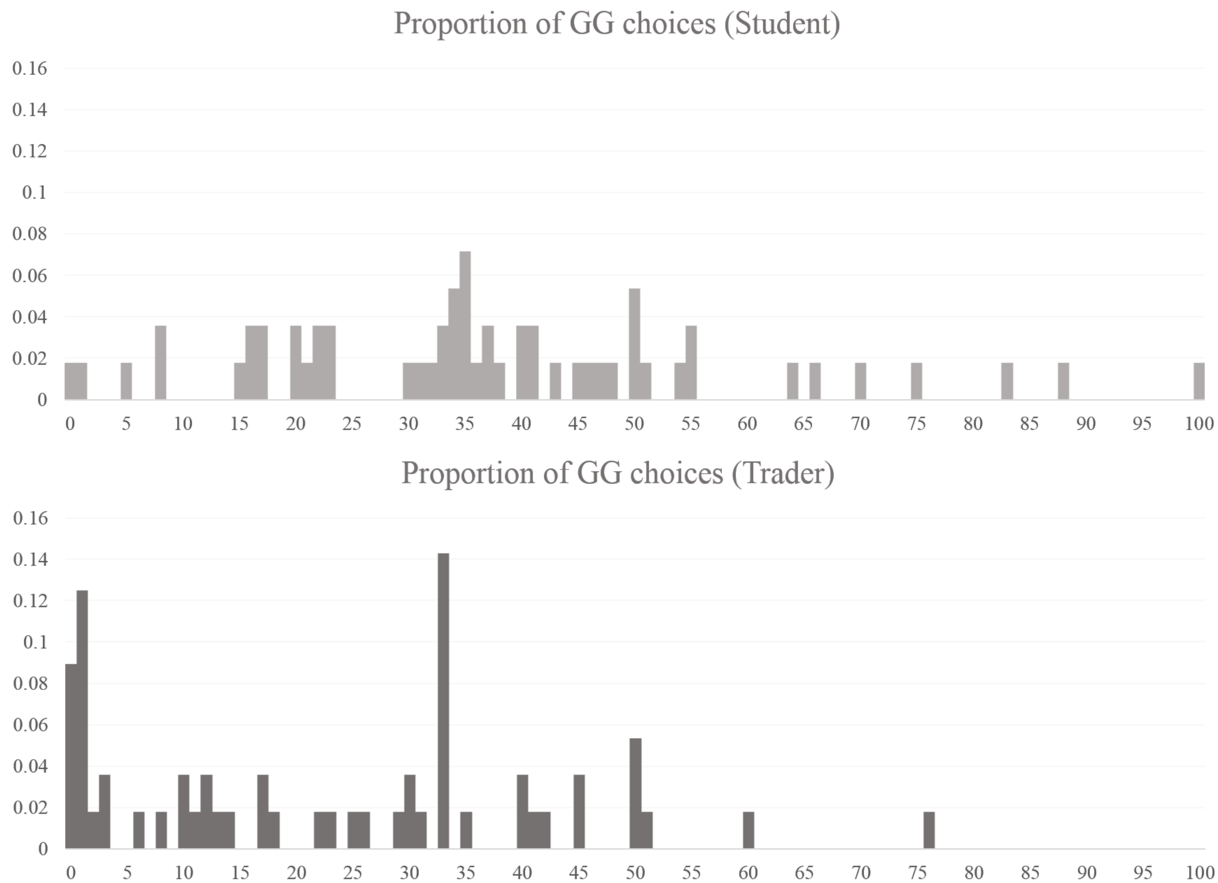


Figure 4: Choices in the GG separated by treatment

Table 5 shows the average and median choices of subjects by session and treatment.

Session	1	2	3	4	5	6	7	Avg.
Trader Treatment (Avg.)	20.6	25.5	26.0	28.7	13.5	16.1	28.0	22.6
Student Treatment (Avg.)	33.5	34.9	36.5	37.4	44.1	37.5	39.2	37.6
Trader Treatment (Median)	7	32	20.5	29.5	11	7.5	25	18.9
Student Treatment (Median)	34.5	35	34.5	44	39	36.5	34.5	36.9
p-value								< 0.001

Table 5: Average (top) and median (bottom) GG choice by treatment and session.

The students' mean and median choices are 37.6 and 35, similar to those reported in the literature for student subjects (see Table 6). In contrast, traders chose much lower numbers with a mean and median choice of 22.6 and 22.5. A one-sided Mann-Whitney U test on the null that the median choice is the same across treatments has a p-value < 0.001. Indeed, as Table 5 shows, the mean choices in all 7 Trader sessions were lower than the mean choice in all 7 Student sessions (the same applies to medians).[21]

	Mean choice	Median choice	Std. deviation	Group size
Trader Treatment	22.6	22.5	18.8	8
Student Treatment	37.6	35	21	8
Nagel (1995)	37.2	33	20	14-16
Ho et al. (1998)	38.9	NA	24.7	7
Agranov et al. (2012)	35.1	33	21	8
Agranov et al. (2015)	36.4	33	20.2	8

Table 6: Comparison of our treatments with previous studies

Following Nagel (1995)[22] and Agranov et al. (2015), we classify a subject as level-0 if their choice belongs to [45,50], as level-1 if it belongs to [30,37], as level-2 if it belongs to [20,25], as level-3 if it belongs to [13,16], and as level-∞ if it belongs to [0,1]. Subjects whose choices do not fall into these intervals are not classified.

Choice (level)	Trader Treatment	Student Treatment
[45, 50] (level-0)	8.9%	12.5%
[30, 37] (level-1)	21.4%	26.8%
[20, 25] (level-2)	5.4%	12.5%
[13, 16] (level-3)	3.6%	5.4%
[0, 1] (level-∞)	21.4%	3.6%
Proportion classified	60.7%	60.7%

Table 7: Classification across treatments

Table 7 shows subjects' classification in our treatments. We are able to classify 61% of subjects (in both treatment). For low levels of sophistication (from zero to three), the proportion of students is higher than that of traders; instead, there is a large proportion of level-∞ traders (21.4%), but very few level-∞ students.

In conclusion, traders choose on average lower numbers and they are 6 times more likely to be classified as fully rational. According to level-k theory, this result suggests that the traders have a higher level of strategic sophistication than students.

[21]Unlike the Trading Game, it could be argued that choices in the GG are independent also within a session. Assuming independence, a Mann-Whitney U test on student-level data also shows a p-value < 0.001.

[22]Nagel (1995) classifies sophistication levels as choices that reside in "neighborhood intervals". A subject is classified as level-k if his choice is within the interval of $50\left(\frac{2}{3}\right)^{k}$. The boundaries of each interval are calculated by rounding to the nearest integers of $50\left(\frac{2}{3}\right)^{(k-\frac{1}{4})}$ and $50\left(\frac{2}{3}\right)^{(k+\frac{1}{4})}$. Level-0 is the exception, as it is truncated at 50.

4.2.2 Individual Guessing Game

According to level-k theory, a subject choosing approximately 30 in the GG is classified as level-1, a low level of sophistication. It is unclear, however, whether the choice of 30 is due to lack of ability (i.e., the subject is not sophisticated in their understanding of the game) or to the belief that all other subjects choose randomly (i.e, they are level-0). With the IGG, we study subjects' behavior in a task in which beliefs about others are irrelevant. A subject who chooses numbers different from 0 in the IGG does not understand the game (regardless of their beliefs about others). More importantly, a subject who chooses all 0s in the IGG but who chooses a higher number in the original GG must have done so based on their belief about the rationality of others.

In our experiment, the proportion of subjects able to solve the IGG is virtually identical in the two samples: 11 traders and 10 students correctly answered all zeros (the two proportions are not statistically different, with a p-value = 0.87).[23] It is interesting to see how this subset of subjects acted in the original GG (Figure 5). The mean and median choice (11.73 and 3, respectively) of traders is significantly lower than the mean and median choice (26.8 and 31.5, respectively) of students (one-sided Mann-Whitney U test p-value = 0.019). By correctly answering the IGG, the 11 traders and 10 students showed that they had the intellectual ability to solve the game. The difference in their GG choices must come from different beliefs about their competitors' choices. The Trader subgroup guessed significantly lower numbers than the Student subgroup. This indicates that traders believed (correctly) that their opponents had a higher strategic level of reasoning compared to the beliefs of students.

[23]Five students and six traders did not enter their numbers in time.

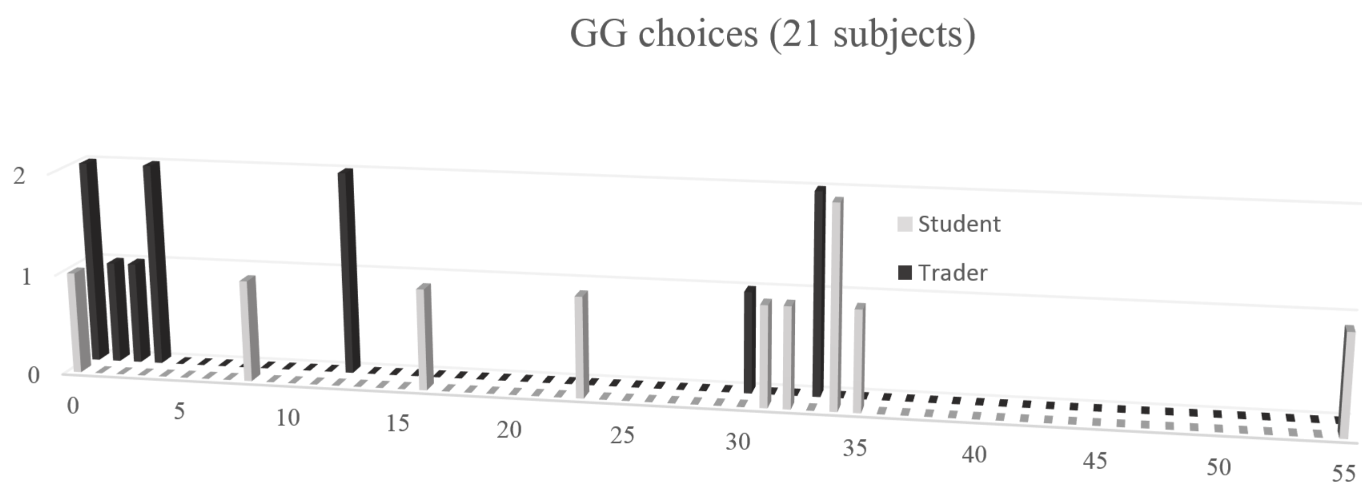


Figure 5: Choices in the GG of the subjects who correctly answered the IGG.

The different choices in the original GG between traders and students is not only driven by differences in these subgroups (i.e., students and traders who solve the IGG). When analyzing the choices in the GG of subjects who did not correctly solve the IGG, we still observe that the mean choice of traders (25.3) is significantly lower than the mean choice of students (39.9), with a one-sided Mann-Whitney U test p-value < 0.001.

Interestingly, 5 of the 10 subjects in this student subgroup were classified as level-1 in the GG. Put differently, 33% of the student subjects who are classified as level-1 in the GG actually show an arbitrarily high level of rationality (because they correctly solved the IGG). This suggests that the IGG could be used to further refine levels in future research using guessing games. In addition, one may wonder whether the 21 subjects who correctly solved the IGG were also closer to the target in the GG. The answer is no. The 46 students who did not correctly solve the IGG were, on average, 15.8 away from the target while the 10 students who correctly solved it were 15.1 away. For the traders, the 45 who did not correctly solve the IGG were, on average, 15.5 away from the target while the other 11 traders who correctly solved it were 13.4 away. In both cases, the distances from the target are not statistically different (one-sided Mann-Whitney U test p-value $= 0.460$ for students and 0.359 for traders).

4.3 Results of individual-level tests

So far we have shown that professional traders, compared to students, trade closer to the fundamental value, aggregate private information better, and choose numbers closer to the Nash Equilibrium in the GG. In this section, we want to understand whether these differences can be explained in terms of cognitive abilities, risk preferences, or confidence measures. One could conjecture that traders' better performance in our experiments is related to higher cognitive abilities (Corgnet et al., 2015; Corgnet et al., 2018), different levels of risk aversion (Porter and Smith, 1995; Caginalp et al., 2000; Porter and Smith, 2008), or lower levels of overconfidence (Scheinkman and Xiong, 2003; Michailova and Schmidt, 2016). Table 8 summarizes the results.

Test	Trader Treatment	Student Treatment	p-value
IQ	8.70	9.82	0.008
CRT	5.14	4.59	0.054
BRET	48.46	41.16	0.001
Confidence	0.24	0.09	0.352

Table 8: Averages of individual-level tests by group. P-values refer to one-sided Mann-Whitney U tests conducted at the individual level.

Neither group is dominant in terms of cognitive abilities. Traders are only marginally better than the students in the CRT (p-value = 0.054) and worse in IQ (p-value = 0.008).[24] Moreover, recall that in the IGG, another task in which cognitive abilities matter, the two populations performed in a similar way, with 20% of traders and 18% of students giving the correct answer.

In terms of risk preferences, there is an important difference: traders are less risk averse than students.[25] The average number of boxes chosen by traders is 48 whereas the average number chosen by students is 41; the difference is statistically significant (one-sided Mann Whitney U test p-value = 0.001). Traders are twice as likely to be exactly risk neutral (45% of traders and 23% of students; one-sided Fisher's Exact test, p-value = 0.014).[26] It is hard to explain the different

[24]The CRT and IQ results are highly correlated. The correlation is 0.45 for the entire population, 0.63 for the traders, and 0.40 for the students. All correlations are significantly different from zero (p-value < 0.0001 for both the entire sample and the traders; p-value= 0.002 for the students).

[25]This result aligns with previous research on professional traders (e.g., Grinblatt et al., 2012). In addition, we have three outliers in our data: two traders collected only 1 box while one student collected 99 boxes which presumably indicates mistakes. These 3 outliers are against this result; removing them only strengthens it: the average number of boxes collected is 50 for traders and 40 for students.

[26]In a recent paper, Angrisani et al. (2020) show that risk preferences using BRET are stable over time and in spite of a negative shock represented by the COVID-19 pandemic.

behavior in the Trading Game or in the GG in terms of different levels of risk aversion. Risk averse agents value the asset less than in the risk-neutral theoretical benchmark. As a result, in the Trading Game, lower traders' risk aversion should generate more, not less overpricing than in the students' treatment. Moreover, risk preferences do not play a role in the GG, since each agent simply maximizes the probability of winning the prize.

Finally, one may conjecture that overconfidence could lead to bubbles, with subjects believing that they can outplay the others and sell off their assets before the bubble bursts. However, our confidence measures for the Trader Treatment and the Student Treatment are not statistically different from each other (p-value=0.352); if anything, in our sample, traders' overconfidence is higher than students'. In addition, it is important to remark that our confidence measures are not statistically different from 0 in either treatment (with a p-value equal to 0.340 in the Trader Treatment and 0.679 in the Student Treatment).

In summary, the differences we observe in terms of asset pricing, information aggregation, and Guessing Game choices are not related to cognitive abilities, risk preferences, or confidence. Differences between traders and students may be due to skills that professional traders learn on the job or to their beliefs about the strategies of other traders (indeed, the evidence from the GG and the IGG shows that traders believe that their peers use higher strategic thinking than do students).

5 Conclusion

We have studied how professional traders behave in laboratory experiments (a trading game and a guessing game) which are informative of financial market behavior. We have found that, compared to undergraduate students, choices made by professional traders more closely align with equilibrium predictions. In a trading experiment with traders subjects, prices are closer to the fundamental value and bubbles do not occur. Moreover, private information is aggregated to a greater extent. In the guessing game, traders exhibit a higher ability to reason strategically. The differences between traders and students are not due to differences in cognitive abilities, risk aversion, or confidence.

References

[1] Agranov, Marina, Elizabeth Potamites, Andrew Schotter, and Chloe Tergiman. (2012). "Beliefs and endogenous cognitive levels: An experimental study." *Games and Economic Behavior,* 75(2): 449-463.

[2] Agranov, Marina, Andrew Caplin, and Chloe Tergiman. (2015). "Naive play and the process of choice in guessing games." *Journal of the Economic Science Association,* 1(2): 146-157.

[3] Alevy, Jonathan E., Michael S. Haigh, and John A. List. (2007). "Information cascades: Evidence from a field experiment with financial market professionals." *The Journal of Finance*, 62(1): 151-180.

[4] Angrisani, Marco, Marco Cipriani, Antonio Guarino, Ryan Kendall, and Julen Ortiz de Zarate Pina. (2020). "Risk Preferences at the Time of COVID-19: An Experiment with Professional Traders and Students." Staff Reports 927, Federal Reserve Bank of New York.

[5] Caginalp, Gunduz, David Porter, and Vernon L. Smith. (2000). "Overreaction, momentum, liquidity, and price bubbles in laboratory and field asset markets." *Journal of Psychology and Financial Markets*, 1: 24-48.

[6] Cason, Timothy N., and Daniel Friedman. (1997). "Price formation in single call markets." *Econometrica: Journal of the Econometric Society*, 311-345.

[7] Cipriani, Marco, and Antonio Guarino. (2005). "Herd behavior in a laboratory financial market." *American Economic Review,* 95.5: 1427-1443.

[8] Cipriani, Marco, and Antonio Guarino. (2009). "Herd behavior in financial markets: an experiment with financial market professionals." *Journal of the European Economic Association*, 7(1): 206-233.

[9] Corgnet, Brice, Mark DeSantis, and David Porter. (2015). "Revisiting information aggregation in asset markets: Reflective learning & market efficiency." *Working paper.*

[10] Corgnet, Brice, Mark DeSantis, and David Porter. (2018). "What makes a good trader? On the role of intuition and reflection on trader performance." *The Journal of Finance*, 73(3): 1113-1137.

[11] Crosetto, Paolo, and Antonio Filippin. (2013). "The "bomb" risk elicitation task." *Journal of Risk and Uncertainty*, 47(1): 31-65.

[12] Crosetto, Paolo, and Antonio Filippin. (2016). "A theoretical and experimental appraisal of four risk elicitation methods." *Experimental Economics*, 19(3): 613-641.

[13] Fréchette, Guillaume R. (2015). "Laboratory Experiments: Professionals versus Students." In *Handbook of Experimental Economic Methodology*, Oxford University Press. 360-390.

[14] Frederick, Shane. (2005). "Cognitive reflection and decision making." *Journal of Economic perspectives*, 19(4): 25-42.

[15] Friedman, Daniel, Glenn W. Harrison, and Jon W. Salmon. (1984). "The informational efficiency of experimental asset markets." *Journal of political Economy*, 92(3): 349-408.

[16] Grinblatt, Mark, Matti Keloharju, and Juhani T. Linnainmaa. (2012). "IQ, trading behavior, and performance." *Journal of Financial Economics*, 104(2): 339-362.

[17] Haigh, Michael S., and John A. List. (2005). "Do professional traders exhibit myopic loss aversion? An experimental analysis." *The Journal of Finance*, 60(1): 523-534.

[18] Harrison, Glenn W., and John A. List. (2004). "Field experiments." *Journal of Economic literature*, 42(4): 1009-1055.

[19] Keynes, John Maynard. (2018). "The general theory of employment, interest, and money." Springer. (Original work published 1937).

[20] King, Ronald R., Vernon L. Smith, Arlington W. Williams, and Mark Van Boening. (1993). "The robustness of bubbles and crashes in experimental stock markets." *Nonlinear dynamics and evolutionary economics*, 183-200.

[21] Levitt, Steven D., John A. List, and Sally E. Sadoff. (2011). "Checkmate: Exploring backward induction among chess players." *American Economic Review,* 101(2): 975-90.

[22] List, John A., and Michael S. Haigh. (2005). "A simple test of expected utility theory using professional traders." *Proceedings of the National Academy of Sciences*, 102(3): 945-948.

[23] List, John A., and Michael S. Haigh. (2010). "Investment under uncertainty: Testing the options model with professional traders." *The Review of Economics and Statistics*, 92(4): 974-984.

[24] Michailova, Julija, and Ulrich Schmidt. (2016). "Overconfidence and bubbles in experimental asset markets." *Journal of Behavioral Finance*, 17(3): 280-292.

[25] Nagel, Rosemarie. (1995). "Unraveling in guessing games: An experimental study." *The American Economic Review,* 85(5): 1313-1326.

[26] Palacios-Huerta, Ignacio, and Oscar Volij. (2009). "Field centipedes." *American Economic Review,* 99(4): 1619-35.

[27] Palan, Stefan. (2013). "A review of bubbles and crashes in experimental asset markets." *Journal of Economic Surveys*, 27(3): 570-588.

[28] Plott, Charles R., and Shynam Sunder. (1982). "Efficiency of Experimental Security Markets with Insider Information: An Application of Rational-Expectations Models." *Journal of Political Economy,* 56: 663-698.

[29] Plott, Charles R., and Shynam Sunder. (1988). "Rational Expectations and the Aggregation of Diverse Information in Laboratory Security Markets." *Econometrica,* 56: 1085-1118.

[30] Porter, David P., and Vernon L. Smith. (1995). "Futures contracting and dividend uncertainty in experimental asset markets." *Journal of Business*, 509-541.

[31] Porter, David P., and Vernon L. Smith. (2008). "Price bubbles." *Handbook of Experimental Economics Results,* 1: 247-255.

[32] Raven, John C. (1941). "Standardization of progressive matrices." 1938. *British Journal of Medical Psychology*, 19(1): 137-150.

[33] Raven, John C. (1990). "Advanced progressive matrices sets 1 and 2." prepared by J. C. Raven. Oxford: Oxford Psychologists Press.

[34] Scheinkman, Jose A., and Wei Xiong. (2003). "Overconfidence and speculative bubbles." *Journal of Political Economy*, 111(6): 1183-1220.

[35] Smith, Vernon L., Gerry L. Suchanek, and Arlington W. Williams. (1988). "Bubbles, crashes, and endogenous expectations in experimental spot asset markets." *Econometrica: Journal of the Econometric Society*, 1119-1151.

[36] Sunder, Shyam. (1992). "Experimental asset markets: A survey." Carnegie Mellon University.

[37] Toplak, Maggie E., Richard F. West, and Keith E. Stanovich. (2014). "Assessing miserly information processing: An expansion of the Cognitive Reflection Test." *Thinking & Reasoning*, 20(2): 147-168.

[38] Weitzel, Utz, Christoph Huber, Jürgen Huber, Michael Kirchler, Florian Lindner, and Julia Rose. (2020). "Bubbles and Financial Professionals." *The Review of Financial Studies*, 33(6): 2659-2696.

6 Appendices

6.1 REE figure

Supply and demand in period 1 when $d_1 = 150$ using our experimental parameters.

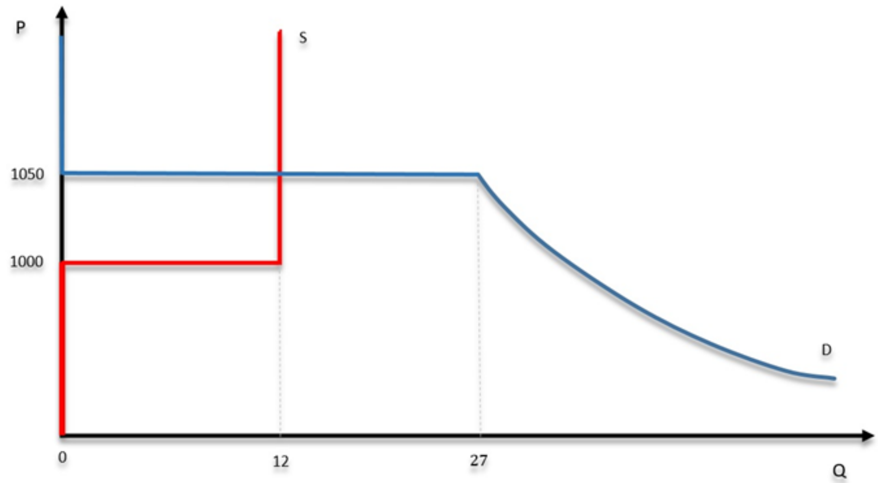


Figure 6: REE when $d_1 = 150$

6.2 Market figures using mean prices

Analysis of Figure 1 using means (instead of medians).

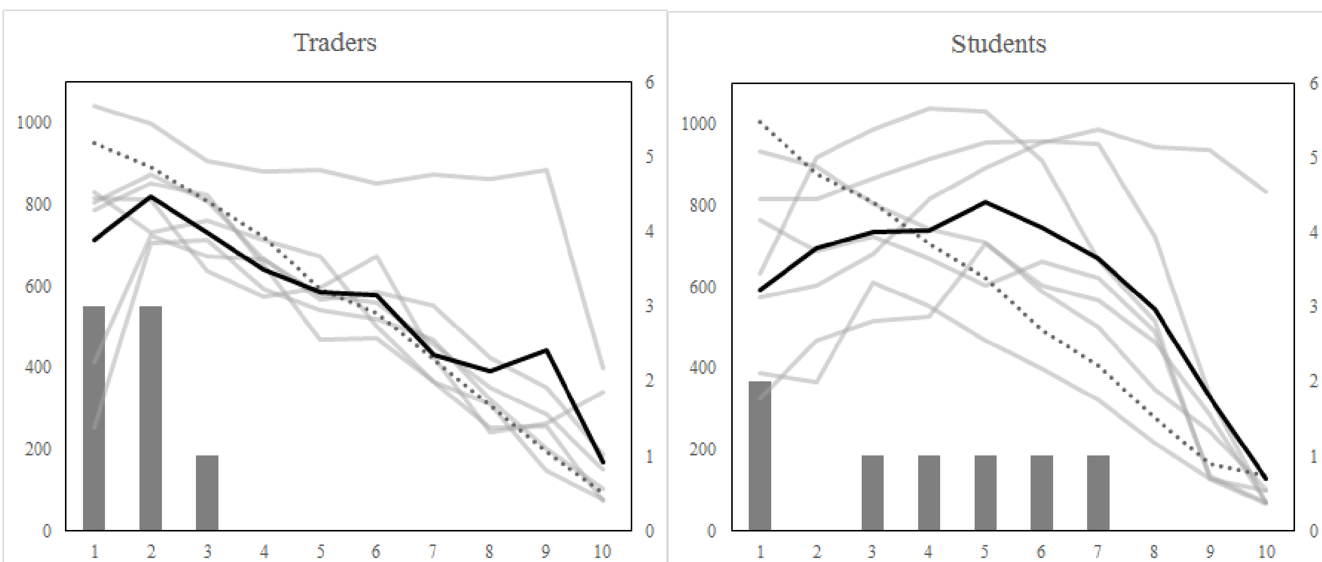


Figure 7: FV (dotted line), mean trading prices by session (gray lines), mean trading price by group (black line), and peak-price period (gray bars) for both treatments.

6.3 Pdfs and cdfs of GG without correct IGG

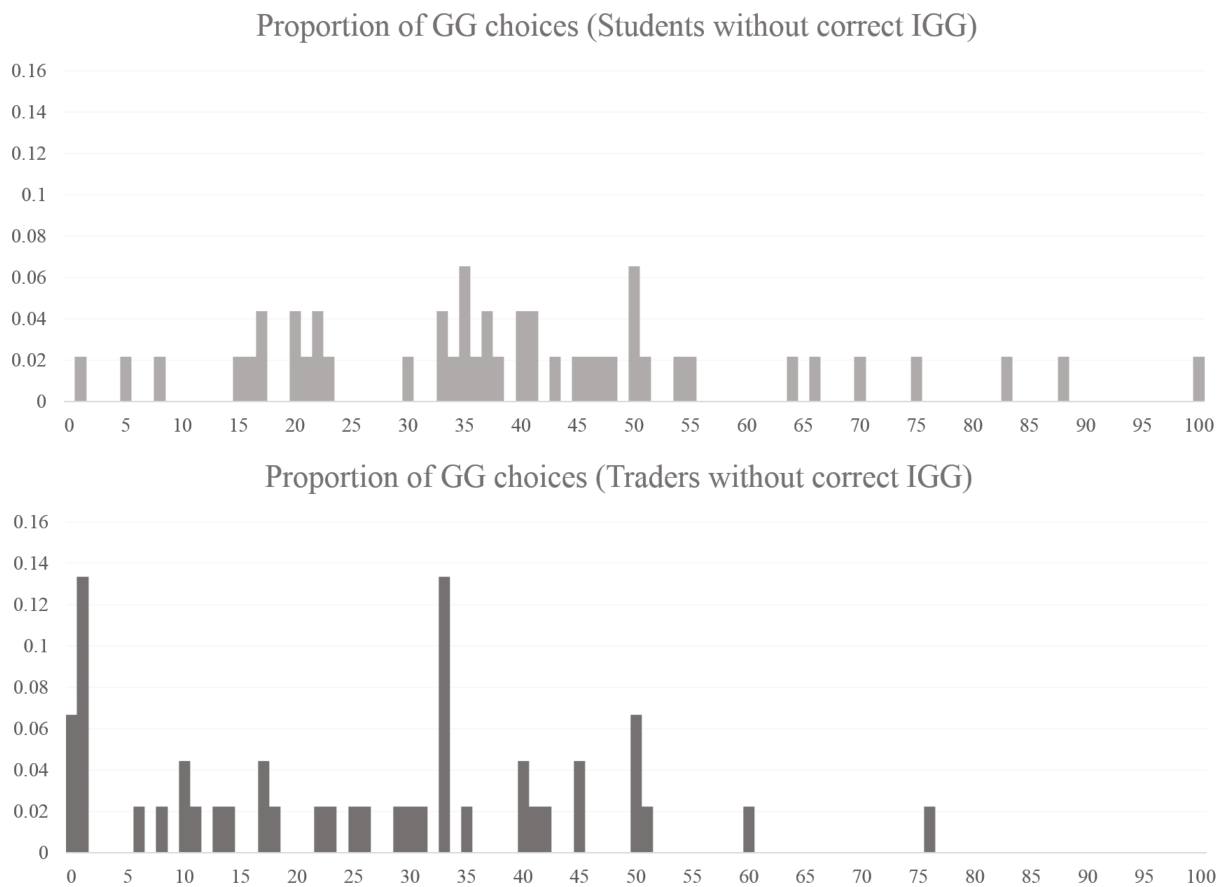


Figure 8: Pdf of choices in the GG separated by treatment (without correct IGG)

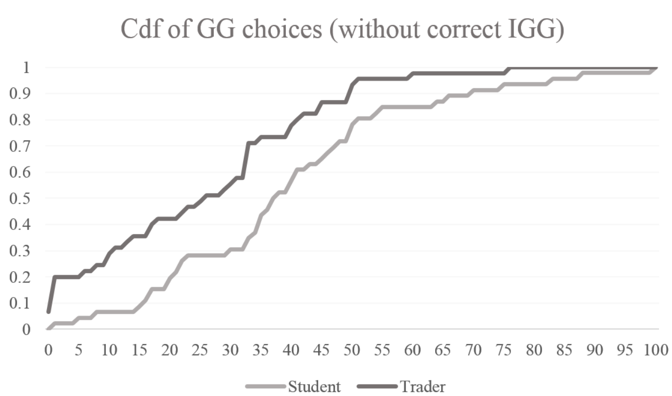


Figure 9: Cdf of choices in the GG for each treatment (without correct IGG)

6.4 Pdfs and cdfs of individual level tests

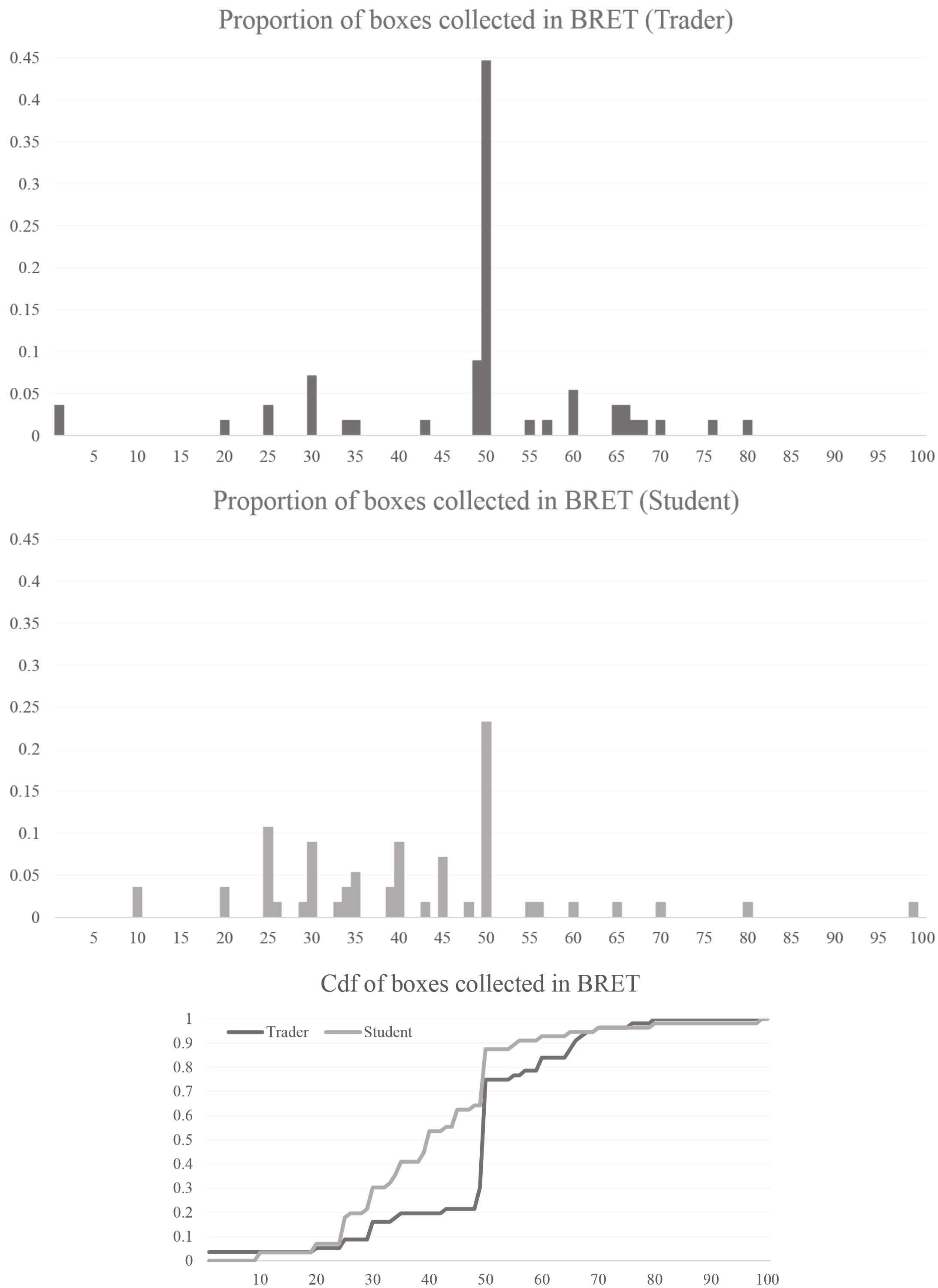


Figure 10: Number of boxes collected in BRET (risk preference) separated by treatment

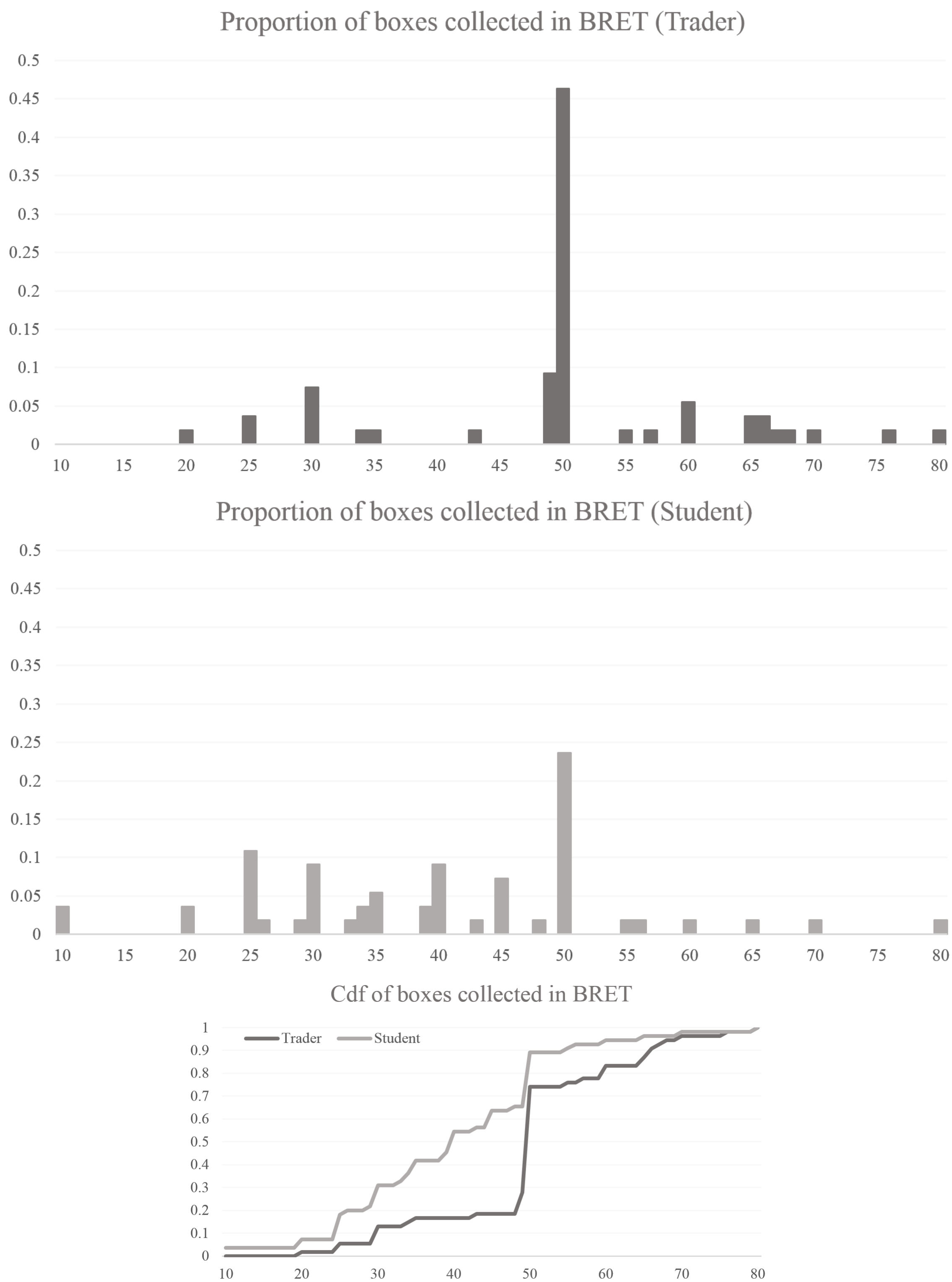


Figure 11: Number of boxes collected in BRET (risk preference) separated by treatment - Excluding 3 outliers

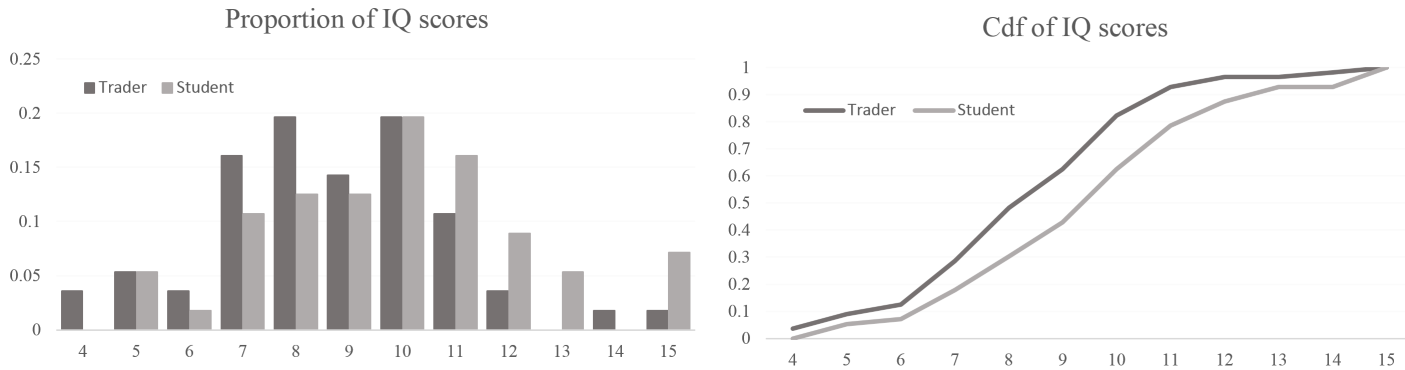


Figure 12: IQ scores separated by treatment

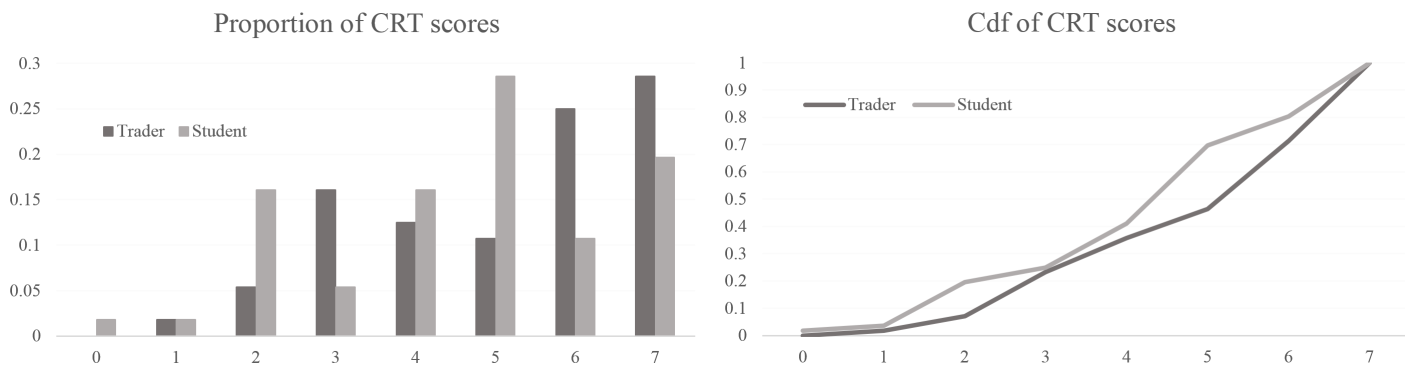


Figure 13: CRT separated by treatment

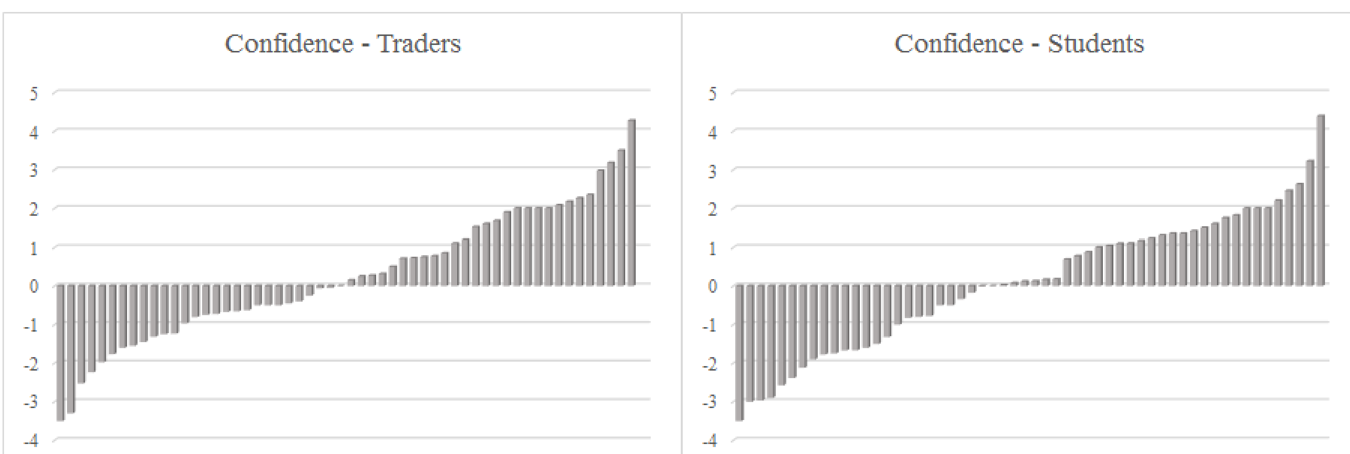
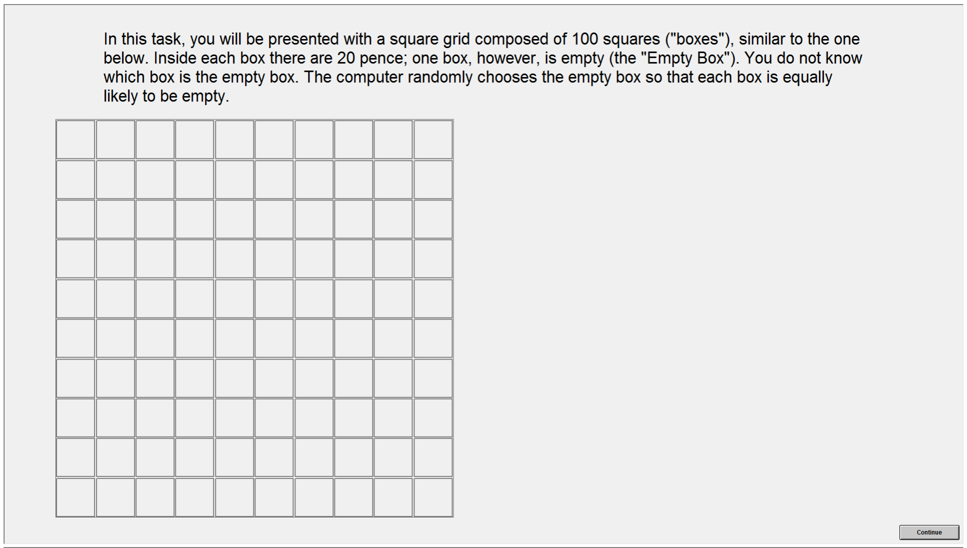
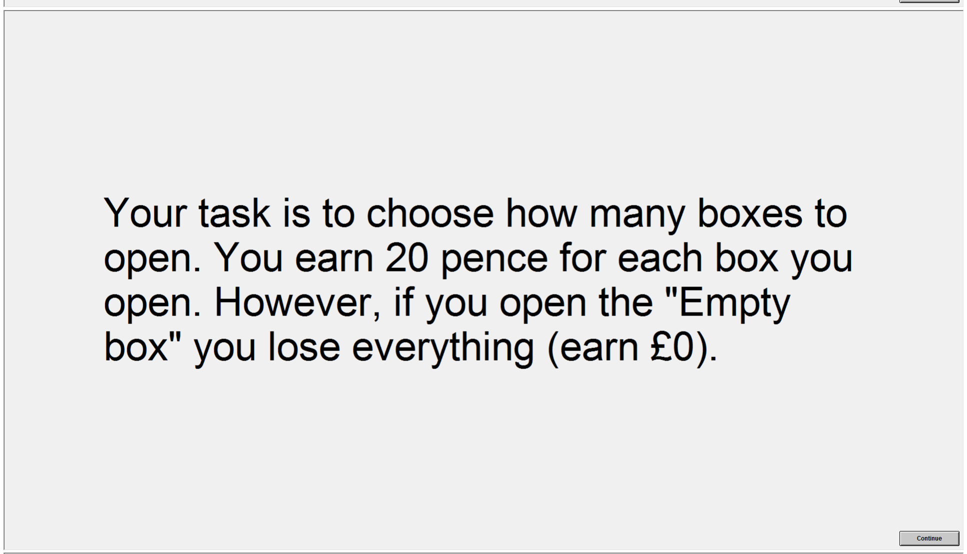
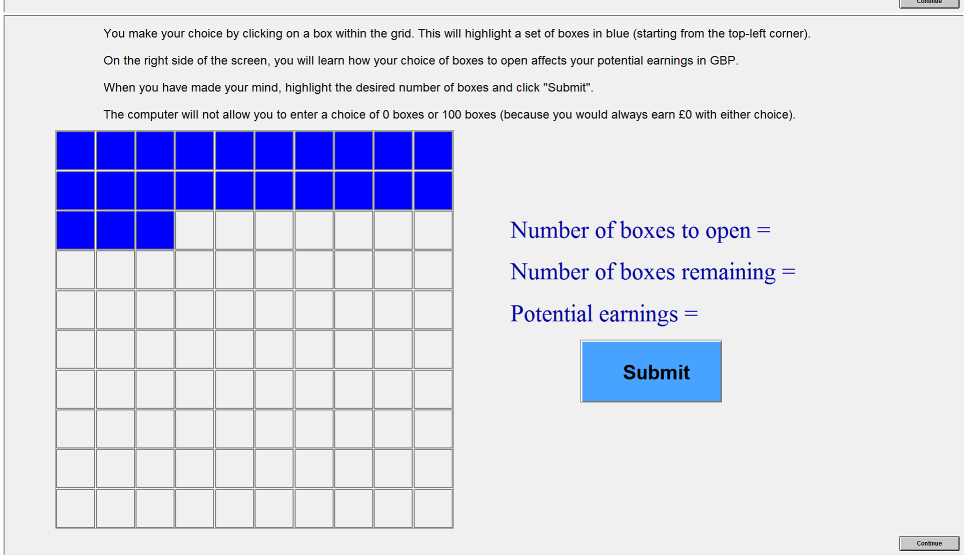


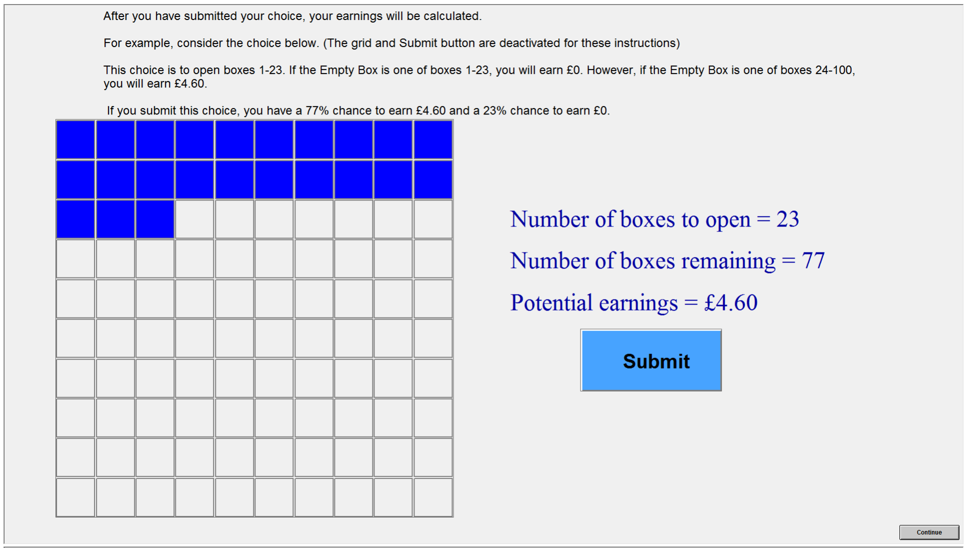
Figure 14: Confidence scores separated by treatment

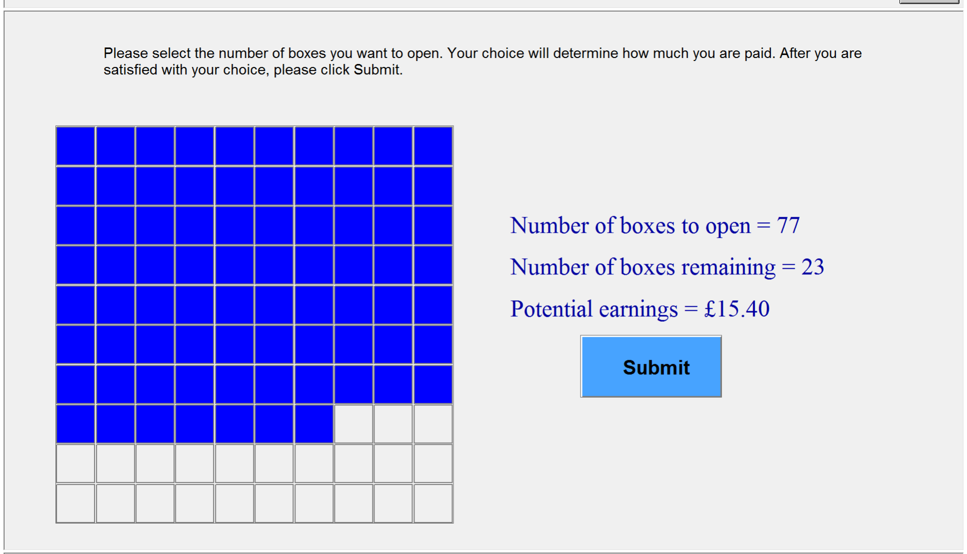
6.5 Bomb Risk Elicitation Task (BRET)

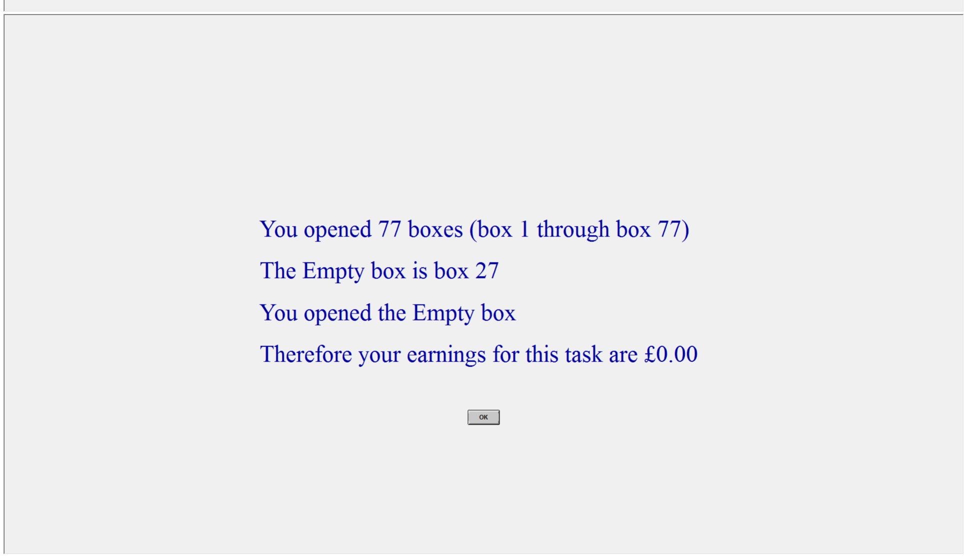




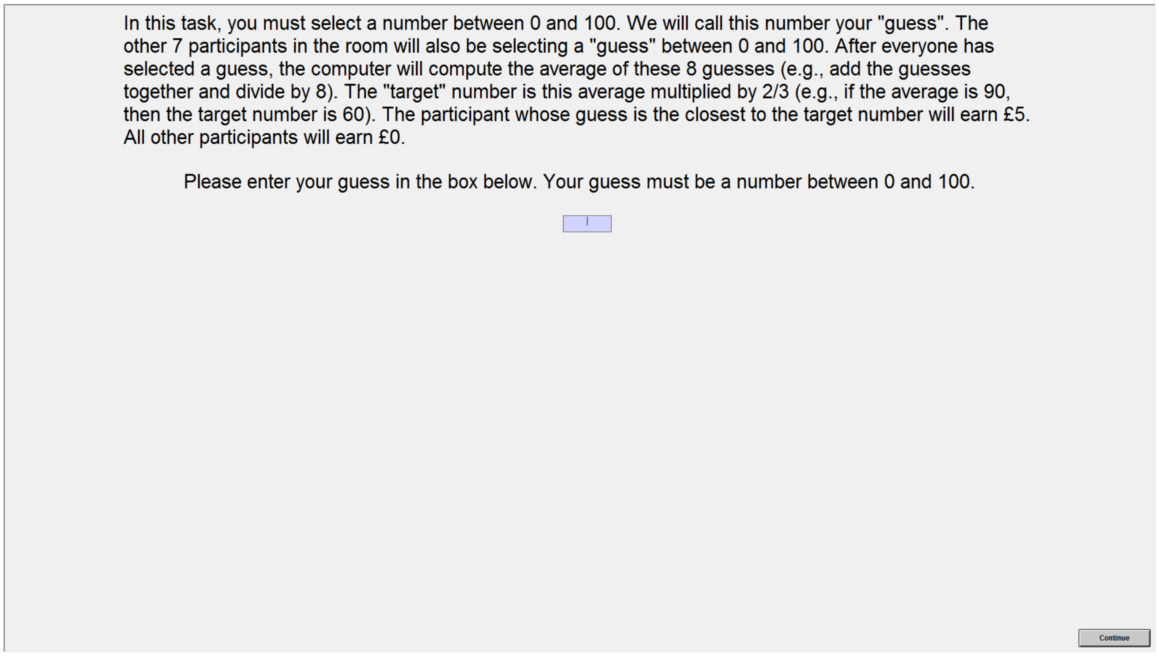



After you have submitted your choice, your earnings will be calculated.
For example, consider the choice below. (The grid and Submit button are deactivated for these instructions)
This choice is to open boxes 1-23. If the Empty Box is one of boxes 1-23, you will earn £0. However, if the Empty Box is one of boxes 24-100, you will earn £4.60.
If you submit this choice, you have a 77% chance to earn £4.60 and a 23% chance to earn £0.
Number of boxes to open = 23
Number of boxes remaining = 77
Potential earnings = £4.60
Submit

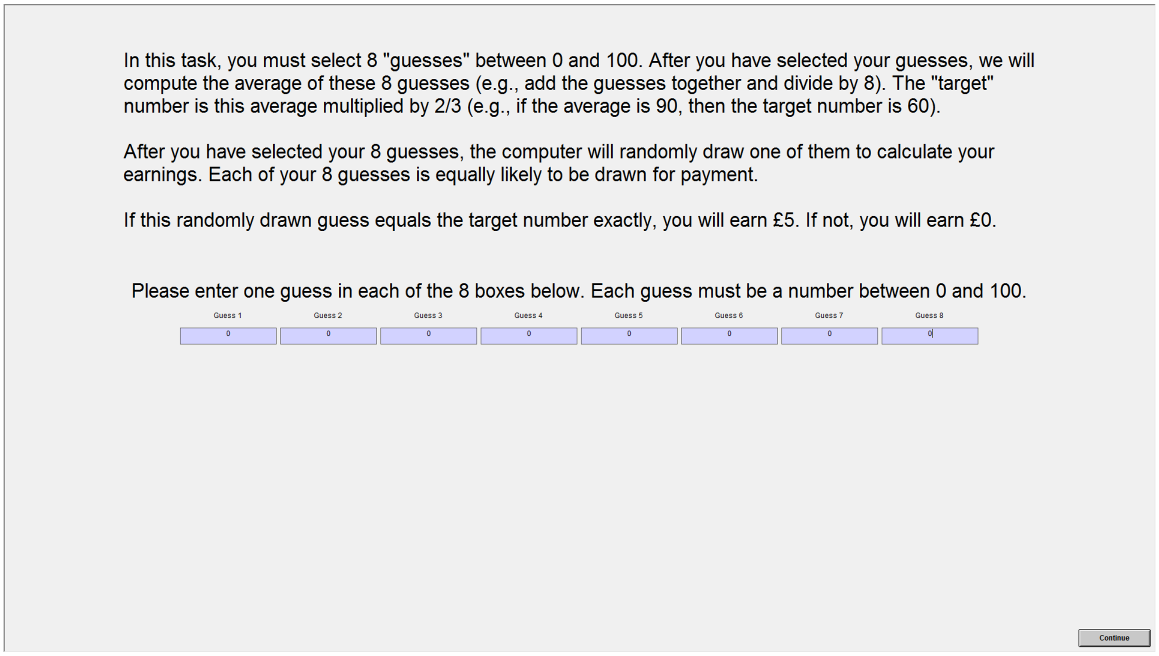

Please select the number of boxes you want to open. Your choice will determine how much you are paid. After you are satisfied with your choice, please click Submit.
Number of boxes to open = 77
Number of boxes remaining = 23
Potential earnings = £15.40
Submit


You opened 77 boxes (box 1 through box 77)
The Empty box is box 27
You opened the Empty box
Therefore your earnings for this task are £0.00

6.6 Guessing Game Screen Shot



6.7 Individual Guessing Game Screen Shot



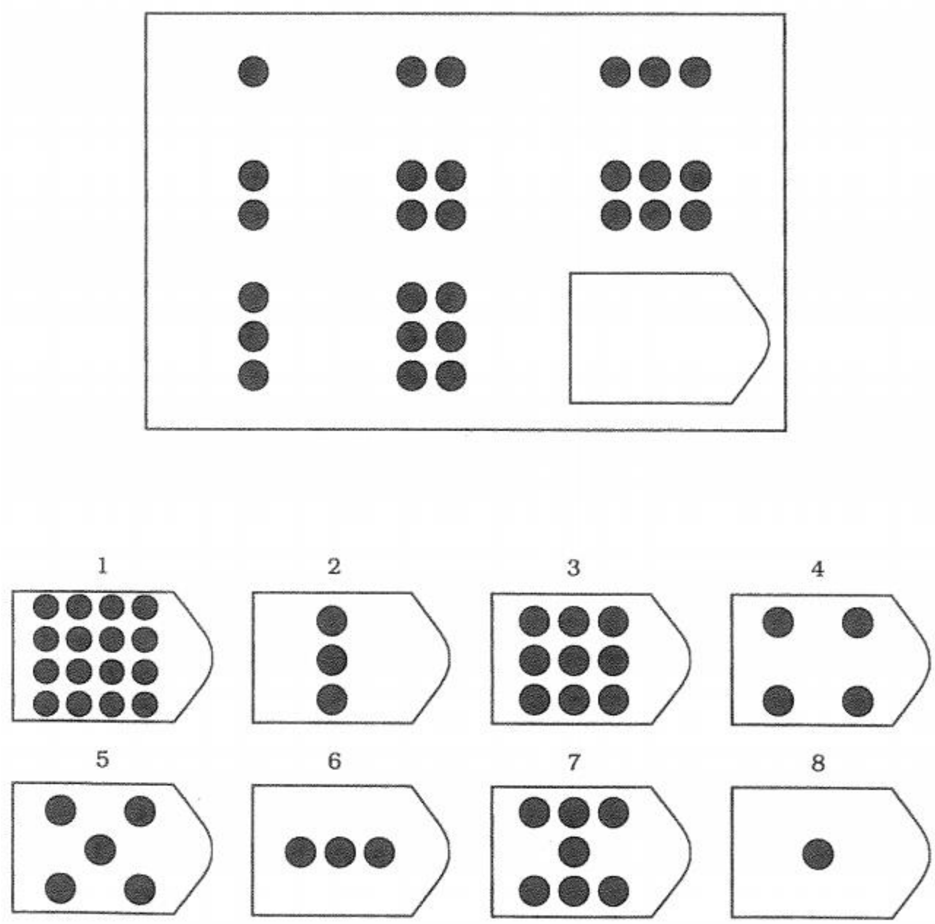
6.8 Raven's Test Instructions

Station #__________________

Please do not turn the page until you are instructed to do so

This is a test of observation and clear thinking. It will involve answering problems such as C3 below. The top part of problem C3 shows a pattern with a piece cut out of it. Look at the pattern, think what piece is needed to complete the pattern correctly both along the rows and down the columns must be like. Then find the right piece out of the 8 pieces shown below. Number 3 is the right piece, isn't it? To submit that your answer is Number 3, you will need to circle the Number 3 piece.

C3



On every page of this booklet there is a pattern with a piece missing. You have to choose which piece is the right one to complete the pattern. When you think you have found the right piece, circle it on your booklet and move onto the next page. If you make a mistake, or want to change your answer, put a cross through the incorrect answer, and circle your correct answer. You will have 10 minutes to complete all 18 pages of this booklet. When everyone is ready, the experimenter will let you begin and start the timer. The experimenter will announce when 10 minutes is finished and, at that time, you will need to stop working and put down your pen.

6.9 CRT

(1) 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

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? ____ minutes

(3) A bat and a ball cost £1.10 in total. The bat costs one pound more than the ball. How much does the ball cost? ____ pence

(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

(5) Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class? ______ students

(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? _____

(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, which statement is true? (Circle the correct answer)

a. Simon has broken even in the stock market

b. Simon is ahead of where he began

c. Simon has lost money

6.10 Confidence Instructions

Station #________________ **R / C**

There are 7 other participants in the room who took the exact same task you just completed. Please answer the following 8 questions.

(The sum of all 8 numbers should equal 100)

What is the percent chance that…

0 of the 7 other participants had more correct answers than you did?	_______%
1 of the 7 other participants had more correct answers than you did?	_______%
2 of the 7 other participants had more correct answers than you did?	_______%
3 of the 7 other participants had more correct answers than you did?	_______%
4 of the 7 other participants had more correct answers than you did?	_______%
5 of the 7 other participants had more correct answers than you did?	_______%
6 of the 7 other participants had more correct answers than you did?	_______%
7 of the 7 other participants had more correct answers than you did?	_______%

6.11 Occupation questions (Traders only)

Occupational Characteristics
In which type of financial institution do you work?

- ❒ Investment bank (please specify if capital market or investment banking division)____________
- ❒ Investment fund
- ❒ Private equity fund
- ❒ Other (e.g., commercial bank) ____

In your current (or past) employment do (did) you operate directly on financial markets (as a trader or portfolio manager)? _______________________

- ❒ Yes
- ❒ No

What percentage of your typical working day do you spend on the following tasks?

A) Trading on financial markets __________________________________
B) Following the financial markets in real time? _______________________________________

Which of these categories best describe your job:

- ❒ Trader
- ❒ Proprietary trader
- ❒ Portfolio manager
- ❒ Sales-trader
- ❒ Sales with management of virtual portfolios (e.g. alpha capture)
- ❒ Sales without
- ❒ Macro-analyst
- ❒ Equity/credit analyst
- ❒ Other: ____

Briefly describe your job.

____

____

____

For how many years have you worked in the financial industry? ___________________________

Demographic Characteristics
What is your age? (You can leave this blank if you prefer not to say) ______________________

Your education: (E.g., BSc Econ and MSc Engineering) _________________________________
What is your gender?

- ❒ Male
- ❒ Female
- ❒ Prefer not to say

6.12 Call for subjects (Traders only)

UCL **CENTRE FOR FINANCE**

www.centreforfinance.org

Laboratory Experiments on Financial Decision Making at UCL
Call for Participants

The Centre for Finance at UCL is running a series of laboratory experiments on financial decision making. We will run **two** experiments with financial professionals.

For **Experiment 1**, we need participants who are either **traders or portfolio managers** or who have had such roles in the past. You are also eligible if you do not have the formal title of trader or portfolio managers, but you perform activities that are closely related to that of a trader or portfolio manager (e.g., sales-trader or sales on the trading floor).

For **Experiment 2**, we need participants from a **broader class of financial professionals**. You are eligible to participate in Experiment 2 if you are currently working in the core business of a financial institution, e.g., as a trader, analyst, sales person, economist, investment banker.

In the study, participants will first read some instructions and then will be asked to make some decisions (e.g., trade a fictitious asset according to a simple trading protocol). **We anticipate that participants will earn an average of £200**; the precise amount that a participant will make depends on his or her own decisions, the decisions of others and some randomness.

To help us in this study, participants must come to our laboratory **only once**, for two hours, on a pre-specified date and time. Our laboratory is located in Bloomsbury, close to Euston Station (Drayton House, 30 Gordon Street, WC1H 0AX – Map).

At this stage we only need a general expression of interest. Please email the Centre for Finance's laboratory at elfe.experiments@ucl.ac.uk as soon as possible indicating your interest in participating. In the subject line of your email, please type either "CFF Experiment 1" or "CFF Experiment 2". In the body of your email, please type your current job position and your name. No other text is required. If you are not sure about your eligibility for Experiment 1, indicate "CFF Experiment". We will contact you with details in the next few days.

The precise dates and times will be decided after coordinating with the participants. We plan to run the experiment in a series of sessions in the period of November 2018 – February 2019. You will be asked to participate in one session and you will have the opportunity to choose the date and time that better suits you. The experiment sessions will be conducted on weekdays after business hours or on the weekend.

Participating in the experiment will be fun. We will not use any physically invasive procedures. Experiments in our laboratory respect all the regulations for activities with human subjects. In particular, participants are guaranteed **anonymity**, and the data collected will remain **strictly confidential**. The names of **participants** or of **their institutions will not be published or revealed anywhere**. The protocol in the laboratory assures that **even those running the experiment are not able to link the behaviour and choices made in the laboratory to a particular individual.**

We thank everyone interested in advance.

Antonio Guarino
Professor of Economics, Department of Economics, UCL
Director, Centre for Finance, UCL
Email: a.guarino@ucl.ac.uk

6.13 Trading Game Instructions

THE EXPERIMENT - PHASE I

The experiment consists of 2 phases. Let us describe Phase I first.

In Phase I, you trade an asset with the other 7 participants in the room. All 8 participants in the room have the same instructions.

Phase I consists of a "Market" with 10 trading periods. In each period, you have the opportunity to buy and sell the asset in exchange for cash.

Each period lasts 150 seconds.

EXPERIMENTAL CURRENCY

The currency in Phase I is denominated in Experimental Currency Units ("ECU"). At the end of Phase I, ECU will be converted into pounds at the exchange rate of

100 ECU = £2.50.

This can also be written as

400 ECU = £10.

INITIAL PORTFOLIO

At the beginning of the first period, we give everyone an initial portfolio of **3** units of the asset and **7,000** ECU. You will find information about your portfolio of assets and cash in the box labeled "**Portfolio**" in the right column of the screen. Your portfolio will change as you buy and sell assets or receive earnings from the assets you own. At your computer station, there is a piece of paper labeled "Appendix A" where you can see a screenshot of the trading screen.

During the experiment, you use assets and cash to trade.

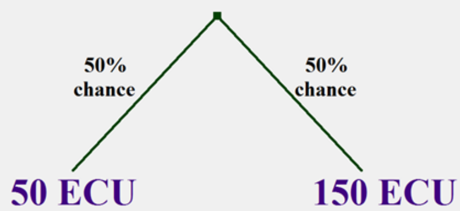
Your assets and your cash carry over from one period to the next. In other words, your final asset holdings and cash in one period become your initial asset holdings and cash in the following period.

ASSET EARNINGS

At the end of each period, the asset produces earnings. Each unit of the asset produces either **50** ECU or **150** ECU.

The computer determines whether the earnings are 50 or 150 with a mechanism simulating the tossing of a fair coin. That is, each period there is an equal chance that the earnings per unit of the asset are 50 or 150.

The diagram below summarises how the asset earnings are determined in each period.



ASSET EARNINGS IN FUTURE PERIODS

The coin toss is repeated each period. Whether the earnings are 50 or 150 in one period does not depend on whether they were 50 or 150 in previous periods.

A unit pays you earnings at the end of each period in which you hold it in your portfolio. For instance, if you buy a unit of the asset in period 3 and you choose to keep it in your portfolio until period 10, you will receive earnings from period 3 until period 10, that is for 8 periods.

In any future period, you know that there is a 50/50 chance that earnings will be 50 or 150. Therefore, if you hold one unit of the asset in a future period, in expectation, it will pay you 50%*50 + 50%*150= **100** ECU.

CALCULATING THE EXPECTED EARNINGS

This table shows how much earning per unit of the asset you should expect in future periods (column 3) and in future and current periods combined (columns 4 and 5) according to whether you expect the earnings to be 50 or 150 in the current period.

Current period	Periods remaining	Future earnings in expectation	Current and future earnings in expectation if current earnings are 50	Current and future earnings in expectation if current earnings are 150
1	9	100*9 = **900**	900 + 50 = **950**	900 + 150 = **1050**
2	8	100*8 = **800**	800 + 50 = **850**	800 + 150 = **950**
3	7	100*7 = **700**	700 + 50 = **750**	700 + 150 = **850**
4	6	100*6 = **600**	600 + 50 = **650**	600 + 150 = **750**
5	5	100*5 = **500**	500 + 50 = **550**	500 + 150 = **650**
6	4	100*4 = **400**	400 + 50 = **450**	400 + 150 = **550**
7	3	100*3 = **300**	300 + 50 = **350**	300 + 150 = **450**
8	2	100*2 = **200**	200 + 50 = **250**	200 + 150 = **350**
9	1	100*1 = **100**	100 + 50 = **150**	100 + 150 = **250**
10	0	100*0 = **0**	0 + 50 = **50**	0 + 150 = **150**

EXAMPLES

In period 1, the asset pays 150.
What is the chance that earnings will be 150 in period 2?

- 0%
- 50%
- 100%

Assume you buy an asset and keep it until the end of period 10.
Do you expect the overall earnings to be higher if you buy it in period 5 or period 8?

- Period 5
- Period 8

In period 1, suppose that you think the current earnings are 150. What do you expect the current and future earnings will be if you hold the asset until the end of period 10?

- 900 ECU
- 950 ECU
- 1000 ECU
- 1050 ECU

In period 3, suppose that you buy an asset and that you think earnings are 150. Suppose you hold the asset until the end of period 6. How much do you expect to earn in those 4 periods?

- 400 ECU
- 450 ECU
- 500 ECU
- 550 ECU

Continue

INFORMATION

You will learn whether asset earnings are 50 or 150 only at the end of each period.

However, at the beginning of each period you will receive some information about earnings.

If earnings are 50, the computer will distribute blue and red balls across participants, as if it were using an urn containing 2 blue balls and 6 red balls. The computer will give each participant one ball. This means that 2 participants receive blue balls and 6 participants receive red balls.

If earnings are 150, the computer will distribute blue and red balls across participants, as if it were using an urn containing 6 blue balls and 2 red balls. The computer will give each participant one ball. This means that 6 participants receive blue balls and 2 participants receive red balls.

Therefore, if earnings are 50 ECU per unit, there is a 2/8 (25%) chance that you receive a blue ball and a 6/8 (75%) chance that you receive a red ball. If earnings are 150 ECU per unit, there is a 6/8 (75%) chance that you receive a blue ball and a 2/8 (25%) chance that you receive a red ball.

Continue

INFORMATION

To recap,
- If, in a period, earnings are 50 ECU per unit, there are more RED balls in the urn.
- If, in a period, earnings are 150 ECU per unit, there are more BLUE balls in the urn.

Therefore, the colour of the ball gives you some information about whether earnings are 50 ECU or 150 ECU.
You will see your ball colour in the box labeled **Earnings Information** on the right side of the screen.

In a period, earnings are 150 ECU.
How many participants will receive a BLUE ball?

- 0
- 2
- 6
- 8

In a period, earnings are 50 ECU.
Will you get a RED ball for sure?

- No
- Yes

In a period, earnings are 50 ECU.
How many participants will receive a BLUE ball?

- 0
- 2
- 6
- 8

In a period, earnings are 150 ECU.
Are you more likely to receive a BLUE ball or a RED ball?

- BLUE
- RED

Continue

TRADERS REQUIRED TO PAY A FEE

At the beginning of each period, the computer randomly selects 4 participants. These participants have to pay a "fee" of **50** ECU for each unit of the asset they have in their portfolio **at the end of the period**. The other 4 participants will not pay a fee.

The fee is automatically subtracted from the earnings at the end of each period. This means that if the asset pays 50, a participant who must pay the fee receives 50-50=0 ECU for each unit they hold at the end of the period. If the asset pays 150, they receive 150-50=100 ECU for each unit they hold at the end of the period.

You will be informed about whether you have to pay the fee at the beginning of the period. This will also be displayed in the box labelled **Fee information** on the right of the screen. Whether you have to pay the fee in one period does not depend on whether you have had to pay the fee in previous periods.

In period 1, you have to pay the 50 ECU fee.
What is the chance that you will have to pay the fee in period 2?

- 0%
- 25%
- 50%
- 100%

Continue

DIFFERENT VALUATIONS

Since every period has 4 participants who have to pay a fee, it will always be the case that other participants value the asset differently than you do.

In other words,
- If you have to pay a fee in a period, you know that there are 4 other participants who earn *more* from the asset than you do in that period.
- If you **do not** have to pay a fee in a period, you know that there are 4 other participants who earn *less* from the asset than you do in that period.

Continue

TRADING

- In each period, trading lasts for 150 seconds.

- During that time, participants trade by submitting Buy and Sell Offers.

Continue

BUY OFFERS

- You can submit a Buy Offer by entering a price in the box titled "Buy Offer (Bid)" and pressing OK.

- You can submit as many Buy Offers as you want, but the sum of the prices of all the offers you submit cannot exceed the amount of cash in your portfolio.

Continue

SELL OFFERS

- You can submit a Sell Offer by entering a price in the box titled "Sell Offer (Ask)" and pressing OK.

- You can submit as many Sell Offers as you want, but the total number of assets you offer cannot exceed the number of assets in your portfolio.

Continue

BUY AND SELL OFFERS

On the top of the screen, you will see 2 boxes: "Buy Offers" and "Sell Offers".

Each box lists all outstanding buy and sell offers. You can see all the offers by scrolling through them. Your own offers are marked by an asterisk in the left column.

You can cancel any offer you submitted that has not been executed. To do so, select one of your outstanding offers and then click the "Cancel" button below the table.

Continue

TRADES

There are 2 ways to trade.

(1) There are "BUY" and "SELL" buttons. Pushing "BUY" will buy one unit of the asset at the lowest (best) submitted Sell Offer. Pushing "SELL" will sell one unit of the asset at the highest (best) submitted Buy Offer.

(2) A trade automatically occurs if the lowest price among all Sell Offers is lower than the highest price among all Buyer Offers.

In this situation, a participant is willing to pay more for the asset than another participant asks for it.

The computer recognizes this situation and the trade occurs automatically at the price of the offer submitted first.

Continue

Example

Suppose that the lowest Sell Offer is 300 and the highest Buy Offer is 200. Then, no trade is possible.

If, instead, you are willing to pay up to 350 for a unit, the only thing you need to do is to submit a Buy Offer of 300 (or higher).

The system recognizes that a trade is possible and immediately executes it. That is, the participant who originally submitted the Sell Offer receives 300 from you and you receive one unit of the asset from them.

Note that it does not matter whether you submit a Buy Offer of 300 or higher; the trade will always be executed at the price of 300 since the Sell Offer was submitted first.

Continue

TRADES (continued)

Therefore,
- To accept an existing Sell Offer and buy the asset, submit a Buy Offer at a price at least equal to the best (lowest) Sell Offer.

- To accept an existing Buy Offer and sell the asset, submit a Sell Offer at a price at most equal to the best (highest) Buy Offer.

The computer immediately executes the trade at the outstanding price.

Continue

TRADES (continued)

When a participant sells a unit of the asset, their cash is increased by the price of the asset, and the number of assets in their portfolio is decreased by one.

When a participant buys a unit of the asset, their cash is decreased by the price of the asset, and the number of assets in their portfolio is increased by one.

Suppose you have 200 in cash and you buy a unit of the asset at a price of 150.
How much cash will you have after the trade is executed?

- 50 ECU
- 150 ECU
- 200 ECU
- 350 ECU

Suppose you have 200 in cash and another participant buys a unit of the asset from you at a price of 200.
How much cash will you have after the trade is executed?

- 0 ECU
- 200 ECU
- 400 ECU
- 600 ECU

Continue

PAST TRADES

You can see information about past trades in the period on the bottom box in the right column of the screen. This box also displays whether you participated in the trade as a Buyer or a Seller or whether the trade was between two other participants ("Others").

Continue

THE END OF THE PERIOD

After the 150 second have elapsed, the period ends.

You are told whether earnings in the period were 50 ECU or 150 ECU.

The earnings from the assets you held at the end of the period are credited to your cash balance.

Your final asset holdings and cash (including the earnings from the assets and after deducting the fee if you had to pay it) become your initial cash and asset holdings in the next period.

Continue

PAYMENT

After 10 periods, trading ends. Your total earnings in the Market equals your final cash balance (after the earnings for period 10 have been added and the fee has been subtracted if you had to pay one).

You are paid based on your total cash earned in the Market.

Continue

END OF INSTRUCTIONS

This is the end of the instructions. If you have any questions, please raise your hand and an experimenter will assist you privately.

When everyone has finished reading the instructions, you will participate in a Practice Market. At the beginning of the first period of the Practice Market, we will give everyone an initial portfolio of **3** units of the asset and **7,000** ECU. This is the same initial portfolio that will be used in the Market.

The Practice Market consists of only 2 periods and you will not be paid based on your earnings in the Practice market. Please use the Practice Market to become familiar with the trading screens and the trading procedures.

Continue

6.14 Trading Platform