DISCUSSION PAPER SERIES

No. 3195

PSYCHOLOGICAL TRAITS AND TRADING STRATEGIES

Bruno Biais, Denis Hilton,
Karine Mazurier and Sébastien Pouget

FINANCIAL ECONOMICS

Centre for Economic Policy Research

www.cepr.org

Available online at: **www.cepr.org/pubs/dps/DP3195.asp**

ISSN 0265-8003

PSYCHOLOGICAL TRAITS AND TRADING STRATEGIES

Bruno Biais, Universite des Sciences Sociales de Toulouse and CEPR
Denis Hilton, Université de Toulouse II
Sébastien Pouget, Université de Toulouse I
Karine Mazurier, Université de Toulouse II

Discussion Paper No. 3195
February 2002

Centre for Economic Policy Research
90–98 Goswell Rd, London EC1V 7RR, UK
Tel: (44 20) 7878 2900, Fax: (44 20) 7878 2999
Email: cepr@cepr.org, Website: www.cepr.org

CEPR Discussion Paper No. 3195

February 2002

ABSTRACT

Psychological Traits and Trading Strategies*

In this Paper we measure psychological traits and show that they significantly affect behaviour and performance in a financial context. Based on the answers of 184 subjects to a psychological questionnaire we measured their degree of overconfidence, ie. the extent to which they overestimate the precision of their information, and self-monitoring, which is a form of social intelligence. The subjects also participated in an experimental financial market under asymmetric information in the spirit of Plott and Sunder (1988). In line with the hypothesis that they suffer from the winner's curse, overconfident subjects are found to earn relatively low trading profits. In contrast, our finding that high self-monitors earn relatively large trading profits is consistent with the hypothesis that they are relatively good at anticipating the trading motivations of the other traders.

JEL Classification: C90, D80, and G10
Keywords: Psychology, overconfidence, self-monitoring, and experimental financial markets

Bruno Biais
Directeur de Recherche
Université des Sciences Sociales
Place Anatole-France
31000 Toulouse Cédex
FRANCE
Tel: (33 5) 61 12 8598
Fax: (33 5) 61 12 8637
Email: biais@cict.fr

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=111911

Denis Hilton
UFR de Psychologie
Université de Toulouse II - le Mirail
5 allées Antonio Machado
31058 Toulouse
FRANCE
Tel: (33 5) 61 504981
Fax: (33 5) 6226 2186
Email: hilton@univ-tlse2.fr

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=146335

Sebastien Pouget
J Mack Robinson College of Business
Georgia State University
University Plaza
Atlanta, GA 30303
USA
Phone: (1 404) 651 2809
Fax: (1 404) 651 2630
Email: fncspp@langate.gsu.edu

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=144824

Karine Mazurier
UFR de Psychologie
Université de Toulouse II - le Mirail
5 allées Antonio Machado
31058 Toulouse
FRANCE
Email: mazurier@univ-tlse2.fr

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=

* Part of this Paper was written as Pouget was at the CSEF at Salerno University. We benefited from helpful comments by seminar participants at Salerno University, the Leeds Business School, the University of Würzburg, the London School of Economics, the London Business School, MIT and at the Psychology and Economics conference in Brussels, the Financial Management Association meetings in Edinburgh, the 2001 Western Finance Association Meetings, and the Psychology and Finance conference in Mannheim, and the CEPR European Summer Symposium in Financial Markets at Gerzensee, especially Peter Bossaerts, Baruch Fischhoff, Nigel Harvey, Joshua Klayman, Marco Pagano, Andrew Parker, Joep Sonnemans, Martin Weber, and Steve Ross. This Paper is produced as part of a CEPR research network on The Industrial Organisation of Banking and Financial Markets in Europe, funded by the European Commission under the Training and Mobility of Researchers Programme (Contract No ERBFMRX-CT98-0222)

Submitted 18 January 2002

Psychological traits and trading strategies

1) Introduction

Behavioural and traditional finance and economics differ because they posit different assumptions about the rationality of human nature. Both are similar however in that they typically test these assumptions using only data on prices and quantities. Allying techniques from experimental economics and experimental psychology, the present paper relates market data to independent measures of the psychological characteristics of the actors involved. This enables us to experimentally test hypotheses about the relationship between psychological characteristics and market behaviour.

Our experimental approach relies on an asymmetric information trading game inspired by Plott and Sunder (1988). Traders observe private signals, and can place limit and market orders in the opening call auction and the ensuing open outcry continuous market. As shown in Biais and Pouget (1999), because of the precision of the private signals observed by some agents in this game, there is a strong winner's curse risk and, in equilibrium, there should be no trade, except at fully revealing prices, and consequently no trading gains or losses. While the experimental data suggests that a fair amount of information was revealed in the prices, we also observe significant deviations from equilibrium. There are frequent trades where one of the players incur losses while the other earn arbitrage profits. In line with the behavioural game theory approach suggested by Camerer (1997), we study if this phenomenon can be explained by psychological variables.

Overconfidence might offer an explanation for the failure of some participants to realize that their trades suffer from winner's curse risk and are consequently loss making. Overconfidence reflects a very prevalent tendency to overestimate our skills, our prospects for success, the probability of positive outcomes, or the accuracy of our knowledge. This bias has attracted a lot of attention from psychologists (see, e.g., Alpert and Raiffa (1982), Lichtenstein, Fischhoff and Phillips (1982) and Russo and Schoemaker (1992) among others). Overconfidence can manifest itself in different ways, as discussed below.

It can manifest itself under the form of overestimation of one's abilities relative to the others, sometimes referred to as the "better than average effect" (see e.g. Taylor and Brown, 1988). These unrealistic positive views of the self can lead to unrealistic optimism about the chances of experiencing positive outcomes (see e.g, Weinstein, 1980). Camerer and Lovallo (1999) suggest that this bias could lead to excess entry by entrepreneurs overestimating their chances of success. Using an experimental procedure designed to identify the effects of the tendency to perceive oneself to be more capable than others on entry decision, Camerer and Lovallo (1999) offer evidence consistent with this hypothesis.

Overconfidence can also manifest itself in the form of exaggerated perception of personal control (see e.g. Langer and Roth, 1975). This tendency to overestimate the extent to which one can influence external events could lead to inappropriate judgements relative to the performance of trading strategies. Fenton O'Creevy et al. (1998) measure the illusion of control of traders at London based investment banks by their tendency to overestimate their ability to influence the movement of a point which they in fact did not control. They found that traders prone to the illusion of control were less likely to make money for their desk.

Yet another manifestation of overconfidence is miscalibration, i.e., the tendency to overestimate the precision of one's information.[1] In a financial market context with asymmetric information, Benos (1998), Odean (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) show theoretically that miscalibration leads to excessively aggressive trading strategies and poor performance. Excessive confidence in one's information can be expected to reduce the extent to which one is willing to learn from market signals, such as the orders and quotes placed by the other traders. While rational agents realize that trade execution reflects information about the signal of their counterparty and adjust their beliefs and strategies accordingly, overconfident agents should fail to make this adjustment and hence will suffer from the winner's curse. While the consequences of miscalibration have been analysed theoretically, the hypothesis that it affects economic behaviour has not yet been tested directly. In the present paper we focus on this form of overconfidence and offer a direct test of its consequences.

In addition to studying a cognitive bias such as miscalibration, the present paper also posits that social dispositions can significantly affect market behaviour and performance. Such dispositions may be especially relevant in markets under asymmetric information, since optimal beliefs and strategy formation require that the agents be highly attentive to the signals emanating from the market in the form of orders, trades and prices. The concept of self-monitoring, introduced by Snyder (1974) may be particularly valuable in this context, as it reflects a disposition to attend to social cues and to adjust one's behaviour to what is appropriate in one's social environment. Thus, Snyder and Gangestad (1986, page 125) write that: ``Individuals high in self monitoring are thought to regulate their expressive self-presentation for the sake of desired public appearances and thus be highly responsive to social and inter-personal cues of situationally appropriate performances." Participants high in self-monitoring can therefore be expected to "read" better the behaviour of other market participants and thus be more likely to avoid the winner's curse.

20 cohorts of students from Toulouse University and the London Business School participated in our experimental trading game. For 184 of the participants, we measured miscalibration using a scale adapted from Russo and Schoemaker (1992), and self-monitoring using the scale developed by Snyder and Gangestad (1986). We related these measures of the psychological characteristics of the participants to their order placement strategies and profits in the trading game. While overconfidence is not found to increase trading intensity, it does significantly reduce trading profits. We also find that high self monitors are able to design rather efficient order placement strategies and correspondingly earn relatively large trading profits.

While behavioural finance studies based on field data offer the clear advantage of documenting real market phenomena, the advantage of experimental approaches is to study controlled environment, allowing more confident inferences about cause and effect relations.[2]

[1] While miscalibration can be correlated to the better than average effect, it is conceptually distinguishable: I can overestimate the quality of my knowledge without believing myself to be better than others.
[2] This argument is similar to the point made by Weber and Camerer (1998, p 168) about the consequences of another psychological phenomenon, namely the disposition effect : "a conclusive test of the disposition effect

Specifically, in our analysis we use psychometric techniques to directly measure psychological characteristics and test if their cross sectional variation between participants is correlated with differences in economic behaviour. Our approach thus allows us to assess the effect of psychological characteristics on economic behaviour independently of other variables. One illustration of the advantage of direct measurement is our finding that the effect of miscalibration on earnings was independent of gender differences. This contrasts with the analysis of Odean (2000b) where gender is used as a proxy for overconfidence. As well as measuring cognitive characteristics, our work also suggests that there is much to be gained by taking social characteristics into consideration, as illustrated by the significant role played by self-monitoring in the experimental financial market. Furthermore, our method allows us to show that the effect of self-monitoring is independent of overconfidence.

Our finding that overconfidence and self-monitoring affect strategies and performance in our experimental financial market is all the more striking that the questions asked to the subjects to measure these traits had nothing to do with financial markets. This suggests these are general features of human functioning which significantly determine agents' economic behaviour. Our sample includes students from the Masters in Finance and MBA of the London Business School as well as students from Toulouse University. While many of the former had previous professional experience in investment and financial markets, we find that the psychological characteristics had similar effects on trading behaviour in both sub-samples.

The next section presents the experimental trading game. Section 3 presents the psychological traits and our hypotheses. Section 4 presents the results. Section 5 offers a brief conclusion summarizing our results and sketching some avenues of further research.

2) The experimental trading game

2.1) The trading game

The structure of the asset payoffs, the endowments and the signals are as in Market 7, Series C, in Plott and Sunder (1988) except that in the present case short sales are allowed and there is a call opening auction before the continuous market.

Private signals

As in Plott and Sunder (1988), there is a single risky asset, paying at the end of the game a liquidating dividend which can be 490 francs, 240 francs or 50 francs with equal probability. Before trading starts the players receive heterogeneous private signals. When the dividend is 490 francs, half the players know that it's not 240 francs while the other half know it's not 50 francs. Similarly when the dividend is 240 francs, half the players know it's not 490 francs, while half the players know it's not 50 francs, and when the dividend is 50 francs, half the players know it's not 490 francs, while half the players know it's not 240 francs. Note that, while the signals "not 50" and "not 490" are pretty strong, the third signal ("not 240") is much more ambiguous and imprecise. We take this into account in our econometric analysis below. Each agent starts each replication of the game with 4 shares and 25000 francs.

---

using real market data is usually difficult because the investors' expectations, as well as the individual decisions cannot be controlled or easily observed in markets like the New York Stock Exchange (NYSE). If an effect is found at the aggregate level there are often competing plausible hypotheses to explain it In this paper we therefore present an experimental investigation of the disposition effect."

Market structure

As in financial markets in the field, players can place market or limit orders to buy or sell. Each replication of the trading game starts with an opening call auction. The subjects can transmit orders to the experimenter as sealed bids for up to ten shares at each price, written on a piece of paper. Using these orders the experimenter constructs an aggregate supply and an aggregate demand curve, and sets the opening price at the level maximizing trading volume. This price is announced publicly to the subjects. In addition the subjects receive written confirmations of the execution of their orders at the uniform opening price.

After the opening call, there is a continuous oral double-auction lasting seven minutes. During this period, the subjects can place limit orders for one share each in continuous time, by announcing them verbally to the experimenter. The experimenter writes these offers on the board The other players see and hear the occurrence of these orders. They can hit these orders by placing market orders or marketable limit orders. Whenever this is the case transactions take place, and this is observed by the other players. As long as their orders have not been hit, subjects can cancel them.

Equilibrium

Biais and Pouget (1999) offer a theoretical analysis of this trading game. They emphasize that the information structure generates a severe winner's curse risk in this market. Traders whose signal is "not 490" seek to make arbitrage profits by selling at prices no lower than 240, while traders whose signal is "not 50" symmetrically seek to buy at prices no greater than 240. Hence market participants should be very concerned, on learning that they have found a counterparty, that it likely signals that the trade is not profitable for them. Realizing this, rational traders avoid loss making orders. As shown in Biais and Pouget (1999), in the arbitrage free perfect Bayesian equilibrium of this trading game, there are no trades except at fully revealing prices (which is in the same spirit as the Milgrom and Stokey (1982) theorem).

2.2) Experimental design

Subjects

We ran the experimental trading game with 20 different cohorts of students from Toulouse University and the London Business School. Subjects were graduate students in economics, finance or management without previous exposure to experiments. For the Toulouse students, 5 cohorts were composed of students in the Masters in Finance (DESS de finance), 5 cohorts were composed of first year PHD students in management (DEA de Gestion), and 6 cohorts were composed of first year PHD students in financial economics (DEA Marchés et Intermédiaires Financiers). The 4 cohorts of students from the London Business School came from the MBA program or the Masters in Finance program. Among them many had experience as investment bankers or traders. The experiment was run in the context of courses taught on stock markets. Each cohort included between 8 and 18 subjects. Overall 268 students played the game. However, our empirical analysis is based on 184 subjects only. These subjects are those for which we have complete data for the trading game, and for the answers to the psychology questionnaire described below. Each cohort participated to 4 replications of the experiment. We randomly drew the realizations of the final value of the asset, by casting a dice in front of the students (to persuade them the draws were indeed random and i.i.d.).

The rules of the game

The rules of the game were presented to the subjects in a one-hour class before the experiment. During this class the subjects asked questions about the rules of the game. The experimenter endeavoured to answer all clarifying questions while refusing to discuss questions such as: How should I play ? What should I do in this circumstance ? Is this a good strategy ? etc... We explained to the students that we did not answer these questions in order not to influence their behaviour during the auction, we also announced them that, after the experiments we would have a debriefing session where we would analyse the game together. Each subject also received a written document stating the rules of the game (an example is displayed in Appendix 1). The experimenter reexplained the game to the subjects, and they asked additional clarification questions. The subjects were also handed forms to write down the orders they placed during the opening call, and to record their trades, cash balances and inventories during the continuous market. At the end of each replication the experimenter announced what was actually the realised value. Subjects then computed their final wealth. The experimenter checked these computations.

Incentives

The students were announced verbally and in the written document that their grade for this course would reflect the final wealth they obtained in the replications. This is in line with Selten, Mitzkewitz and Uhlich (1997) who also used grades to incentivize subjects in their experiment. For the Toulouse students, the grade for the course is between 0 and 20. There is a final exam, for which grades are typically between 6 and 14. Students participating to 4 replications of the game earned bonus points (to be added to their final exam grade to determine the course grade) equal to the sum of their final wealth at the end of the four replications, minus 95000, divided by 3000. It turned out that the minimum number of bonus points earned in the experiment was close to 1 and the maximum close to 7. For the London Business School Students, the total grade for the course is between 0 and 100. The final exam is graded between 0 and 50, there is a presentation in class graded between 0 and 20, and in addition the students receive a number of points equal to the sum of their final wealth at the end of the four replications, minus 95000 and divided by 300. We believe that rewarding subjects based on exam grades, as opposed to relatively small amounts of money is likely to induce serious, optimising behaviour, and to deter gambling or arbitrary and irrational attitudes. To avoid influencing the students into trades that they did not feel beneficial, we announced them during the description of the trading game that they did not *have* to place orders.

2.3) Descriptive statistics

Mean Absolute Deviations

On average, the mean absolute deviation between the call opening price and the true value of the asset was 103. For the double auction, the mean absolute deviation was 114. These means are computed as weighted averages across replications of the game, where each replication is weighted by the number of trades. (To compute the mean absolute deviation for the call auction (resp. double auction), the weight is based on the trades which took place at the opening (resp. during the continuous market)). Note that the call auction leads to a slightly lower mean absolute deviation, although it takes place before the double auction/continuous market, i.e. under greater uncertainty.

Figure 1 represents graphically the mean absolute deviation during the call auction and during the continuous double auction. It illustrates that the mean absolute deviation is much lower when the value of the asset is equal to 240. In this case, indeed, all subjects have observed rather strong and precise signals, which facilitates price discovery. On the other hand, when the value is 490 or 50, while there is some price adjustment towards the true value, prices (and in particular opening prices) seem to remain somewhat “anchored” to the central possible asset value, 240. To document these points further, and study how useful the opening price is to predict the true value, we computed the empirical frequency of the three different possible fundamental values (490, 240, and 50) conditional on the opening price. To simplify matters we only condition on whether the opening price is rather high (above 245), intermediate (between 235 and 245), or rather low (below 235). The intermediate price range (235 to 245) is rather tight, to reflect the above finding that the mean absolute deviation is small when the value is 240. Conditional on the opening price being rather high, the probability that the value is 490, is 85 %. Conditional on the opening price being intermediate, the probability that the value is 240, is 67 %. Conditional on the opening price being rather low, the probability that the value is 50, is 80 %. These conditional probabilities are strikingly large, and suggest that the opening price is very informative about the true value.

Unprofitable orders

On average, during the call auction, 18.3 % of the orders placed in the market are potentially unprofitable (i.e., for buy (resp. sell) orders, are placed at prices above (resp. below) the true value of the asset). This percentage is rather low, relative to the pure noise case under which it would amount to 50% (as explained in Biais and Pouget, 1999). This reinforces the view that the opening call auction operates rather efficiently. During the double auction/continuous market, the percentage of potentially loss-making orders is 34.5%. In the following sections we offer an analysis of the role of psychological traits and biases which provides interpretations for these deviations from rationality.

3) Psychological traits and judgmental biases

3.1 Overconfidence and miscalibration

Definition

The notion of judgmental overconfidence has been invoked in order to explain anomalies in investor predictions and behaviour (see Hilton, 2001 for a review). For example, Daniel, Hirshleifer and Subrahmanyam (1998) argue that overconfidence about the precision of private information can help explain under- and over-reactions in securities markets. In related vein, Barber and Odean (2000b) claim that men’s greater (over)confidence in their judgment leads them to trade more and to take riskier positions than women. While these studies can help assessing how cognitive biases influence market behaviour, neither assess overconfidence directly. One intriguing study (Fenton O'Creevy et al., 1998) which did measure a construct similar to overconfidence, illusion of control (defined as the tendency to overestimate the extent to which one can influence external events) found that traders subject to the illusion of control (measured by the subject’s perception of their ability to influence the movement of a point which they in fact did not control) were less likely to make money for their trading desk.

The psychological literature has identified different kinds of overconfidence such as the "better-than-average" effect - the tendency to believe oneself to have superior characteristic to the average person (Taylor and Brown, 1988), illusion of control (Langer and Roth, 1975) and miscalibration - the tendency to overestimate the quality of our judgments compared to an objective standard. These attitudes are not the same: for example, I might well underestimate the extent of my ignorance, while believing that my judgements have the same accuracy as those of the others. Conversely, I might well wrongly believe that my accuracy is above that of the others, while assessing rationally the extent of my ignorance. Finally, I might overstimate my knowledge compared to others while haveing a realistic assessment of my ability to influence outcomes, and so on.

In our experimental investigation, we focus on whether a particular kind of overconfidence - miscalibration - has an adverse effect on financial behaviour in an experimental financial market where participants have private signals of varying ambiguity. To assess this kind of overconfidence, Lichtenstein, Fischhoff and Phillips (1982), Russo and Schoemaker (1992) and Klayman, Soll, Gonzales-Vallejo and Barlas (1999) ask subjects to make range predictions such that they are 90% sure that the actual value will fall within the range specified. Overconfident subjects give ranges that are too narrow, such that actual values fall outside the range more than 10 % of the time. For example, Russo and Schoemaker (1992) found that business managers had the correct answer between the stated range between 42% and 62% of the time. In Klayman, Soll, Gonzales-Vallejo and Barlas (1999), the correct answer fell inside the participants' confidence range 43% of the time. Using the same procedure to elicit currency predictions, Stephan (1998) found similarly pronounced overconfidence even a domain where the participants (Frankfurt currency traders) should have high expertise.

Our focus on miscalibration does not of course imply that we consider other judgmental biases such as the better-than-average effect and illusion of control to be less interesting or even less likely to influence financial behaviour. However, we do consider that there may be good grounds for differentiating these constructs. For example, while Barber and Odean (2000b) use gender as a proxy measure for overconfidence (they argue that men are more overconfident than women), and attribute gender differences in financial behaviour to differences in overconfidence between the two sexes, there seems to be little evidence that men are more miscalibrated than women (see Lichtenstein, Fischhoff and Phillips, 1982 for a review). For example, while Gigerenzer, Hoffrage and Kleinbolting (1991) note that "Sex differences in degree of overconfidence in knowledge have been claimed by both philosophy and folklore" they go on to observe that "Our study, however, showed no significant differences between the sexes in either overconfidence or calibration". One of the contributions of our study is therefore to examine the respective impacts of gender and miscalibration on financial behaviour in a controlled experimental setting.

Measurement of overconfidence in terms of miscalibration

In line with Lichtenstein, Fischhoff and Phillips (1982), Russo and Schoemaker (1992) and Klayman, Soll, Gonzales-Vallejo and Barlas (1999), to measure overconfidence in terms of miscalibration, we asked subjects, for ten items, to provide an upper and lower limit such that they were 90% sure the correct answer was between the two. The ten questions are listed in Appendix 2.

184 students from Toulouse University or the London Business School both participated to

the experimental trading game and filled our psychology questionnaire. 60 of these were females and 124 were males.

For rational subjects, the expected proportion of answers lying outside the confidence interval is 10%. In contrast, in our sample, the average proportion of answers inside the confidence interval was 40%. This suggests that overconfidence is prevalent in the population we study. Note also that this percentage is very similar to those reported by Russo and Schoemaker (1992) (between 42% and 62%) and Klayman, Soll, Gonzales-Vallejo and Barlas (1999)(43%).

In our econometric analysis (presented in the next section), we use the level of miscalibration of the subjects - measured as the proportion of questions for which the true answers falls outside the stated range - as an explanatory variable of their trading behaviour and performance.

While the mean degree of overconfidence in our 184 subjects sample was 60%, the minimum was 0, the first quartile was 44%, the median is 60%, the third quartile was 80%, and the maximum was 100%. Thus the degree of overconfidence varies across individuals.

Psychometric issues

Using individual measures of overconfidence to explain the subjects' trading strategies and performance is appropriate only if overconfidence is a stable trait, with permanent effects on behaviour. Recent psychological research has offered evidence that this is indeed the case. Klayman, Soll, Gonzales-Vallejo and Barlas (1999) show that questions requesting a subjective confidence interval (such as those we use in the present paper) elicit a strong and stable bias. They conclude (page 240): "Clearly, there are strong, stable individual differences in overconfidence in this task", that is, the answers of different individuals typically reflect different levels of over-confidence, and the tendency of each individual to express over-confident judgement tends to be stable over time and over tasks. Parker and Fischhoff (2001) also analyse individual differences in cognitive styles, and offer evidence of stable individual differences in miscalibration. Their psychometric study shows that accurate calibration is one of the stable and most significant ingredients of decision making competence. Psychometric research has also shown that overconfidence is distinct from intelligence (Stanovich and West, in press). In our sample, for 29 subjects IQ test scores were also available. In line with earlier results obtained by the psychometric literature, the correlation coefficient between this score and our measure of overconfidence is very low (.03).

One way to assess the internal psychometric validity of a measurement scale is to compute its Cronbach alpha. The intuition of this measure is the following. Suppose you measure one variable based on the answer to 10 questions, or items. It is desirable that the ten items point in the same direction. One way to check that would be to measure the correlation, across subjects, between their average answer to the first five questions and their average answer to the last five questions. This is referred to the split-half correlation. Of course, comparing the first five and last five questions is arbitrary. For example, why not comparing the answers to even questions and odd questions instead? Cronbach alpha is the mean of all split-half correlations among items. In our data, the Cronbach alpha coefficient of our measure of overconfidence is 0.60. This points at reasonable psychometric internal validity.

Hypotheses

Overestimation of the accuracy of one's beliefs, as measured by our questionnaire, is likely to be associated with a tendency to underestimate the extent to which a given situation is uncertain and risky. To illustrate this, consider the following example. Suppose that, conditional on given private and public information, the most likely value of the asset is 490. In this situation, miscalibrated, overconfident subjects are likely to overestimate the probability that the value is 490, and to put insufficient weight on the possibility that the asset is actually worth less. This leads to overestimating the attractiveness of opportunities to purchase the asset, and underestimating the risk that these trades be loss-making, i.e., winner's curse risk. In turn, this generates excessively aggressive buying strategies, and, correspondingly, winner's curse induced losses. This discussion, which is in line with the theoretical analyses of Daniel, Hirshleifer and Subrahmanyam (1998) and Odean (1998), leads us to posit the following hypothesis.[3]

H1: More overconfident subjects tend to follow more aggressive trading strategies.

H2: More overconfident subjects tend to suffer more from the winner's curse, and correspondingly to earn lower trading profits.

3.2) Self -Monitoring

Definition

While calibration is a concept developed by cognitive psychology, self-monitoring has been emphasized in social psychology. It can be thought of a form of social intelligence, as it reflects the disposition to attend to social cues, and to adjust one's behaviour to what is expected by one's social environment. As defined by Snyder and Gangestad (1986, page 125) self monitoring reflects a tendency to regulate one's expressive self-presentation according to what is appropriate in a given situation and to be highly responsive to social and inter-personal cues. Parker and Fischhoff (2001) note that " decision making competence should correlate positively with self-monitoring … representing awareness of one's own actions."

Self-monitoring has been applied to management (see for example DeBono and Snyder (1985) for advertising and Berscheid, Matwychuk and Snyder (1984) and Jenkins (1993) for human resources management.) It has been shown to correlate positively with performance. For example, Kilduff and Day (1994) showed that high self-monitors are more likely to be promoted in managerial careers than low self-monitors. Mehra, Kilduff and Brass (2001) find that self-monitoring has positive effects on individual's workplace performance.

Measurement and Psychometric issues

Jenkins (1993) offers evidence suggesting that self-monitoring is a stable personality trait throughout one's life span. Snyder and Gangestad (1986) have developed (and checked the psychometric validity of) a scale to measure this construct. In the present paper we directly import their 18 items questionnaire (presented in Appendix 2).

While the mean degree of self-monitoring in our 184 subjects sample was 47%, the minimum was 6%, the first quartile was 33%, the median 44%, the third quartile was 61%, and the maximum was 100%. Thus the degree of self-monitoring varies across individuals.

[3] These hypotheses are in line with the interpretation offered in Odean (2000a) for the empirical observation that individual investors' frequent trading does not enhance gross returns and reduces net returns – by raising transactions costs.

In our 184 subjects sample, the coefficient of Cronbach's alpha for this is 0.63, which points at reasonable internal consistency of the measure. Furthermore, the correlation between the index of self-monitoring and the index of overconfidence was quite low, as it equalled 0.0075. This suggests that the two constructs are quite distinct.

Hypothesis

In the context of our experimental trading game one could expect subjects high in self monitoring to be more sensitive to the interpersonal dimension of the game, and better adjust their attitude and strategy to the behaviour of the others. In particular, the sensitivity to social cues is likely to help the subjects better interpret the motivations of the actions of the others, and thus avoid the winner's curse.

Consequently, we posit the following hypothesis:

H3: Subjects higher in self-monitoring tend to suffer less from the winner's curse, and correspondingly to earn greater trading profits.

4) Empirical analysis of the impact of psychological traits on trading strategies and performance

4.1) The variables we analyse

In this section we test the above discussed hypotheses on the consequences of psychological traits on trading strategies and performance. We consider 3 different aspects of the subjects' trading strategies and performance:

i) how active they are in the market – which we measure by the total quantity they supply or demand, at all prices, and irrespective of whether it is executed or not,

ii) how aggressive their trading strategies are – which we measure by the proportion of the quantity they supply or offer which ends up executed, hereafter referred to as the execution ratio,

iii) their trading profits, measured as the sum over all trades of the true value minus the transaction price multiplied by the signed quantity traded.

Summary statistics on these variables are presented in Table 1. The figures suggest that there is quite a bit of variability across subjects.

To filter out some of the noise in the data, we focus on the deviations between the actions or traits of the subjects and those of the group in which they traded. More precisely we take the following steps: We compute the average trade or profit for each of the 20 cohorts of subjects. Then, for each subject, we compute the difference between his or her trade or profit and the corresponding cohort average. We regress these variables onto the two psychological variables: overconfidence and self-monitoring. For the latter we also substract, for each individual, the average of his or her cohort, and we also divide by this average. Thus if the coefficient of the regression of Y onto X is equal to β, this can be interpreted as follows: a one percent increase in the psychological characteristic X of individual *i* relative to his cohort leads to an increase of his action or performance (relative to his of her cohort average) equal to β X.

In addition to the psychological traits, we also include two control variables in the regressors: We control for the gender of the subjects. We also take into account the frequency with which (during the 4 replications of the game), they observed a relatively imprecise private signal ("not 240").[4]

4.2) The total quantity posted

Table 2 presents the estimates of the OLS regression of the total quantity posted (averaged across the four replications of the game) onto the psychological variables and the control variables. Consistently with the findings of Barber and Odean (2000b) (which were based on field data) men trade more than women. The coefficient of the gender dummy (taking positive values for women) is significantly negative. On the other hand, the psychological variables are not found to have any significant effect on trading intensity. Note also that subjects tend to place fewer orders when their signals are imprecise ("not 240"). Maybe this is because they realize that in this situation they face a very severe winner's curse problem, and thus prefer to stay out of the market, which is indeed their equilibrium strategy, as shown in Biais and Pouget (1999).

4.3) The aggressiveness of the trading strategies

The psychological variables explain very little of the variation of this variable. This can be due to measurement errors or misspecification.

Yet, we find that overconfidence (weakly significantly) enhances the aggressiveness of trading strategies in the continuous market. This positive relation is consistent with H1, in line with the theoretical results of Daniel, Hirshleifer and Subrahmanyam (1998) and Odean (1998).

Also, high self monitors have a greater execution ratio in the call market. This may reflect that these subjects tend to better anticipate the behaviour of the others in the market, resulting in relatively accurate predictions of the aggregate supply and demand curves. Based on these predictions, they place orders which end up in the market.

4.4) Trading profits

The basic regressions

Consistent with hypothesis H2, overconfident subjects tend to obtain lower trading profits. This suggests that these subjects suffer more from the winner's curse. Because they are overconfident, they fail to realize the extent of their ignorance, and the associated risk that the value of the security is not what they a priori believe. While they do not tend to place more orders than the other traders, their orders tend to be loss making, possibly reflecting the excessive confidence these traders have in their beliefs.[5]

---

[4] We have also conducted the analysis including additional control variables, such as the degree in which the students were enrolled, and the number of players in their cohort. Overall these variables were not significant, and they did not alter the sign, magnitude or significance of the psychological variables. Hence, for parsimony, we decided not to include them in the final regressions.

[5] While we find that performance is reduced by overconfidence, it is not correlated with gender. This stands in contrast with the arguments developed by Barber and Odean (2000b). Note that while in our paper poor performance reflects the winner's curse, in Barber and Odean (2000b) it has a very different origin, namely the transactions costs (commissions, spreads, etc….) associated with frequent trades.

Consistent with hypothesis H3, high self monitors tend to earn greater profits, especially in the call market. Thus the above mentioned aggressiveness of their trading strategies does not seem to be dysfunctional on average. Rather, in line with our discussion above, it seems to reflect their ability to produce a relatively appropriate mental image of the trading behaviour of the other subjects at this stage of the game, and to exploit it profitably. The relatively high earnings of self monitors suggest that, in line with H3, they possess superior abilities to portray the thought process and trading motivations of the other players, which helps them avoid the winners' curse.

Also note that, in the call market, participants tend to generate lower trading profits when they have more imprecise information.[6] While this result is not surprising, it may be worth pointing that, in the equilibrium prevailing with perfectly rational subjects, the winner's curse is perfectly unravelled, and subjects with imprecise signals do not make losses. Thus, their losses in the experimental financial market reflect imperfect rationality.

Interactions

To obtain further insights about the consequences of psychological traits on earnings in the trading game, we added to the regressors interaction variables reflecting: i) the product of the level of overconfidence of the subject and his or her level of self-monitoring, ii) the product of the level of overconfidence of the subject and the imprecision of his or her signal, and iii) the product of the level of self-monitoring of the subject and the imprecision of his or her signal. The results are in Table 5. Note that overconfidence and self-monitoring remain significant even after including the interaction variables.

The interaction between overconfidence and the imprecision of the signal is (weakly) significantly positive This suggests that overconfidence is particularly harmful when subjects have observed precise signals. This is in line with the findings of Oskamp (1982). He studied the behaviour of psychologists in an experimental clinical situation. He analysed how their judgements varied as they received more information, and how confident they felt in these evaluations. He found that "As they received more information, their confidence soared. Furthermore, their certainty about their own decisions became entirely out of proportion to the actual correctness of those decisions (see Oskamp, 1982, page 292)."

This result also offers an interpretation for our finding that the aggressiveness of the trading strategies of overconfident subjects is particularly prevalent during the call market. During the call market they face large uncertainty, since they only have observed one signal. During the continuous market, they face less uncertainty since they have observed more signals (the call opening price, the bids of the others). In this less uncertain environment, they react particularly strongly to their beliefs.

The interaction between self-monitoring and the imprecision of the signal is significantly negative in the call market. Thus, the above mentioned aggressive trading strategies used by high self-monitors in the call market generate losses for subjects with imprecise signals.

[6] While in the call market it is rather clear that subjects having observed "not 240"have relatively imprecise information, the situation is more ambiguous after the opening call auction. In fact, combined with the observation of the opening price, the signal "not 240" can be quite informative. Indeed, as shown in Table 4, after observing "not 240" and the opening price, subjects tend to earn relatively large profits in the continuous market.

When they have precise signals, high self-monitors are able to place limit orders sufficiently aggressive to end up in the money, and at the same time sufficiently reasonably priced to avoid strong winners' curse. Fine tuning the tension between these two considerations is relatively easy for high self monitors who have observed precise signals. For example, when they have observed "not 50" they can place limit orders to buy at 240. In contrast, for subjects who have observed imprecise signals, it is much more difficult to calibrate orders to avoid the winners' curse. In that case, the desire to obtain execution leads high-self monitors to place loss making orders. Indeed for subjects who have observed "not 240", avoiding the winner's curse would call for refraining from placing orders. This appears to be particularly difficult for high self-monitors, reflecting their general inclination to participate in social interactions.

During the call market, the interaction between overconfidence and self-monitoring is significantly positive, while the coefficient of overconfidence is significantly negative. This suggests that, while overconfidence reduces profits, it is less harmful for high self-monitors. These subjects, because they are relatively good at picturing the thought process of the others, are less focused on their own private signal. This appears to mitigate the harmful consequences of the excessive confidence miscalibrated subjects have in that signal.

4.5) Robustness

To assess the robustness of our results we ran the regressions separately for the Toulouse University students and the London Business School students. For brevity we report and discuss only the analysis of trading profits (arguably the most important of the variables we analyse). The results are in Table 6. The sign of the estimates are the same for the two populations.[7] This is consistent with the view that the psychological variables we study i) are stable across different populations, and ii) play similar roles in these populations.

We also estimated the trading profits regression over the population of 29 subjects from Toulouse for which we observe a measure of IQ. Because of the small size of that sample the estimation results must be taken with a grain of salt. It is nevertheless comforting that neither the sign nor the magnitude or the significance of the coefficients of the psychological variables is affected by the inclusion of the IQ of the subjects in the regressors. This suggests that the effect of the psychological variables captured in our statistical analysis does not reflect an "intelligence level" omitted variable.

In addition to profits, we also examined a slightly different measure of performance in our trading game: the proportion of potentially unprofitable orders. Recall that such orders are not placed in the Perfect Bayesian Equilibrium of our trading game. The main difference between this measure and profits is that the former reflects potential losses, corresponding to orders which were potentially unprofitable but were not executed, while the latter reflects only realized losses. Thus while the former measures whether a subject deviates from equilibrium, the latter focuses on cases where such deviations occurred and other subjects took advantage of them. Overall the results we obtained for the proportion of potentially unprofitable orders are qualitatively comparable to those we obtained when focusing on profits.[8] This points at the coherence of the empirical results.

[7] The t statistics are greater when the two samples are combined than in each of the two samples, reflecting the larger size of the grand sample, and consistently with the view that the effect is at play in both subsamples.
[8] The detailed estimation results are omitted for brevity, but are available from the authors for the interested reader.

5) Conclusion

The contribution of this paper is to measure two psychological traits which have been shown to be prevalent and important by previous work in experimental psychology: overconfidence[9] and self-monitoring[10], and to show that they significantly affect behaviour and performance in an experimental financial market under asymmetric information (similar to the trading game analysed by Plott and Sunder, 1988).

Overconfident subjects can be expected to suffer from the winner's curse, to the extent that they underestimate the extent of their ignorance, and correspondingly the losses they can incur when trading based on incomplete information. The theoretical analyses of Odean (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) indeed show that overconfidence can lead to excessively aggressive trading strategies and poor performance. In our experiment, we find that overconfidence has the following effects: It does not lead subjects to place more orders. But miscalibrated participants put excessive confidence in their view of the market. Correspondingly, they are particularly exposed to the winners' curse, and earn significantly lower profits. Our empirical approach is different from Barber and Odean's (2000b), because we measure overconfidence in terms of miscalibration, using a psychometric scale, while they measure overconfidence using gender as a proxy. While we find gender effects on activity of similar direction as Barber and Odean (2000b), we do not find that these results are mediated by differences in calibration. This seems to us to underline the importance of specifying what kind of overconfidence – miscalibration, the better than average effect, illusion of control - may be influencing trading behaviour in a particular case. We also find that overconfidence is particularly dysfunctional in situations where the subjects face relatively little uncertainty, as when they have observed precise private signals, or after observing the call opening price. This is consistent with previous results in experimental psychology that overconfidence is more pronounced when more information is available (Oskamp, 1982).

While overconfidence has been studied by several papers in finance, self-monitoring remained, so far, outside the focus of financial economics. Self-monitoring reflects the ability to catch social cues and adjust one's behaviour to one's social environment. This form of social intelligence can be relevant in markets with asymmetric information, to the extent that it enables traders to conduct introspection about the thought processes of the others, and the motivation of their trading strategies, and thus to avoid the winner's curse. We find that high self monitors tend to follow relatively aggressive order placement strategies in the opening call market. Such strategies are not dysfunctional on average, however: overall, high self-monitors earn significantly greater trading profits. Trading in the call market is particularly difficult for agents with bounded rationality, since designing efficient strategies in this context requires forming a mental image of the actions of the others, and the resulting joint distribution of aggregate supply and demand and value.[11] Our results suggest that high self-monitors may be relatively good at conducting such thought experiments.

Our result that psychological traits affect behaviour and performance in our experimental financial market is all the more striking that the questions asked to the subjects to measure these traits had nothing to do with financial markets. This points at robustness of the

---

[9] See, e.g., Lichtenstein, Fischhoff and Phillips (1982), Russo and Schoemaker (1992) and Klayman, Soll, Gonzales-Vallejo and Barlas (1999).

[10] See e.g. Snyder (1984), Snyder and Gangestad (1986), Parker and Fischhoff (2001), DeBono and Snyder (1985), Berscheid, Matwychuk, and Jenkins (1993), Kilduff and Day (1994), Mehra, Kilduff and Brass (2001).

[11] See Pouget (2001).

psychological constructs independent of the context in which the questions are asked. Furthermore, the sign and significance of the coefficients of overconfidence and self-monitoring are found to be comparable in the sub-sample including students from Toulouse University and in the sub-sample including students from the London Business School. This points at robustness of our results across samples. Furthermore, our results (based on experimental data) are in line with the findings of Fenton O'Creevy et al (1998) (based on questionnaire and field data). This points at robustness of the analysis across types of data sources.

Our methodology, which involves measuring psychological traits and correlating them with economic behaviour, could prove useful to shed light on the impact of psychological variables in various economic situations. An interesting avenue of research would be to consider other traits than those analysed in the present paper. [12] Another promising direction would be to study the extent to which different traits enhance or impede performance in certain market circumstances but not others. This last point raises the issue of how market structure moderates or exacerbates the consequences of psychological characteristics.[13] Yet another important direction of further research is to extend our theoretical models of the behaviour and reasoning process of economic agents, to take into account the impact of psychological variables. This is in the line of the behavioural game theory approach discussed by Camerer (1997) and of the analysis of the consequences of confirmatory bias by Rabin and Schrag (1999).[14]

[12] In the context of the present paper, we tried to measure such cognitive biases as the confirmation, availability and representativeness biases. Unfortunately, our measures of these biases had insufficient psychometric validity (i.e., they were too noisy), to be included in the present analyses. Camerer (1987) and Anderson and Sunder (1995) offer interesting analyses of the consequences of the representativeness bias. It could be interesting, in further research, to build on their approach.

[13] Camerer, Loewenstein and Weber (1986) offer an interesting analysis of how market environments can mitigate the adverse consequences of the hindsight bias relative to an individual decision making context.

[14] The models analysed by Benos (1998), Odean (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) offer interesting first steps in that direction.

Bibliography

Anderson, M., and S. Sunder, 1995, Professional traders as intuitive Bayesians, Organizational behaviour and Human Decision Processes, 185-202.

Barber, B., and T. Odean, 2000a, Trading is hazardous to your wealth: the common stock investment performance of individual investors, forthcoming Journal of Finance.

Barber, B., and T. Odean, 2000b, Boys will be boys: Gender, overconfidence and common stocks investments, forthcoming Quarterly Journal of Economics.

Benos, A., Aggressiveness and survival of overconfident traders, Journal of Financial Markets, 353-383.

Berscheid, E., A.Matwychuk and M. Snyder, 1984, Research on personnel selection, Working paper, University of Minnesota, Minneapolis.

Biais, B., and S. Pouget, 1999, Microstructure, incentives and convergence to equilibrium in experimental financial markets, Working paper, Toulouse University.

Camerer, C., G. Loewenstein, and M. Weber, 1989, The curse of knowledge in economic settings: An experimental analysis, Journal of Political Economy, 1232-1254.

Camerer, C., 1987, Do biases in probability judgement matter in markets? Experimental evidence. *American Economic Review*, 981 -997.

Camerer, C., 1997, Progress in behavioural game theory, Journal of Economic Perspectives, 167 -188.

Camerer, C., and D. Lovallo, 1998, Overconfidence and excess entry: An experimental approach, *American Economic Review*, 306-318.

DeBono, K., and M. Snyder, 1985, Appeals to image and claims about quality: understanding the psychology of advertising, Journal of Personality and Social Psychology, p 586 -597.

Fenton O'Creevy, M., N. Nicholson, E. Soane, and P. Willman, 1998, Individual and contextual influences on the market behaviour of finance professionals, ESRC conference paper.

Gigerenzer, G, Hoffrage, U and Kleinbolting, H. (1991). Probabilistic mental models: A Brunswikian theory of confidence. Psychological Review, 98, 506-28.

Jenkins, J. M., 1993, Self-monitoring and turnover: The impact of personality on the intent to leave, Journal of Organizational Behavior, 14: 82-89.

Klayman, J., J. B. Soll, C. Gonzales-Vallejo, and S. Barlas, 1999, Overconfidence:: it depends on how, what and whom you ask, *Organizational Behavior and Human Decision Processes*, 216-247.

Langer, E., and J. Roth, 1975, Heads I win, Tails it's chance : the illusion of control as a function of the sequence of outcomes in a purely chance task, Journal of Personality and Social Psychology, 951-955.

Lichtenstein, S., Fischhoff, B., and L. Phillips (1982) "Calibration of probabilities: The state of the art to 1980, in *Decision making and change in human affairs*, edited by H. Jungermann, and G. deZeew, Amsterdam: D.Rede.

Milgrom, R., and N. Stokey, 1982, Information, trade and common knowledge, Journal of Economic Theory, 17 -27.

Odean, T., 1998, Volume, volatility, price and profit when all traders are above average, Journal of Finance, 1887 -1934.

Oskamp, S., 1982, Overconfidence in case-study judgments, in Judgement under uncertainty: heuristics and biases, ed D. Kahneman, P. Slovic and A. Tversky, Camdridge University Press.

Parker, A. and B. Fischhoff, 2001, Decision-Making Competence: An Individual Differences Approach, Working paper, Virginia Tech and Carnegie Mellon University.

Pouget, S., 2001, The Walrasian tâtonnement to economize on cognitive transactions costs: an experiment, Working paper, Toulouse University.

Rabin, M. and J. Schrag, 1999, First impressions matter : a model of confirmatory bias, Quarterly Journal of Economics, 37-82.

Russo J. and P.J.H. Schoemaker, 1992, Managing over-confidence, *Sloan Management Review*, 33, 7-17.

Selten, R., M. Mitzkewitz, and G. Uhlich, Duopoly strategies programmed by experienced players, *Econometrica*, May 1997, 517-556.

Snyder, M., 1974, Self monitoring of expressive behavior, Journal of Personality and Social Psychology, 526-537.

Snyder, M., and Gangestad, 1986, On the nature of self- monitoring: matters of assessment, matters of validity. Journal of Personality and Social Psychology, p 125 -139.

Stephan, E., 1998, Anchoring and adjustment in economic forecasts: the role of incentives, ability and expertise. Conference on Judgemental Inputs to the Forecasting Process, University College London.

Stanovich, K.E. and West, R.F. (in press). Individual differences in reasoning: Implications for the rationality debate? Behavioral and Brain Sciences.

Taylor, S., and J. Brown, 1988, Illusion and well being: A social psychological perspective on mental health, Psychological Bulletin, vol 103, 193-210.

Weinstein, N., 1980, Unrealistic optimism about future life events, Journal of Personality and Social Psychology, vol 39, 806-820.

Table 1: Summary statistics on the dependent variables

	Minimum	First quartile	Median	Mean	Third Quartile	Maximum
Total quantity posted	1	9	15	31	43	238
Quantity posted during the call	0	6	12	28	40	216
Quantity posted during the continuous	0	1	2.25	3	4.06	21.33
Execution ratio	0	12%	28%	31%	44%	100%
Execution ratio during the call	0	4%	17%	22%	33%	100%
Execution ratio during the continuous	0	50%	73%	68%	93%	100%
Trading profits	-2008	-130	3	62	240	4414
Profits during the call	-1660	-23	0	90	182	4400
Profits during the continuous	-1879	-87	0	-28	63	1082

Table 2:
Regression of the total quantity posted onto psychological traits and control variables

(184 observations; t stat are in parenthesis)

	Overall	**During the call**	**During the continuous market**
Intercept	14.81 (2.78)	14.21 (2.76)	0.6 (1.56)
Self-monitoring	8.46 (1.29)	7.69 (1.21)	0.77 (1.63)
Overconfidence	-8.56 (-1.30)	-8.5 (-1.33)	-0.06 (-0.13)
Gender (1 for woman)	-12.58 (-2.34)	-11.74 (-2.25)	-0.83 (-2.14)
Proportion of signals equal to “not 240”	-32.89 (-2.53)	-31.89 (-2.53)	-1 -1. 06
R2	8.1%	7.8%	5.3%

Table 3:
Regression of the aggressiveness of the trading strategies (measured by the execution ratio) onto psychological traits and control variables

(184 observations; t stat are in parenthesis)

	Overall	**During the call**	**During the continuous market**
Intercept	-0.04 (-1.58)	-0.02 (-0.68)	0.03 (0.8)
Self-monitoring	0.01 (0.15)	0.07 (1.97)	-0.07 (-1.37)
Overconfidence	0.04 (1.15)	0.003 (0.1)	0.08 (1.68)
Gender (1 for woman)	0.04 (1.59)	0.03 (1.1)	-0.03 (-0.87)
Proportion of signals equal to "not 240"	0.09 (1.32)	0.03 (0.4)	-0.06 -0.64
R2	2.9%	2.4%	2.9%

Table 4:
Regression of trading profits onto psychological traits and control variables

(184 observations; t stat are in parenthesis)

	Overall	**During the call**	**During the continuous market**
Intercept	58.81 (0.59)	126.55 (1.39)	-67.74 (-1.36)
Self-monitoring	240.97 (1.97)	263.79 (2.35)	-22.82 (-0.37)
Overconfidence	-245.93 (-2.00)	-180.68 (-1.6)	-65.25 (-1.06)
Gender (1 for woman)	-8.28 (-0.08)	5.45 (0.06)	-13.73 (-0.27)
Proportion of signals equal to "not 240"	-172.31 (-0.71)	-394.09 (-1.76)	221.78 1.82
R2	4.6 %	6.0%	2.4%

Table 5:
Regression of trading profits onto psychological traits and control variables and interaction variables

(184 observations; t stat are in parenthesis)

	Overall	**During the call**	**During the continuous market**
Intercept	68.14 (0.69)	135.26 (1.50)	-67.13 (-1.33)
Self-monitoring	636.55 (2.50)	665.16 (2.87)	-28.61 (-0.22)
Overconfidence	-570.15 (-2.66)	-469.30 (-2.4)	-10.85 (-0.92)
Gender (1 for woman)	1.14 (0.01)	12.00 (0.13)	-10.86 (-0.21)
Proportion of signals equal to "not 240"	-213.06 (-0.88)	-428.19 (-1.94)	215.13 (1.74)
Interaction variable: overconfidence . self monitoring	393.27 (1.33)	532.34 (1.97)	-139.07 (-0.92)
Interaction variable: Proportion of signals equal to "not 240" . self monitoring	-1285.82 (-1.73)	-1323.12 (-1.96)	37.31 (0.10)
Interaction variable: overconfidence . Proportion of signals equal to "not 240"	1153.90 (1.82)	1036.74 (1.80)	117.16 (0.36)
R2	8.45 %	10.99%	2.93%

Table 6:
Regression of overall trading profits onto psychological traits and control variables for the Toulouse and London samples

(t stat are in parenthesis)

	Toulouse University	**London Business School**
Intercept	85.16 (0.72)	-8.97 (-0.05)
Self-monitoring	180.57 (1.30)	471.12 (1.78)
Overconfidence	-168.23	-524.23

	(-1.18)	(-2.00)
Gender (1 for woman)	-21.13 (-0.18)	111.73 (0.44)
Proportion of signals equal to "not 240"	-246.32 (-0.83)	-28.86 (-0.07)
R2	2.93%	14.58%
Number of observations	138	46

Appendix 1:
Instructions to the subjects in the trading game

In this trading game you will have the opportunity to buy and sell shares. The instructions of the game are below. If you follow them carefully and make good decisions you can win a considerable amount of points for your final grade.

You will play 4 replications of the trading game. At the beginning of each replication you will receive 25000 francs and 4 shares. During the game you will have the opportunity to place orders to buy or sell the shares. (You can sell more shares than you own, i.e., short sales are allowed). At the end of each replication, you will compute the value of your final wealth, equal to the sum of:

your initial cash: 25000 F,

minus the cost of your share purchases,

plus the proceeds from your share sales,

plus the final value of your portfolio.

The final value of your portfolio is equal to the number of shares you own at the end of the replication, multiplied by the final value of each share. The final value of the shares, at the end of each replication, is drawn randomly (and independently from the previous draws). It can be 490, 240 or 50, with equal probability: one third. For example, if your only trade was the purchase of one share at price 200, and the final value of the shares is 240, your final wealth is: 25000 - 200 + 5* 240. Since you can sell more shares than you own, you can end up with a negative number of shares held at the end of the replication. For example, if you sold 6 shares at 100 each and the final value of the shares is 50, your final wealth is: 25000 +600 - 2*50, given that you have sold 2 shares more than you owned.

At the beginning of each replication you will receive a private information (keep it secret, don't reveal it to the others !). If the value of the shares is 490, half the players know it is not 240, while the others know it is not 50. If the value of the shares is 240, half the players know it is not 490, while the others know it is not 50. If the value of the shares is 50, half the players know it is not 240, while the others know it is not 490.

Each replication of the trading game includes two phases:

First, you can place limit orders to buy or sell (up to 10 shares at each price), by writing them on a piece of paper. These orders are then aggregated into supply and demand curves, crossed to determine the opening price, in a call auction. The opening price is set to maximize trading volume, as explained in class. This price, but not the orders, is announced publicly to the players. After this announcement, you receive execution reports, telling you which of your orders are filled. All limit sell orders placed at prices below or equal to the opening price are executed at this price. All limit buy orders placed at prices above or equal to this price are executed at the opening price. The remaining orders are not executed. For simplicity, they are automatically cancelled after the opening call.

Second there is continuous market, which lasts 7 minutes, during which you will have the opportunity to:

announce offers to sell or buy, which I will write on the board (to make life easier for me when I write the offers on the board, they are all for one share only, but you can place many offers),

announce that you desire to trade with one of the offers available on the board, and which have not been executed yet; cancel or revise your offers when they have not been executed yet.

After the 4 replications, you will compute the sum of your final wealth during the game. To obtain the number of bonus points to be then added to your grade at the exam, substract 95000 to this sum, and divide the result by 3000.

Appendix2: Measuring the psychological traits

Overconfidence

	Low	**High**
Martin Luther King's age at death.		
Length of the Nile River (in miles).		
Number of countries that are members of OPEC.		
Number of books in the Old Testament.		
Weight of an empty Boeing 747 (kgs).		
Year in which J.S. Bach was born.		
Gestation period (in days) of an Asian elephant.		
Diameter of the moon (in miles).		
Air distance from London to Tokyo.		
Deepest known point in the Oceans (in ft.).		

Self-Monitoring (Snyder and Gangestad, 1986)

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 subject is a self-monitor is the percentage of answers coded with a 1.

	True	**False**
I find it hard to imitate the behaviour 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 centre 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 favour.		
I have considered being an entertainer.		
I have never been good at games like charades or improvisations.		
I have trouble changing my behaviour 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.		

Figure 1: Mean absolute deviation between the true value of the asset and transaction prices in the call market and the continuous oral double auction