Judgmental overconfidence, self-monitoring and trading performance in an experimental financial market

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April 2, 2004

Abstract

We measure the degree of overconfidence in judgment (in the form of miscalibration, i.e., the tendency to overestimate the precision of one's information) and self-monitoring (a form of attentiveness to social cues) of 245 participants and also observe their behaviour in an experimental financial market under asymmetric information. Miscalibrated traders, underestimating the conditional uncertainty about the asset value, are expected to be especially vulnerable to the winner's curse. High self-monitors are expected to behave strategically and achieve superior results. Our empirical results show that miscalibration reduces and self-monitoring enhances trading performance. The effect of the psychological variables is strong for men but non-existent for women.

Key words: Psychology and Finance, Overconfidence, Miscalibration, Self-Monitoring, Experimental Finance, Trading Game, Asymmetric Information, Winner's Curse.

Biais is at Toulouse University (IDEI-CRG-GREMAQ), Hilton and Mazurier are at the Social Psychology Department at Toulouse University, and Pouget is at the Finance Department, Robinson College of Business, Georgia State University. Part of this paper was written as Pouget was at Toulouse University and then at the CSEF at Salerno University. We benefited from helpful comments by the editor, Mark Armstrong, and the referees, as well as seminar participants at Salerno University, the Leeds Business School, the London School of Economics, the London Business School, MIT, the University of Munich, the University of Würzburg and at the Psychology and Economics conference in Brussels, the Financial Management Association meetings in Edinburgh, the 2001 Western Finance Association Meetings, the Psychology and Finance conference in Mannheim, the CEPR European Summer Symposium in Financial Markets at Gerzensee and the 12th WZB Conference on Markets and Political Economy in Berlin. We also thank Peter Bossaerts, Rachel Croson, Baruch Fischhoff, Nigel Harvey, Joshua Klayman, Marco Pagano, Andrew Parker, Vesna Prasnikar, Steve Ross, Jim Shanteau, Mark Snyder, Joep Sonnemans, Robbie Sutton, Jean Tirole, Eric Vernette and Martin Weber for helpful comments and discusssions. An earlier version of this paper was circulated under the title: "Psychological dispositions and trading behaviour". Pouget gratefully acknowledges research support from Georgia State University.

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1) Introduction

Allying techniques from experimental economics and experimental psychology, we relate market data to independent measures of the psychological characteristics of the actors involved. This enables us to test hypotheses about the consequences of psychological variables for market behaviour.

Our experimental approach relies on an asymmetric information trading game directly inspired by Plott and Sunder (1988). The value of the asset can be high (490), medium (240), or low (50). The traders observe different private signals. For example when the value of the asset is high, half the participants are privately informed that it is not low, while the others learn privately that it not medium. Traders can place limit and market orders in a call auction and an open outcry continuous market. There is a strong winner's curse risk in this trading game. For example, if an agent with a bullish signal (not 50) offered to buy, say at 270, this bid would systematically be hit by traders with bearish signals (not 490), while traders with neutral signals (not 240) would be much more reluctant to engage in trading. Biais and Pouget (1999) show that in equilibrium in this trading game 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 is revealed in the prices, we also observe significant deviations from equilibrium. Very high prices signal unambiguously that the asset value is 490 and very low prices signal that the value is low. However, in the experiment, transaction prices close to 240 convey a more ambiguous signal. For such prices the proportion of cases in our experiments where the true asset is 240 is only 52%. Consequently, in the 48% of cases where the price deviates from true value, some of the players must earn non-negligeable profits at the expense of others. In line with the behavioural game theory approach suggested by Camerer (1997), we study whether this phenomenon can be predicted by psychological factors.

A specific kind of overconfidence in one's judgment, which we refer to as miscalibration, can 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. Miscalibrated people tend to overestimate the precision of their information. We measure this bias using a confidence-interval task (Alpert and Raiffa, 1982).[1] In an experimental asset market, Kirchler and Macejovsky (in press) used a confidence-interval technique and found evidence of overconfidence in predictions of price variations. In a financial market context with asymmetric information, Benos (1998), Odean (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) show theoretically that this form of overconfidence leads to poor performance. Our experimental approach is particularly well suited to test this conclusion, since we can rely on direct measures of psychological variables, as well as of trading performance.

In these theoretical analyses, underperformance in the market will stem from overconfidence in the precision of one's private signal. In the simple information structure of our game, participants cannot overestimate the precision of their private signal. Yet, we expect miscalibrated participants to overestimate the precision of their information set, which includes their signal as well as the observation of the market prices. When conditional uncertainty about the value of the asset is high, rational agents will recognize this. In contrast, miscalibrated traders will be less aware of this, and thus show excessive confidence in their assessment of the value of the asset. Hence, we expect them to be especially vulnerable to the winner's curse. We identify market circumstances where this problem is likely to be particularly acute. As mentioned above, in our experimental data, when the opening price is close to 240, there is actually almost one chance in two (48%) that the true value of the asset is 490 or 50. In this context, miscalibrated participants whose signal does not rule out that the value is 240, will overconfidently believe the asset is worth 240. Thus they will be prone to fall into a winner's curse trap whereby they will incur losses through trading with other participants who make gains at their expense.[2]

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[1] Other kinds of overconfidence, such as a prevalent tendency to overestimate our skills, our prospects for success, or the probability of positive outcomes have also attracted a lot of attention from psychologists (see, e.g., Taylor and Brown, 1988). Miscalibration is conceptually distinguishable from "positive illusions" such as the belief that one is above average or the illusion of control. Indeed, a psychometric study by Regner et al. (2003) finds no correlation between miscalibration and such "positive illusions".

[2] The winner's curse traps we identify are not without similarities with the information traps analysed by Camerer, Noeth, Plott and Weber (1999). However our emphasis on (and measurement of) psychological

In addition to studying a cognitive bias such as miscalibration, in this paper we also study how social dispositions can affect market performance. Self-monitoring is a disposition to attend to social cues and to adjust one's behaviour to one's social environment (Snyder, 1974). High self monitors are role players who habitually anticipate the effect of their behaviour on others, and in addition anticipate that the others will behave strategically. Anticipating that other market participants will be trying to manipulate the market as they themselves do, high self monitors will be less likely to take market prices at face value. Rather, they will reason about the signals and strategies that generated these prices. For example, when observing a price near to 240, they will not so readily jump to the conclusion that this indicates that the value is 240. Thus, they should be relatively unlikely to fall into winner's curse traps and thus should avoid the corresponding trading losses.

26 cohorts of students from Toulouse University and the London Business School participated in our experimental trading game. For 245 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), and collected data about behaviour and performance in the experimental market.

Our basic analysis focuses on the direct link between psychological characteristics of the participants and their trading profits. We find that miscalibration reduces trading performance in the experimental market, while self-monitoring enhances it. To gain further insights into the nature of the relation between psychological variables and market outcomes, we then analyse winner's curse traps. To do so, we focus on situations where the market price is close to 240, while the value of the asset is in fact 50 or 490. We analyse the consequences of psychological characteristics for agents who are in such market circumstances, while their private signal does not rule out that the value is 240. We find that their profits are reduced by miscalibration and increased by self-monitoring. The impact of both psychological factors is significant. In contrast, for participants who were not exposed to winner's curse traps, the psychological variables have no significant impact on profits. Our results therefore suggest that winner's curse traps are the major channel of the impact of miscalibration and self-monitoring in our experimental market.

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characteristics differs from their study of the mutual consistency between mistaken beliefs.

Since we measure psychological characteristics independently of trading performance and gender, our experiment offers an opportunity to study the relationships between these variables. In line with Barber and Odean (2001) we find that men tend to trade more than women, but while they use gender as a proxy for overconfidence, we find no correlation between gender and miscalibration. When we split the data by gender, and run the analysis separately for men and women, we find different patterns of behaviour. While miscalibration does not significantly affect performance in women, it does lead to worse performance in men. This effect is significant and robust across samples.[3]

While behavioural finance studies based on field data offer the clear advantage of documenting phenomena occurring in natural markets, the advantage of experimental approaches is to study controlled environments, allowing more confident inferences about cause and effect relations.[4] To assess causal relations between independent variables (e.g. miscalibration, self-monitoring) and dependent variables (e.g. trading strategies, earnings) we use a quasi-experimental design (Cook and Campbell, 1979). Rather than experimentally manipulating participants' beliefs (as, e.g., Camerer and Lovallo, 1999), we measured pre-existing variations in participants' calibration of their judgment and self-monitoring several weeks before they participated in the trading game. Precautions were taken to ensure that participants would not associate the psychological measurements with the trading game. This quasi-experimental method licences inferences by the method of difference (Mill, 1872/1973), as all things being equal there should be no other factors than (say) high versus low miscalibration which distinguish these two groups when we contrast their earnings. This entitles us to attribute any significant variations in dependent variables (e.g. earnings) to the causal impact of the independent variables (e.g. miscalibration).

The measures of miscalibration and self-monitoring on which we rely have been developed and used previously by experimental psychologists. Jenkins (1993) and Snyder and Gangestad (1986) have documented the internal psychometric validity of the self-monitoring scale. More

[3] It is also robust to the inclusion of IQ in the regressors for a subsample where this variable was available.

[4] 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 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."

recently, Klayman, Soll, Gonzales-Vallejo and Barlas (1999), Jonsson and Allwood (2003) and Parker and Fischhoff (2001) offer evidence of stable individual differences in miscalibration. The experimental psychology literature also suggests that significant variations in miscalibration and self-monitoring exist in numerous populations outside our sample, ensuring the external validity of our independent variable. Note further that the questions we asked to the participants to measure miscalibration and self-monitoring had nothing to do with financial markets *per se,* yet they nevertheless affect strategies and performance in the experimental market. This points to the robustness of the psychological constructs independent of the context in which the questions are asked. Finally note that 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 effect of psychological characteristics is robust across 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 summarising our results and sketches some avenues of further research.

2) The experimental market

2.1) The trading game

The market

The structure of the market, 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 auction in addition to the continuous market. As in Plott and Sunder (1988), there is a single risky asset, which pays a liquidating dividend at the end of the game 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 is not 240 francs, while the other half know that it is not 50 francs. Similarly when the dividend is 240 francs, half the players know it is not 490 francs, while half the players know it is not 50 francs, and when the dividend is 50 francs, half the players know it is not 490 francs, while half the players know it is not 240 francs. Each agent starts each replication of the game with 4 shares and 25000 francs (of experimental currency).

As in financial markets in the field, players can place market or limit orders to buy or sell. We consider two treatments for the experimental market. In the first treatment, each replication of the trading game starts with an opening call auction, followed by a continuous market. In the call auction, the participants can transmit limit 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 maximising trading volume. This price is announced publicly to the participants. In addition the participants 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 participants 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, participants can cancel them.

In the second treatment, the market starts with a seven-minute continuous oral double auction, followed by a closing call auction. Apart from this difference in the sequencing, the two treatments are identical. As discussed in Section 4, comparing the first and second treatments is useful to disentangle the impact of the different trading mechanisms (call versus continuous) from the impact of the sequencing (market close versus market opening). This is similar to the field data analysis of Amihud and Mendelson (1987, 1991). In their 1987 paper they found that transaction prices set during the opening call auction on the NYSE were particularly noisy. To test whether this was due to the trading mechanism (the call auction) or the opening of the market, in their 1991 paper they replicated their analysis with data from the Japanese market. While the opening call prices in the Tokyo stock exchange also included a large noise component, the afternoon call auction prices did not.

Equilibrium

If all market participants had the same utility function, the Milgrom & Stokey (1982) theorem would directly apply, and there should be no trade except at fully revealing prices, and hence no trading profits or losses. The intuition of this result is rather clear in our simple information structure: traders with bullish signals ("not 50") might be inclined to buy, but, if they offer to purchase the security at prices above 240, they run the risk of trading with agents with bearish signals ("not 490"), earning arbitrage (i.e., riskless) profits at their expense. Consequently, traders who have observed "not 50" should not offer to buy at prices above 240. Extending this logic, Biais and Pouget (1999) show that even when traders have different preferences, there is a Perfect Bayesian Equilibrium with no trade, except at fully revealing prices. In this equilibrium, traders who have observed "not 50" offer to buy at prices lower than or equal to 240, traders who have observed "not 490" offer to sell at prices greater than or equal to 240, and traders who have observed "not 240" stay out of the market. Given that the others follow these strategies, deviating from them cannot be beneficial to a trader, as it would expose her to the strong winner's curse risk of trading with an agent seeking to make arbitrage profits.

2.2) Experimental design

Participants

We ran the experimental trading game with 26 different cohorts of students from Toulouse University and the London Business School (20 cohorts participated in the first treatment and 6 in the second one). Participants were graduate students in economics, finance or management without previous exposure to experiments. For the Toulouse students, 7 cohorts were composed of students in the Masters in Finance (DESS de finance), 7 cohorts were composed of first year Ph.D students in management (DEA de Gestion), and 8 cohorts were composed of first year Ph.D 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. Each cohort included between 8 and 18 participants. While 344 students participated in our trading game, our empirical analysis is only based on the 245 participants, for whom we have complete and reliable data for the trading game and answers to the psychological questionnaires described below. 94 of these participants were females and 151 were males. Each cohort participated in 4 replications of the experiment. We randomly drew the realisations of the final value of the asset, by casting a dice in front of the students (so that they would understand the draws were indeed random and i.i.d.).

The rules of the game

The rules of the game were presented to the participants in a one-hour session before the experiment. During this session the participants 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 participants that we did not answer these questions in order not to influence their behaviour during the auction, we also announced that, after the experiments we would have a debriefing session where we would analyse the game together. At the beginning of an experimental session, each participant 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 participants, and they asked additional clarification questions. The participants 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. Participants then computed their final wealth and the experimenter checked these computations.

Incentives

The experiment was run in the context of courses taught on stock markets. The experimenter told the students that their grade would reflect the final wealth they obtained in the experimental market. This was announced verbally and also stated in the written document handed to the students (see Appendix 1). This device is similar to Selten, Mitzkewitz and Uhlich (1997), Isaac, Walker and Williams (1994) and Williams (2003) who also used grades to incentivize participants in their experiments.[5] 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

[5] Williams (2003) analyses experimental markets where participants are rewarded with credit points and obtains similar results to the literature using cash-rewards. In their experimental analysis of public goods, Isaac et al (1994) conclude (p 31-32): "The results of a series of (extra-credit, multiple-session) baseline experiments … are consistent with the (cash, single session) experimental results reported by Isaac and Walker (1988)." Furthermore, Camerer and Hogarth (1998), drawing the lessons of the experimental literature, conclude (page 8): "In the kind of tasks economists are most interested in, like trading in markets, bargaining in games and choosing among risky gambles, the overwhelming finding is that increased incentives do not change average

and 14. Students participating in 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. For both Toulouse and London students, the experiments took place before the final exam. We believe that rewarding participants 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 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

To document the informational efficiency of the prices set in our experimental market, we compute the mean absolute deviation between transaction prices and the true value of the asset. For the call auction, this mean is computed as a simple average across replications of the game, pooling all the cohorts together. On average, it is equal to 118. To compute the mean absolute deviation for the continuous double auction market, we use the weighted average transaction price, where the weights are the proportion of the transactions that occurred at each price. This is equal to 108.

Figure 1 represents graphically the mean absolute deviation during the call auction and during the continuous double auction. As expected, the mean absolute deviation in the call auction (Panel A) is greater in the first treatment, where the call auction is held at the opening of the market, than in the second treatment, where the call auction is used to close the market. More surprisingly, in the continuous market (Panel B), the mean absolute deviation is lower when

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behaviour substantially (although the variance of responses often decreases.)”

the market opens with the oral double auction. This suggests that this market structure could be more conducive of price discovery. Also the mean absolute deviation is lower when the value of the asset is equal to 240. In this case, indeed, all participants have observed rather strong and unambiguous signals, which facilitate price discovery. On the other hand, when the value is 490 or 50, while there is some price adjustment towards the true value, prices seem to remain somewhat "anchored" to the central possible asset value, 240.

To document these points further, and study how informative transaction prices are about the true value, we computed the empirical joint distribution of prices and fundamental values, which is depicted in Figure 2. This figure illustrates that prices tend to be relatively higher when the value is 490, and relatively lower when the value is 50. Thus, the prices set in our experimental market under heterogeneous information do reveal part of the information of the traders. For example, when the call auction price is above 250, the actual value of the asset is never equal to 50, and there are seven chances out of 8 that it is equal to 490. Similarly, when the call auction price is lower than or equal to 220, the frequency of the low value realisation is 78%, while those of the intermediary and high values are 7% and 15%, respectively. The prices set in our experimental market are not fully revealing, however.[6] In particular, the diagnosticity (or information content) of prices close to 240 is relatively low. For example, when the call price is greater than 220 and lower than or equal to 250, the frequency of the low value realisation is 17%, that of the intermediary value 52%, and that of the high value realisation 31%. Thus, when the call price falls in this interval there is only about one chance out of two that the actual value of the asset is 240.[7] Hence, when the price is in this intermediary range, there is still substantial uncertainty as to the actual value.

Trading behaviour

Table 1 presents summary statistics about the trading behaviour of the participants. Traders offer to buy or sell a median number of 11 shares during the call auction. Only 16 % of these offers are filled. This reflects the fact that traders place offers to buy at low prices and to sell at high prices which end up not executed. In the continuous market, participants offer to buy or sell a median number of two shares, and 70 % of these offers are filled. This relatively

[6]This contrasts with our theoretical analysis of the game, discussed above, where transaction prices should be fully revealing. This might stem from imperfect rationality.

[7]Thus, when the value is 490, or when it is 50, the absolute deviation between the value and the price can be

large execution ratio reflects the finding that, in contrast with the call auction, traders in the continuous auction do not place buy orders at very low prices or sell orders at very high prices. In line with the zero-sum nature of the trading game, the median profit is equal to 0. While the median profit is null, some significant gains are earned and significant losses incurred in the trading game. In the call market, trading profits vary from -10 for the first quartile, to 145 for the third quartile. In the continuous market, profits vary from -79 for the first quartile, to 78 for the third quartile. In the above discussed Nash equilibrium of the trading game, rational agents will recognize the winner's curse risk arising because of heterogeneous information and correspondingly design their strategies to cope with this. Hence, in equilibrium, no losses are incurred, and no profits earned. Yet, in practice in the experimental game, as shown in Table 1, large profits are made, and significant losses incurred. In the next sections we discuss how psychological factors can give rise to such phenomena.

3) Psychological traits and judgmental biases

3.1) Overconfidence and miscalibration

Definition

The notion of overconfidence has been invoked in order to explain anomalies in investor predictions and behaviour (see Hilton, 2001 for a review). Several analyses in financial economics emphasize a form of overconfidence in one's judgement known as miscalibration, corresponding to the tendency to overestimate the precision of one's information. In the theoretical analysis of Daniel, Hirshleifer and Subrahmanyam (1998) overconfidence about the precision of private information can help explain under- and over-reactions in securities markets. Odean (1998) shows theoretically that miscalibration can lead to excessive trading volume. In line with this, Barber and Odean (2000b) offer empirical evidence that men trade more frequently than women and attribute this to their greater overconfidence.

Our experimental analysis of the consequences of miscalibration in financial markets complements these theoretical and field data based approaches. Our focus on miscalibration

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quite large, as illustrated in Figure 1.

does not of course imply that we consider other forms of overconfidence 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, Odean (1998) relies on two distinct parameters to model miscalibration and the better-than-average effect.[8]

Our measure of miscalibration

While the above mentioned studies can support the claim that cognitive biases influence market behaviour, they do not assess overconfidence in judgment directly. To directly analyse the consequences of miscalibration in financial markets, we rely on the measurement tools developed by the experimental psychology. To assess miscalibration, Lichtenstein, Fischhoff and Phillips (1982), Russo and Schoemaker (1992) and Klayman, Soll, Gonzales-Vallejo and Barlas (1999) use a confidence interval procedure in which participants are asked to make range predictions such that they are 90% sure that the actual value will fall within the range specified. Miscalibrated participants typically give ranges that are too narrow, such that actual values fall outside the range more than 10 % of the time.[9] For example, Russo and Schoemaker (1992) found that business managers had the correct answer within 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 in judgment even in a domain where the participants (Frankfurt currency traders) should have high expertise.

In line with Russo and Schoemaker (1992) and Klayman, Soll, Gonzales-Vallejo and Barlas (1999), we used a confidence interval technique to measure miscalibration. Thus we asked participants, 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. While for

[8]Indeed, Régner, Hilton, Cabantous and Vautier (2003) offer empirical evidence that other forms of overconfidence, such as the better-than-average effect, the illusion of control or unrealistic optimism are not correlated with miscalibration.

[9] Underconfidence in one's judgment can be obtained through designating confidence intervals that are too wide. This is especially likely to happen when the task is easy (Klayman et al., 1999). However such miscalibration is hardly ever observed on difficult tasks. In our sample, only one person was actually underconfident, with no answer outside the confidence interval, and two persons were perfectly calibrated, with just one miss. Consequently for present purposes miscalibration can be considered as almost always indicating overconfidence in judgment.

rational participants the expected proportion of answers lying inside the confidence interval is 90%, in our sample the average proportion of answers inside the confidence interval was 36%. This shows that our participants exhibited over-confidence in their judgment. Note also that this percentage of miscalibration is very similar to those reported by Russo and Schoemaker (1992) and Klayman, Soll, Gonzales-Vallejo and Barlas (1999). In addition, we found no significant differences between men and women in terms of miscalibration. Specifically, the percentage of answers lying inside the confidence interval is 37% for men and 34 % for women. The t-statistic for the difference between these two averages (1.08) is not significantly different from 0. This result is in line with other studies of miscalibration which similarly found little or no gender differences (e.g. Jonsson and Allwood, 2003; Gigerenzer, Hoffrage and Kleinbolting, 1991; and Lichtenstein, Fischhoff and Phillips, 1982.[10]) Because we measure miscalibration independently from gender, we can examine the respective impacts of these two characteristics on financial behaviour in a controlled experimental setting.

In our econometric analysis, we use the level of miscalibration of the participants - measured as the proportion of questions for which the true answers falls outside the stated range - as an explanatory variable for their trading behaviour and performance. While the mean degree of overconfidence in our 245 participants sample was 64%, the minimum was 0, the first quartile was 50%, the median is 70%, the third quartile was 80%, and the maximum was 100%. Thus the degree of overconfidence varies markedly across individuals.

Psychometric issues

Using individual measures of miscalibration to explain the participants' trading strategies and performance is appropriate only if miscalibration is a stable trait, which persists over time and generalises across different kinds of judgmental task. 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

[10]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".

are strong, stable individual differences in overconfidence in this task", that is, the answers of different individuals typically reflect different levels of overconfidence, and the tendency of each individual to express overconfident judgements tends to be stable over time and over tasks (see also Jonsson and Allwood, 2003). Parker and Fischhoff (2001) 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. Finally, psychometric research has also shown that miscalibration is distinct from intelligence – indeed Stanovich and West (1998) report a modest negative correlation (-.20) between intelligence and good calibration. In our sample, for 42 participants, 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 miscalibration is very low (.01).

One way to assess the internal psychometric validity of a measurement scale is to compute its Cronbach alpha. The intuitive meaning of this measure can be explained as follows. Suppose you measure one variable based on the answers to 10 questions, or items. It is desirable that the ten items point in the same direction, i.e., that they be well correlated. One way to check that would be to measure the correlation, across participants, between their average answer to the first five questions and their average answer to the last five questions. This is referred to as 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. The corresponding formula is:

$$\alpha = [M/(M-1)]\ [1 - (\Sigma_{j=1}{}^{M}\ \mathrm{Var}(x_j))/\mathrm{Var}(\Sigma_{j=1}{}^{M}x_j))],$$

where M is the number of items, x_j is the j^{th} item, and variances are computed across participants. Intuitively, α is a synthetic measure of the correlation between the items, and varies between 0 and 1. If the items are independent, α =0, and if they are perfectly correlated it is equal to 1. In our data, the Cronbach alpha coefficient of our measure of overconfidence is 0.58. This suggests the different items we use to measure miscalibration tend to be positively correlated, although the correlation is only moderately strong.

Hypotheses

Miscalibration leads to overconfidence in the precision of one's information, i.e., miscalibrated agents underestimate conditional uncertainty.[11] In our simple information structure there is little scope for exaggerating the precision of one's private signal, but miscalibrated agents can exaggerate the precision of their information set, including their signal as well as market outcomes, such as transaction prices, which they fail to interpret correctly.[12]

For example, if the opening price is equal or close to 240, miscalibrated traders may exaggerate the probability that the true value is 240.[13] As discussed above, prices close to 240 are unreliable indicators of underlying value in our experimental market. Indeed, when the opening price is greater than 220 and lower than or equal to 250, there is only about one chance out of two that the actual value of the asset is 240. We expect miscalibrated traders, unaware of this large conditional uncertainty, to be especially vulnerable to the winner's curse. Given transaction prices close to 240, they will overconfidently believe that the value is 240 if their own signal does not rule out this value. They will trade on this belief, risking being picked off by rational traders.

We argue that the process underlying the formation of overconfident beliefs in the trading game is similar to that underlying the formation of overconfident judgements when answering the calibration questionnaire. Both reflect overestimation of the diagnosticity of informational cues, and underestimation of conditional uncertainty. For example, a salient cue in the question about Martin Luther King's age at death would be that he was a famous political leader. Overconfident respondents who underestimate the variability in ages of famous political leaders accordingly overestimate the diagnosticity of this cue, and thus provide excessively narrow confidence intervals for their answer to the question. Likewise, we expect

[11] This is in line with the finding that miscalibration is correlated with intolerance of ambiguity, the tendency to believe, for example, that things are black and white rather than various shades of grey (see e.g. Lichtenstein, Fischhoff and Phillips, 1982; Regner et al. 2003).

[12] Our emphasis on the adverse consequences of underestimating conditional uncertainty shares similarities with that of Odean (1998). However, while he emphasises overestimation of the precision of private signals, we analyse overconfidence in the information content of transaction prices, which is public information in our experimental market.

[13] In the continuous market such conditioning can arise because the agent observes the transaction price. In the call auction, agents place demand and supply schedule specifying the number of shares they want to trade at a given price. This demand should reflect the information content of the price, as shown, e.g., by Grossman and Stiglitz (1980).

that in the trading game miscalibrated agents will similarly overestimate the diagnosticity of market cues, such as the market opening at or around 240. Correspondingly they will underestimate the conditional variance of the true value in this case, and thus the probability that the true value is in fact 50 or 490.

In line with the above discussion, we posit the following hypothesis:

H1: *Miscalibrated participants tend to suffer more from the winner's curse, and correspondingly should earn lower trading profits.*

3.2) Self -Monitoring

Definition and hypothesis

While miscalibration is a concept that has been principally developed in cognitive psychology, the concept of self-monitoring has received more attention in social psychology. It reflects the disposition to attend to social cues, and to adjust one's behaviour to what is expected in one's social environment (see Snyder and Gangestad, 1986). 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 high self-monitoring has positive effects on individual's workplace performance.

There is a behavioural aspect and a perception aspect to self monitoring. High self monitors can be thought of as impression managers whose behaviour is strategically attuned to create impressions that gain them advantage in a given situation. In the context of the trading game, this would correspond to a more strategic and manipulative behaviour. High self monitors would place orders enabling them to make profits without revealing their private information to the other market participants. They might also make offers that do not reflect their own beliefs or signals, but which aim to manipulate others' beliefs and perceptions.

In addition, Monson (1983) reports evidence consistent with a projection effect: that is, high self monitors expect others to be like them. Specifically, they are more likely to interpret others' behaviour as stemming from situational constraints rather than revealing internal dispositions or values. By analogy, in the market game they may assume that other market participants are also behaving strategically and trying to manipulate the market as they themselves do. Accordingly, high self monitors should be less likely to take market prices at face value, and will reason about the signals and strategies that generated them. They will thus be less likely "to underestimate the extent to which other players' actions are correlated with their information" (Eyster and Rabin, 2003) and thus should avoid the winner's curse. Specifically, in contrast to highly miscalibrated agents, conditional on prices close to 240, they will not so readily jump to the conclusion that the value is 240.[14]

In line with the above discussion, we posit the following hypothesis:

H2: *Participants higher in self-monitoring should be better able to trade strategically and suffer less from the winner's curse, and correspondingly they should earn greater trading profits.*

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-item questionnaire (presented in Appendix 2). We measure the degree of self-monitoring as the percentage of questions (out of 18) for which the answer indicated high self-monitoring. While the mean degree of self-monitoring in our 245 participants sample was 47%, the minimum was 0, 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. The average self-monitoring score is 51% for men and 41 % for women. The t-statistic for the difference between these two averages (-4.01) is significantly different from 0,

[14] This implies that high self-monitors will set wider "confidence intervals" for signals coming from social sources (as in our experimental market), though it does not necessarily imply that they will do the same for non-social sources (e.g. general knowledge questions).

which suggests men are higher self-monitors than women.

In our 245 participants sample, the coefficient of Cronbach's alpha for the self-monitoring scale is 0.70, which points at reasonable internal consistency of the measure. Furthermore, the correlation between the index of self-monitoring and the miscalibration score was quite low, as it equalled 0.0073. This suggests that the two constructs are quite distinct. Finally note that, for the 42 participants for whom we observed a measure of IQ, the correlation between IQ and self-monitoring was found to be low, as it was estimated to be equal to -0.11.

4) Psychological determinants of trading performance

In this section we test the above discussed hypotheses on the consequences of psychological traits on trading performance. Trading outcomes are averaged across the four replications of the experiment. To filter out some of the noise in the data, we focus on the deviations between the psychological traits of the participants and those of the group in which they traded. More precisely we take the following steps: we compute the average trait for each of the 26 cohorts. Then, for each participant, we compute the difference between his or her trait and the corresponding cohort average, and we divide it by the cohort average. Thus the variable can be interpreted in terms of percentage difference with the cohort average.

4.1) Univariate analysis

Miscalibration & trading profits

To document the link between miscalibration and trading profit, we broke the population into four groups or quartiles, each composed of 25% of the participants, and ranked in terms of miscalibration. Thus the first quartile is composed of the least miscalibrated participants, while the fourth quartile is composed of the most miscalibrated participants. Figure 3 plots the average trading profits of each of the four quartiles. Clearly, the more miscalibrated the participants, the lower their trading profits. For example the average trading profit of the first quartile (composed of the 25% least miscalibrated participants) is 131.36, while the corresponding average for the fourth quartile (composed of the most miscalibrated participants) is -147.67. The t-statistic for the difference between these two averages is 3.17.

While the above results clearly suggest that miscalibration impedes performance, consistent with hypothesis H1, one might wonder about the robustness of this result. To speak to this issue, we replicated the analysis presented in Figure 3, breaking down the observations in 3 subsamples. Our experimental analysis was first conducted with students from Toulouse University. Then we replicated this analysis with students from the London Business School. Finally, after the first round of the reviewing process, we collected data from a new sample of participants. Comparing the results obtained for these three populations enables one to assess whether the results obtained for the first Toulouse sample are robust out of that sample. Figure 4 depicts the average trading profits of each miscalibration quartile for the three subsamples. It shows that the negative association between miscalibration and performance is robust across samples. In particular, in each of the three subsamples, the least miscalibrated agents obtain large positive profits. Note however that the strength of the impact of miscalibration on performance varies across subsamples. In particular, it is more pronounced for the LBS students.

As discussed above, miscalibration does not significantly differ across gender. Yet it might affect performance differently, to the extent that male and female participants could act upon their more or less miscalibrated views of the world in different ways. To answer this question we replicated the analysis presented in Figure 3, breaking down the observations by gender. The results are depicted in Figure 5. The figure suggests that miscalibration has a more significant effect on performance in men than it does in women. We come back to this point below.

Self-monitoring & trading profits

As in our analysis of miscalibration, we broke the population into four groups or quartiles, each composed of 25% of the participants, and ranked, this time, in terms of self-monitoring. Thus the first quartile is composed of the lowest self-monitors, while the fourth quartile is composed of the highest self monitors. Figure 6 plots the average trading profits of each of the four quartiles. It illustrates that high self-monitors tend to earn greater profits. For example the average trading profit of the first quartile (composed of the 25% lowest self-monitors) is -62.45, while the corresponding average for the fourth quartile (composed of the highest self-monitors) is 53.78. The t-statistic for the difference between these two averages is only 1.18, because the variance within each quartile is large.

These results provide some support to the hypothesis that self-monitoring enhances performance (H2). To assess the robustness of the link between self-monitoring and performance, we replicated the analysis breaking down the observation in 3 subsamples, corresponding to the first round of data collection in Toulouse, the LBS replication, and the second Toulouse sample. Figure 7 depicts the average trading profits of each self-monitoring quartile for the three subsamples. The positive association between self-monitoring and performance is more or less upheld. It shows up quite strongly in the LBS sample. It is less obvious in the second Toulouse sample, where the highest self-monitors earn the highest profits but where the lowest self-monitors also earn positive profits.

As discussed above, the impact of miscalibration on performance differs across gender. Is it also the case for self-monitoring? To investigate that point we replicated the analysis presented in Figure 6, breaking down the observations by gender. The results are depicted in Figure 8. The figure suggests that self-monitoring affects profits for men, but not for women.

4.2) Multivariate analysis

The basic regressions

To analyse these points further we regressed trading profits (averaged across the four replications of the game) onto the two psychological variables. We also include in the regressors the gender of the participants.[15] Because all the variables are centred, there is no intercept in the regression.

The first column of Table 2 presents the estimates for the basic specification. Consistently with H1, miscalibration significantly reduces profits. The coefficient of self-monitoring is

[15] 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,

positive, consistent with hypothesis H2, but not significantly so. These results are in the line of our discussion of Figures 3 and 6 above.

Winner's curse traps

In Section 3.1, we identified a scenario in which overconfidence in judgment was likely to be particularly harmful. Our conjecture was the following: when transaction prices are close to 240, miscalibrated agents exaggerate the probability that the value is 240, when their own private signal does not rule it out. They place orders reflecting this view of the market. These orders are picked off by more rational agents. Thus, miscalibrated agents suffer from the winner's curse and correspondingly incur losses. In Section 3.2, we also conjectured that high self monitors should be less likely to fall in such winner's curse traps. Indeed, as discussed above, they are likely to be more strategic and less likely to take market prices at face value and jump to the conclusion that prices close to 240 can only mean that the value is 240.

To test these hypotheses, we need to empirically characterize the occurrence of winner's curse traps. We define a winner's curse trap as follows: the opening call auction price is strictly greater than 220 and lower than or equal to 260, but the true value is not 240, and yet the participant's signal does not rule out 240. We then split our sample into two subsamples. The first one includes the 98 participants who were never exposed to a winner's curse trap. The second one includes the 84 participants who faced at least one winner's curse trap. We run the regression of profits on the psychological variables and gender separately in the two subsamples. This additional statistical analysis can be performed only for the first treatment sample because in the second treatment we did not collect data on the signals observed by the participants.[16]

The estimates are in the last two columns of Table 2. While the miscalibration and the self-monitoring interaction variables are significant in the subsample of participants who faced winner's curse traps, they are not significantly different from zero in the other subsample. In the sample where winners' curse traps occurred the adjusted R^2 is more than twice as large as

we decided not to include them in the final regressions.

[16] This was due to the fact that one of the experimenters, Pouget, was not present in the second set of experiments, and it was difficult in practice to collect all the data. Note however that the first treatment is a natural setting for the winner's curse trap to operate, as the opening call auction prices is a natural anchor for the beliefs formed in this market.

in the grand sample. This suggests that the winner's curse traps are the major channel of the impact of the two psychological variables on performance in our trading game.[17]

4.3) Gender

The regression estimates presented in Table 2 indicate that trading profits do not differ significantly across genders. Does that imply that gender does not affect behaviour and performance in our experimental market?

Barber and Odean (2001) analysed trades placed by individual investors through a discount broker. They found that men traded more than women and showed that such frequent trading did not enhance gross portfolio performance. [18] Thus, after deducting trading costs, they found that the performance of women was superior to that of men. They concluded that men's lower performance was due to overconfidence.

To further compare the behaviour arising in our experimental market to that observed in the field by Barber and Odean (2001), we study the determinants of trading activity in our data. We consider two possible measures of trading activity: the number of shares offered or demanded by a trader, and the number of shares actually traded. We regress trading activity on the two psychological variables, as well as on gender. The estimates, presented in Table 3, imply that men participate significantly more actively in the market than women.[19] This result replicates in our experimental setting the field data results of Barber and Odean (2001). The estimates in Table 3 also suggest there is no significant association between miscalibration or self-monitoring and trading frequency.[20] The lack of association between miscalibration (as measured by our method of confidence intervals) and trading frequency has also been found in field data (Glaser and Weber, 2003).

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[17] For the sake of comparison, the second column of Table 2 presents the results of the profit regression for the first treatment sample without splitting it according to the occurrence of winner's curse traps.

[18] Note however that, using a different statistical approach for Finnish individual traders, Grinblatt and Keloharju (2001) find that gender is unrelated to the propensity to sell.

[19] For completeness, we also ran the regression, as in the analysis of trading profits, separately for the first treatment, and splitting the sample according to the occurrence of winner's curse traps. The signs of the coefficient estimates are unchanged across specifications.

[20] We also ran the regression separately for the male and female subsamples. In both cases we found that overconfidence did not increase trading activity. While self monitoring is not significantly related to trading activity in the male sample, it significantly increases it in the female sample.

It should be noted that the nature of transaction costs differs in our analysis and in Barber and Odean (1997). In their analysis, transaction costs are imputed by the researchers to each trade. Hence there is a mechanical link between trading frequency and costs. In the present paper, transaction costs arise endogenously because of winner's curse effects. Hence there is no mechanical link between trading frequency and costs. Thus, the same stylised fact, namely that men trade more than women, has different consequences for transaction costs and thus trading performance in their analysis and ours.

While we find no direct consequence of gender on miscalibration or trading performance, a more complex relationship between psychological variables, gender and performance may exist. Figures 5 and 8 suggest that psychological variables affect performance for men, not for women. To analyse this issue further, we ran the regression of trading profits onto psychological variables separately for male and female participants. The estimates are in Table 4.

The first column presents the estimates for the basic specification. Miscalibration significantly reduces the trading profits of men (the point estimate is -465.12, with a t-statistic of -3.7), while the positive impact of self-monitoring on profits is not significant (the point estimate is 184.68, with a t-statistic of 1.7). The results obtained in the female subsample are quite different: the coefficients of miscalibration and self-monitoring are much smaller (-149.47 and -32.56 respectively), and both are insignificant (the t-statistics are -1.49 and -0.34 respectively). The two middle columns of the table present the results obtained for the first treatment subsample and the second treatment subsample. In both cases, miscalibration significantly hurts men, not women.[21] The last two columns of Table 4 document the different reaction of men and women to winner's curse traps. The psychological characteristics of male participants strongly influence their reaction to winner's curse traps, which is reflected by high t-statistics for the psychological variables, and relatively large adjusted R^2. In contrast, the trading performance of female participants facing winners' curse traps is not significantly affected by the psychological variables.

To summarize: while men and women do not significantly differ in terms of miscalibration,

[21] One of the reasons why the effect of psychological variables is weaker in the second treatment data, pooling the two genders maybe that, in that subsample, the proportion of women (56%) is larger than in the subsample corresponding to the first treatment (35%).

their propensity to act on their miscalibrated beliefs is different, and this leads to different patterns of trading performance.

4.4) Intelligence

For 42 participants from the Masters in Finance at Toulouse University, IQ measures were available (as they were used to select the students for the program). This offers an opportunity to study if there are links between the psychological characteristics we analyse, gender, trading performance and IQ. For example, one can study if cognitive abilities, such as calibration, matter in the game because they are a proxy for general intelligence. To conduct this analysis, we regressed trading profits onto psychological characteristics and IQ measures. Since, as shown above, men and women behave differently in the game, we estimated the regressions separately for the two genders. The results are in Table 5. Even after including IQ measures, miscalibration significantly reduces trading performance for men, but not for women. This points to the robustness of our results and the unique role played by miscalibration for male performance in the experimental financial market. The estimates in Table 5 suggest that IQ does not impact significantly the performance of men. For women, the point estimate is significant and rather large, and the t-stat (weakly) suggests that higher intelligence may enhance the performance of female participants. We find the complex pattern of results obtained for men and women to be intriguing, and of similar complexity to those obtained by Gysler, Kruse and Schubert (2002) in their experimental study of gender differences in miscalibration, ambiguity and risk aversion. This suggests that further research and more systematic data collection could shed interesting light on the issue of gender, psychological characteristics and economic performance.

4.5) Call and continuous markets

Our experimental market includes a call batch auction and a continuous limit order market. The data used for the first version of this paper was collected in the context of an experimental market starting with an opening call auction and then continuing with a continuous market. We chose this market structure because it is similar to that of many of the major stock exchanges in the world: Eurex in Frankfurt, Euronext in Paris, Brussels and Amsterdam, or SETS in London.

The estimates of the regression of trading profits onto psychological variables and gender for this first experimental treatment are in the first two columns of Table 6. The coefficients of the psychological variables are large and significant in the call market, and smaller and insignificant in the continuous market. Two effects could contribute to this difference:

i) The call auction in the first experimental treatment is at the opening of the market, where the uncertainty about the value of the asset is maximal. It could be that the impact of psychological traits on trading performance is stronger when there is more uncertainty.

ii) The call market involves different thought processes than the continuous market. In the former, traders have to reason about the order placement strategies of the others and about the determination of transaction prices by the confrontation of supply and demand curves. The continuous market is much simpler. There is no uncertainty about the transaction price, which is simply the price of the limit order chosen by the participant who placed it, and observed by the others. When they decide to initiate a trade, by hitting a limit order, participants do not have to imagine the orders that have been placed by the others, they can observe them directly. Thus, the call auction is cognitively more demanding than the continuous market. This could be why psychological variables matter more in the former than in the latter.

To test which of these two effects was at the root of the results we obtained, we collected new data in a second experimental treatment, where the market opened with a continuous auction and closed with a call auction. If the difference between the call and continuous markets observed in the first treatment reflected the sequencing of these mechanisms (explanation i)), we should observe a reversal of the results in the second treatment: psychological variables should have greater and more significant coefficients in the opening continuous market than in the closing call auction. If the difference was due to the difference in cognitive demands between the two markets (explanation ii)), we should obtain similar results in the second treatments as in the first one.

The four columns of Table 6 presents the estimates of the regression of trading profits on our two psychological variables and on gender in the four possible market settings: opening call, ensuing continuous market, opening continuous market, closing call.

There is no strong reversal of the results, i.e., it is not the case that, in the second treatment, psychological variables matter in the opening continuous market and not in the closing call auction. The point estimate of the coefficient of overconfidence in the call auction is only slightly lower (in absolute value) in the second treatment (-245.55) than in the first (-281.94). The point estimate of the coefficient of overconfidence in the continuous market is larger (in absolute value) in the second treatment (-115.15) than in the first (-76.33), but it remains lower than in the call auction. Lower significance of the estimates in the second treatment can in part be due to the smaller number of observations.

To summarise: our results suggest that the impact of psychological variables is greater in the call auction because it is a more complex trading mechanism. The impact of the psychological variables in the call auction is magnified at the opening, because price discovery has not been achieved and uncertainty is large.

5) Conclusion

This paper experimentally analysed the consequences of psychological variables for financial behaviour. We focused on two psychological traits which have been extensively studied in experimental and social-personality psychology. Miscalibration is a form of judgemental overconfidence consisting in overestimation of the precision of one's information. Self-monitoring is a form of attentiveness to social cues. Using psychological questionnaires, we measured these two variables for 245 participants and also observe their behaviour in an experimental financial market. In this experimental market, similar to that analysed by Plott and Sunder (1988), the true value of the asset can be high (490), medium (240) or low (50) and traders receive heterogeneous private signals which enable them to rule out one of the three values.

We formulated two hypotheses: we expected miscalibrated traders, underestimating the conditional uncertainty of the asset value, to be especially vulnerable to the winner's curse. We also expected high self-monitors to behave strategically and achieve superior results. Empirically, we found that miscalibration reduces and self-monitoring enhances trading performance. We identified situations where winner's curse effects should be particularly severe. These arise when the price is close to 240, but the true value isn't. In such circumstances, traders with private signal "not 50" or "not 490" will fall in a winner's curse trap if they overconfidently believe that the true value is 240. We find that miscalibrated participants obtain lower profits in such circumstances. In contrast high self-monitors succeed in avoiding these winner's curse traps, consistent with the hypothesis that self monitoring facilitates game theoretic reasoning. Our experiment offers an opportunity to study the relationships between gender, psychological variables and trading performance. Men are not found to be more miscalibrated than women. On the other hand, while psychological characteristics do no significantly affect the profits of female participants, miscalibration significantly reduces the performance of men.

Both psychologists (e.g. Taylor and Brown, 1988) and economists (e.g. Bénabou and Tirole, 2003) have argued that positive illusions such as inflated self-esteem and optimism may lead individuals to attain better outcomes, for example through motivating them to work harder and persist when the going gets tough.[22] However, our experimental results suggest that realism can produce more positive outcomes in market situations in which agents compete and where perspicacity and accuracy in judgment may count for more than motivation and persistence. This is in line with psychological studies which show that realism facilitates performance when accuracy of judgment is important for selecting successful effort investment strategies (Försterling and Morganstern, 2002). Similar findings have been obtained in economic domains. For example, Fenton O'Creevy et al. (1998) measured the illusion of control of traders working in London-based investment banks through their tendency to overestimate their ability to influence the movement of a point on a screen which they in fact did not control. They found that traders prone to this form of illusion of control were indeed judged by their desk managers to earn less. A similar demonstration of the negative effect of inflated self-assessments on economic performance comes from Camerer and Lovallo's (1999) experimental finding that being led to overestimate one's chances of success on a new venture relative to others leads to excessive market entry and financial losses. Finally, using field data, Landier and Thesmar (2003) show that firms started by optimistic entrepreneurs (who have a higher tendency to overestimate their firm's chances of success relative to others in the same business category) tend to grow less, die sooner and be less profitable. In sum, the markets studied seem to punish – not reward – miscalibration and positive illusions.

[22] See also Aspinwall and Taylor (1992) and Murray and Holmes (1997).

Our methodology, which involves directly 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. For example, it could be interesting in future work to study when, why and how particular forms of overconfidence will influence economic behaviour. For example, Glaser and Weber (2003) find that frequency of trading in their field data is predicted by measures of the better-than-average effect but not by miscalibration. In addition, we suggest that high self-monitors were more successful in our experimental market because they are better able to engage in game-theoretic reasoning, and in particular to anticipate the link between the signals of the other players and their actions. It would be interesting to investigate further the relation between self-monitoring and the ability of players to estimate the correlation between the actions of others and their information. Indeed, as shown theoretically by Eyster and Rabin's (2003), underestimation of this correlation leads to winner's curse and trade in adverse-selection settings where conventional analysis predicts no trade. An interesting avenue of research would also be to consider other traits than those analysed in the present paper.[23] Finally, another promising direction would be to study how different market structures moderate or exacerbate the consequences of psychological characteristics.[24] Systematic studies to answer these questions could help yield a body of knowledge able to complement classical mechanism design based on insights from behavioural game theory, in the spirit of Camerer (1997).

[23] 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 analysis. 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, or on the theoretical analysis of confirmatory bias offered by Rabin and Schrag (1999). Hirshleifer (2001) discusses several psychological biases in relation with financial markets.

[24] 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.

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Table 1: Summary statistics on the behaviour of the participants in the trading game
Average across the four replications of the game

	Minimum	First quartile	Median	Third Quartile	Maximum
Quantity posted during the call	0	5	11	34	227
Quantity posted during the continuous market	0	1	2	4	21
Execution ratio during the call	0	3%	16%	34%	100%
Execution ratio during the continuous market	0	50%	70%	89%	100%
Trading profits during the call	-1660	-10	0	145	2900
Trading profits during the continuous market	-1879	-79	0	78	1083

Table 2:
Regression of trading profits onto psychological traits and control variables

(t stat are in parenthesis)

	Total trading profits (All data)	**Total trading profits (1st treatment only)**	**Total trading profits for participants who never faced a winner's curse trap (1st treatment only)**	**Total trading profits for participants who faced at least one winner's curse trap (1st treatment only)**
Miscalibration	-359.32 (-4.06)	-361.58 (-3.54)	-75.24 (-0.63)	-618.39 (-3.67)
Self-monitoring	123.33 (1.57)	169.89 (1.67)	-89.86 (-0.68)	292.38 (1.91)
Gender (1 for woman)	-5.75 (-0.15)	11.06 (0.20)	-23.00 (-0.35)	23.49 (0.25)
Adjusted R2	6.52%	6.47%	0 %	16.74 %
Number of observations	245	182	98	84

Note: For these analyses we consider a winner's curse trap to exist where the call price is close to 240 but the value is 50 or 490, and the participant's private signal does not rule out 240.

Table 3:
Regression of trading activity onto psychological traits and control variables

(t stat are in parenthesis)

	Total quantity posted (All data)	Total quantity traded (All data)	Total quantity traded (1st treatment only)	Total quantity traded by participants who never faced a winner's curse trap (1st treatment only)	Total quantity traded by participants who faced at least one winner's curse trap (1st treatment only)
Miscalibration	-9.57 (-1.51)	-1.5 (-1.06)	-1.61 (-0.88)	-1.50 (-0.77)	-0.61 (-0.19)
Self-monitoring	6.23 (1.11)	1.67 (1.25)	2.75 (1.51)	0.15 (0.07)	4.81 (1.63)
Gender (1 for woman)	-8.73 (-3.08)	-1.3 (-2.06)	-1.8 (-1.79)	-1.58 (-1.48)	-2.40 (-1.32)
Adjusted R2	4.92%	2.3%	2.6%	0%	2.52%
Number of observations	245	245	182	98	84

Note: For these analyses we consider a winner's curse trap to exist where the call price is close to 240 but the value is 50 or 490, and the participant's private signal does not rule out 240.

Table 4:
Regression of trading profits onto psychological traits and control variables for men and women separately

(t stat are in parenthesis)

	Total trading profits (All data)		Total trading profits (1st treatment only)		Total trading profits (2nd treatment only)		Total trading profits for participants who never faced a winner's curse trap (1st treatment only)		Total trading profits for participants who faced at least one winner's curse trap (1st treatment only)	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**	**Men**	**Women**
Miscal.	-465.12 (-3.70)	-149.47 (-1.49)	-465.54 (-3.31)	-155.39 (-1.38)	-631.43 (-2.2)	-87.91 (-0.34)	-50.78 (-0.30)	-108.09 (-0.73)	-776.99 (-3.61)	-204.90 (-1.06)
Self-monit.	184.68 (1.71)	-32.57 (-0.34)	251.29 (1.94)	-107.94 (-0.80)	-103.09 (-0.6)	55.36 (0.41)	-73.52 (-0.44)	-140.95 (-0.67)	390.59 (2.07)	-64.80 (-0.32)
Adj. R2	9.44%	0.34%	9.58%	0.85%	9.8%	0	0	0	23.12%	0
Number of obs.	151	94	123	59	28	35	64	34	59	25

Note: For these analyses we consider a winner's curse trap to exist where the call price is close to 240 but the value is 50 or 490, and the participant's private signal does not rule out 240.

Table 5:
Regression of trading profits onto Miscalibration, self-monitoring and IQ
For men and women

(t stat are in parenthesis)

	Male participants	**Female participants**
Miscalibration	-852.12 (-1.98)	-70.89 (-0.24)
Self-monitoring	753.35 (1.53)	434.53 (1.2)
IQ	-82.44 (-1.01)	137.90 (1.69)
Adjusted R2	19.79%	7%
Number of observations	26	16

Table 6: Regression of trading profits onto psychological traits and control variables in various market structures

(t stat are in parenthesis)

	Trading profits (1^{st} treatment only)		**Trading profits (2^{nd} treatment only)**	
	Opening Call Auction	**Ensuing Continuous market**	**Opening Continuous Market**	**Closing Call Auction**
Miscalibration	-281.94 (-3.09)	-76.33 (-1.24)	-115.15 (-1.32)	-245.55 (-1.76)
Self-monitoring	197.41 (2.19)	-25.04 (-0.41)	5.64 (0.12)	-1.02 (-0.01)
Gender (1 for woman)	20.06 (0.40)	-9.09 (-0.27)	-21.01 (-1.16)	-16.96 (-0.59)
Proportion of signals equal to “not 240”	-437.67 (-1.96)	353.14 (2.34)	–	–
Adjusted R2	7.72%	1.42%	1.60%	1.53%
Number of observations	182	182	63	63

Appendix 1:
Instructions to the participants 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 maximise 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, subtract 95000 to this sum, and divide the result by 3000.

Appendix 2:
Measuring the psychological traits

Miscalibration

	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 participant 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.		

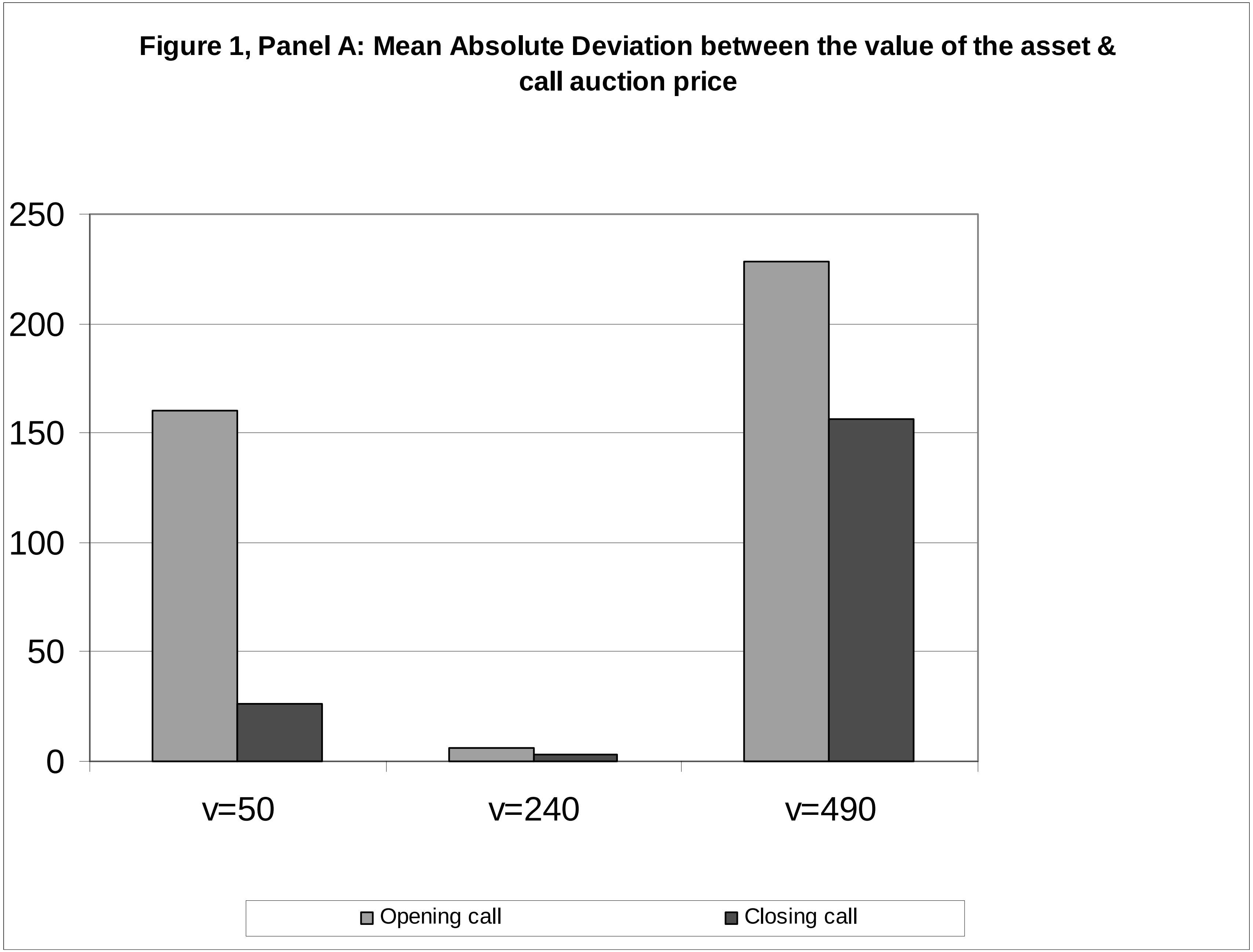


Figure 1, Panel A: Mean Absolute Deviation between the value of the asset & call auction price
250
200
150
100
50
0
v=50
v=240
v=490
Opening call
Closing call

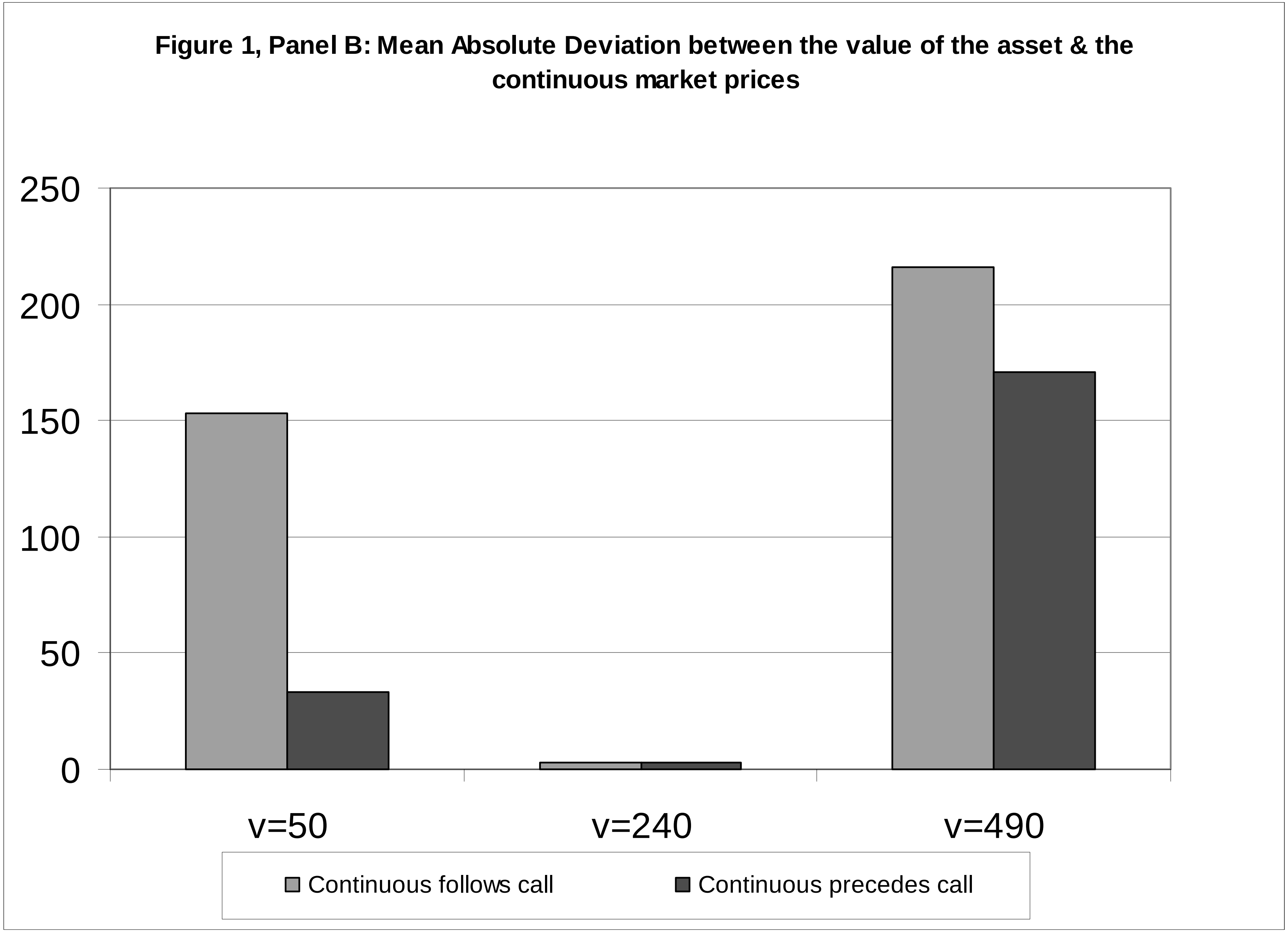
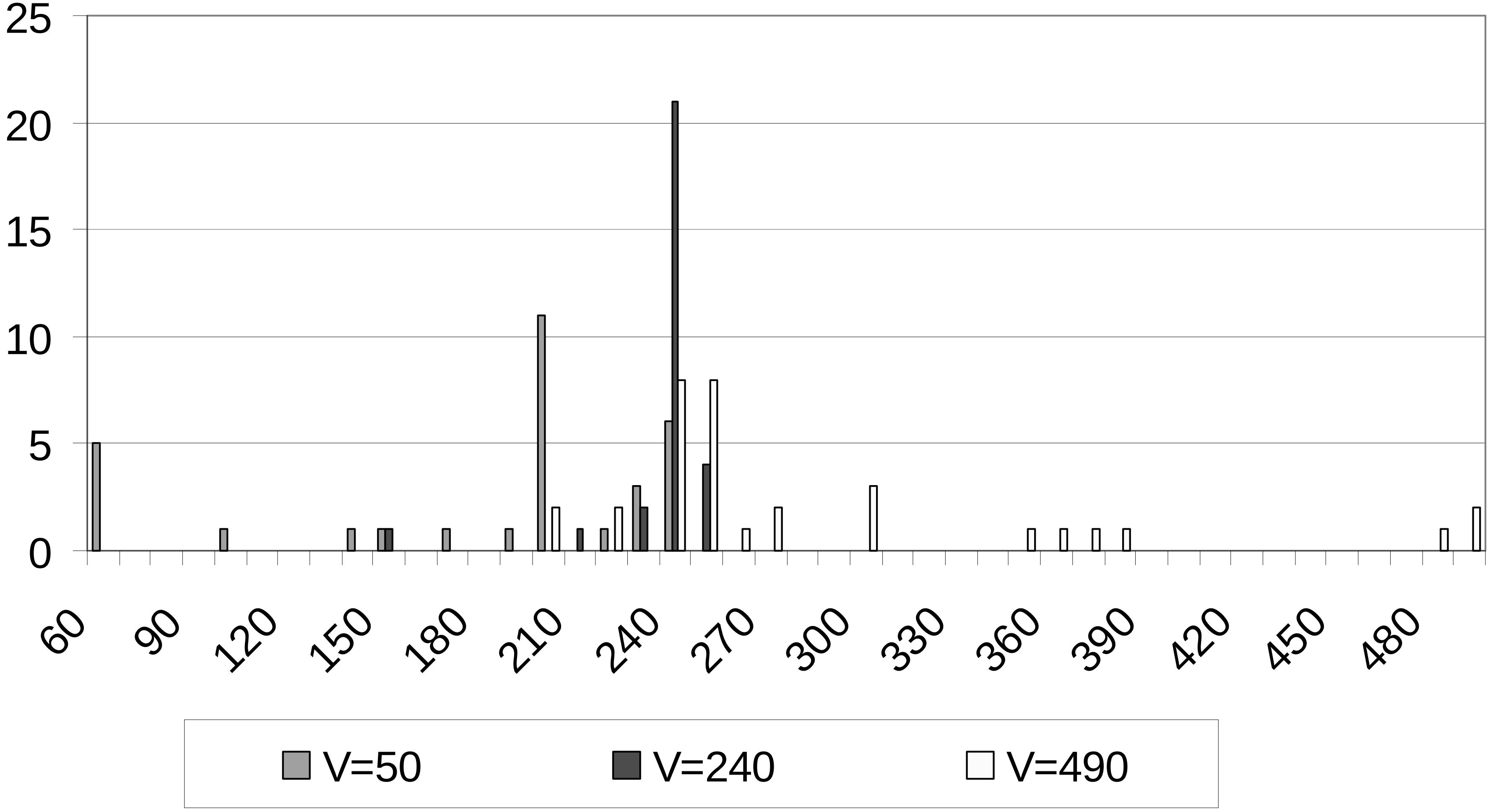


Figure 1, Panel B: Mean Absolute Deviation between the value of the asset & the continuous market prices
250
200
150
100
50
0
v=50
v=240
v=490
Continuous follows call
Continuous precedes call

Figure 2, Panel A: Frequency of call auction prices, for different final values



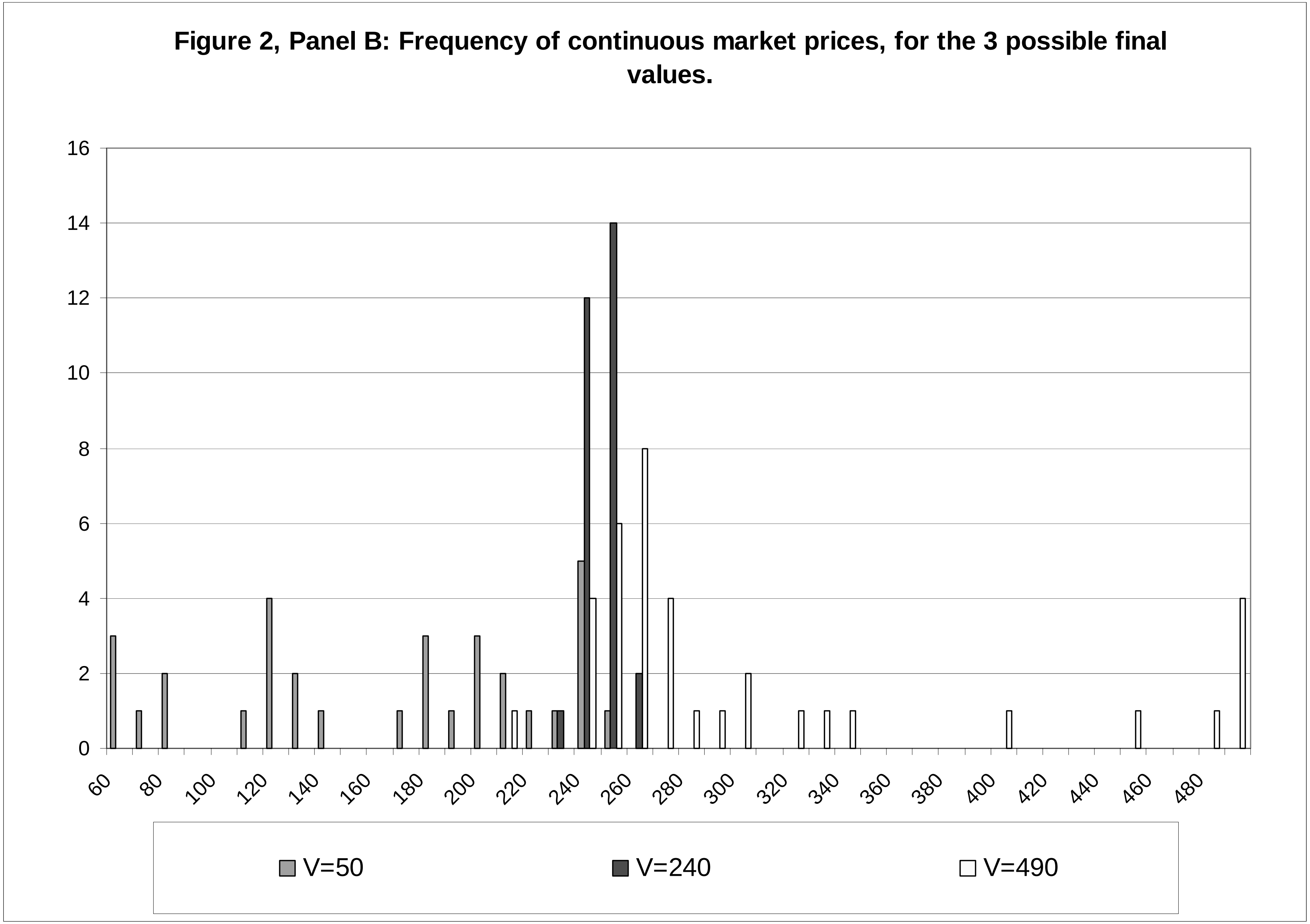


Figure 2, Panel B: Frequency of continuous market prices, for the 3 possible final values.
16
14
12
10
8
6
4
2
0
60
80
100
120
140
160
180
200
220
240
260
280
300
320
340
360
380
400
420
440
460
480
V=50
V=240
V=490

Figure 3: Average trading profits for each miscalibration quartile.

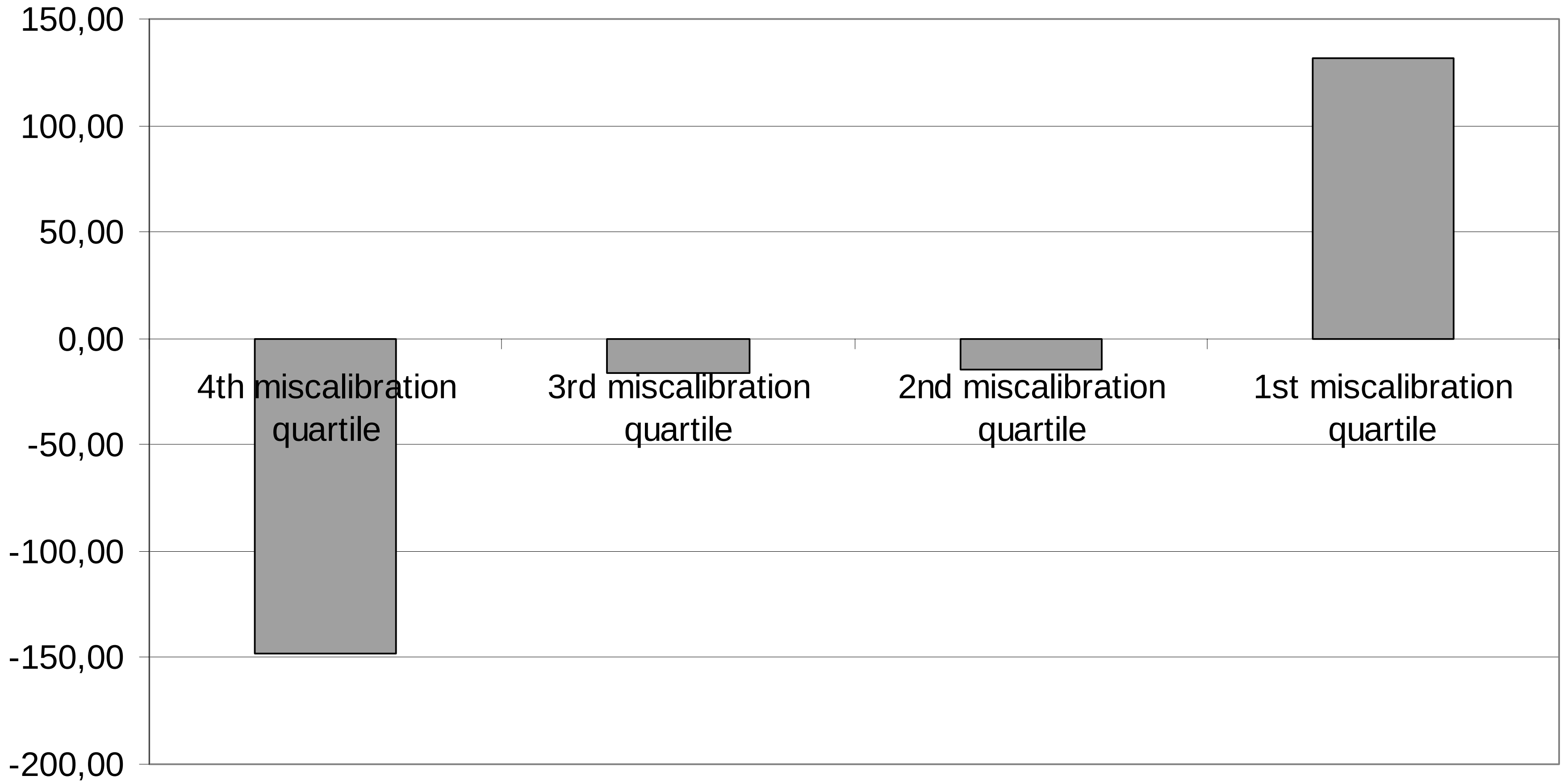


Figure 4: Average for each miscalibration quartile, in each of the 3 sub-samples

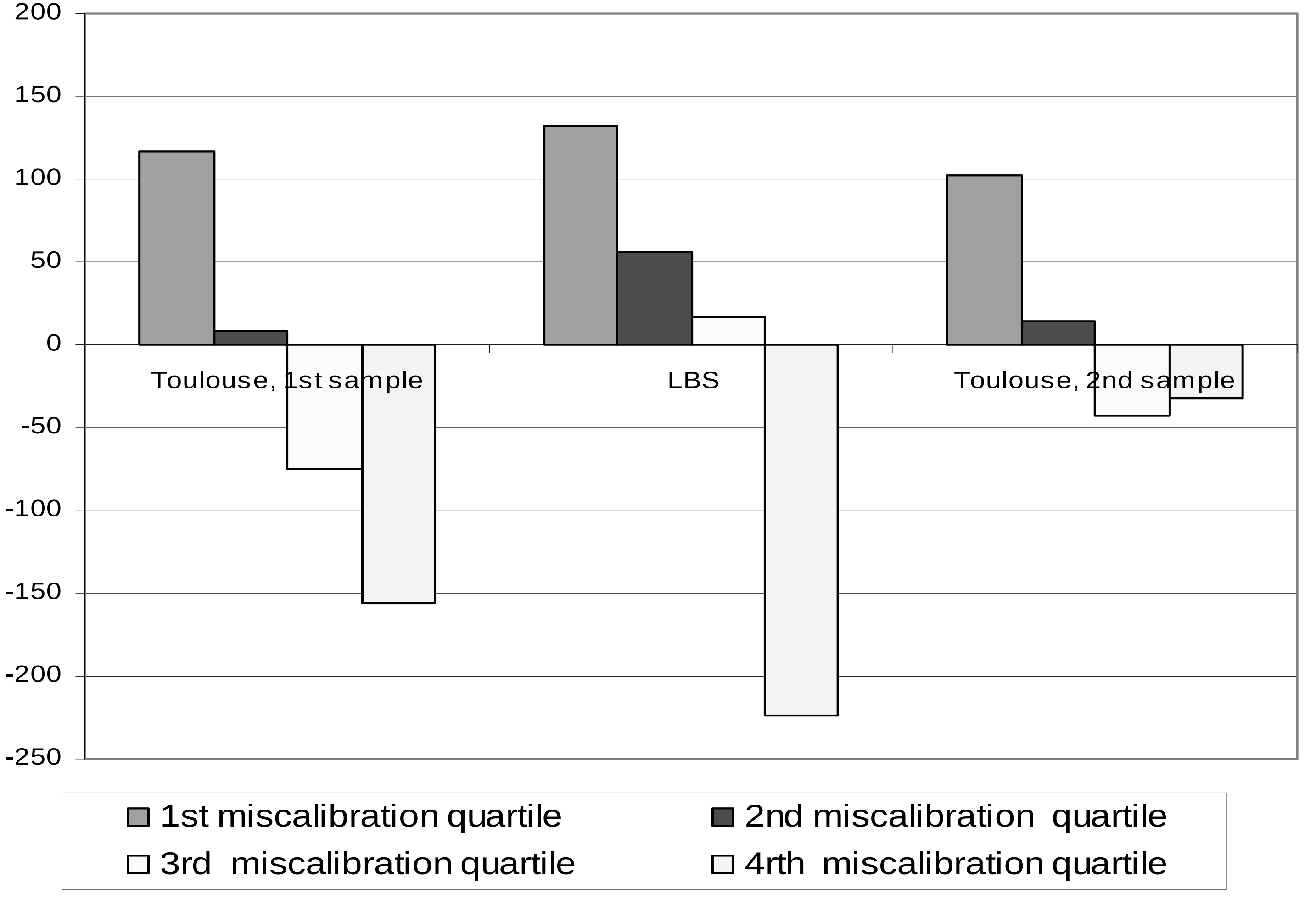


Figure 5: Average earnings of each miscalibration quartile, by gender

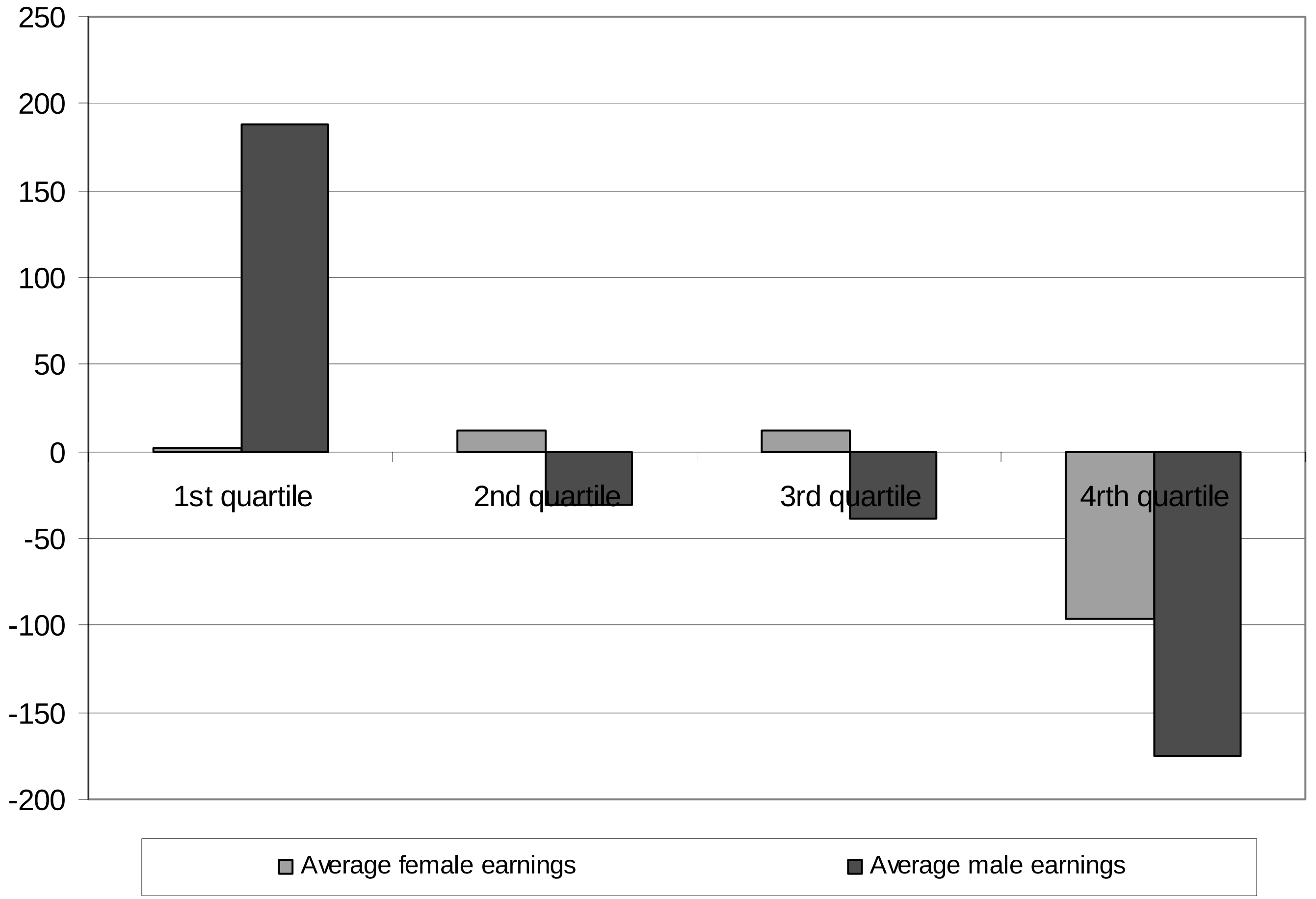


Figure 6: Average trading profits for each self-monitoring quartile.

Figure 7: Average trading profit of each self-monitoring quartile in the three subsamples

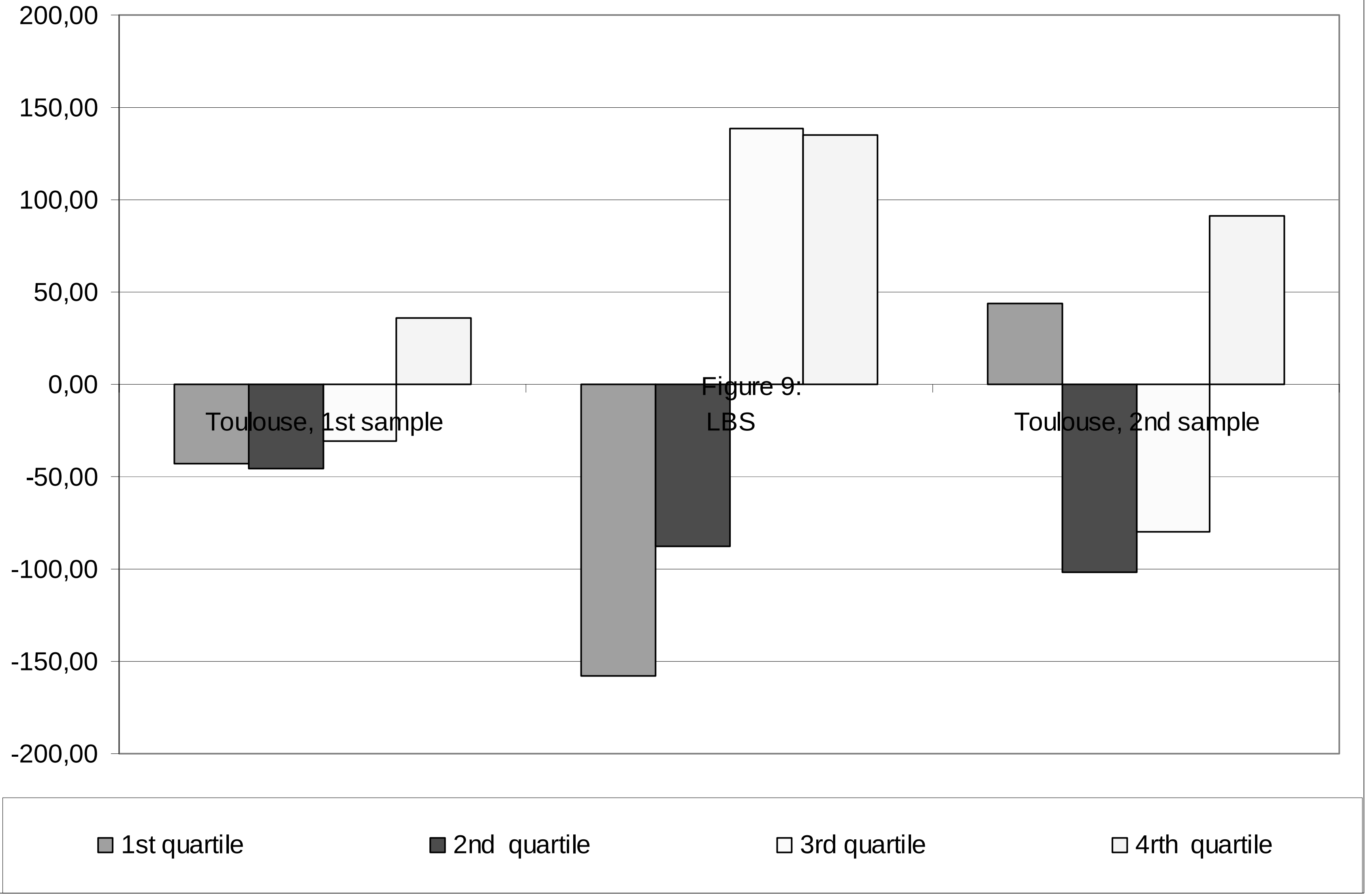


Figure 8: Average earnings of each self-monitoring quartile, by gender