



Munich Personal RePEc Archive

Overconfidence, Risk Aversion and Individual Financial Decisions in Experimental Asset Markets

Michailova, Julija

Helmut Schmidt University

2010

Online at <https://mpra.ub.uni-muenchen.de/53114/>
MPRA Paper No. 53114, posted 22 Jan 2014 14:33 UTC

Overconfidence, Risk Aversion and Individual Financial Decisions in Experimental Asset Markets

Julija Michailova¹

*Department of Economics, Helmut Schmidt University, Holstenhofweg 85,
22043 Hamburg, Germany*

Phone: +494065413401

Fax: +494065412043

E-mail: julija_michailova@yahoo.com

Abstract

We investigate the influence of overconfidence and risk aversion on individual financial decision making in the experimental asset markets of the Smith, Suchanek and Williams (1988) type, with no informational asymmetries. Subjects, based on their pre-experimental overconfidence scores, were assigned to the two types of markets: least overconfident subjects formed five “rational” markets and most overconfident subjects formed five “overconfident” markets. The asset market experiment was followed by post hoc risk aversion measurement. Our results revealed that in the suggested setting, performance and trading activity were overconfidence dependent only for female participants. Mistakes in price forecasting, that are negatively correlated with overconfidence, could partially account for the increase in trading activity and losses. In the decreased sample differences in individual outcomes were overconfidence and not risk aversion driven.

Keywords: overconfidence; miscalibration; overprecision; risk aversion; financial decisions; economic experiments

¹ Corresponding author.

1. Introduction

By allowing psychological bias [...] to affect their investment decisions, investors can do serious harm to their wealth (Baker and Nofsinger 2002:98). In this paper we experimentally investigate the influence of two behavioral factors, namely the degree of overconfidence and risk aversion, on financial decision making of economic subjects.

Overconfidence is one of the biases that have potential importance for financial decision taking (Kahneman and Riepe 1998). In the experimental finance literature the term overconfidence is used to refer to a group of effects, including miscalibration, the better than average effect and illusion of control. Moore and Healy (2008) name it subsequently overprecision, overplacement and overestimation. Miscalibration (overprecision) suggests that individuals overestimate the precision of their knowledge (cf. Lichtenstein et al. 1982). The better than average effect (overplacement) occurs when a person tends to believe she possesses the above average abilities (cf. Taylor and Brown 1988). Illusion of control is linked to the exaggeration of the degree to which one can control one's fate (cf. Langer 1975). Overestimation is not a one-to-one mapping of Langer's illusion of control, since alongside exaggeration of the level of control and chances of success it also includes overestimation of the one's actual ability and performance (cf. Moore and Healy 2008). In this paper overconfidence is operationalized as miscalibration (overprecision).¹

Interest in the topic of economic consequences of investors' overconfidence generated a large body of literature. Research findings suggest that in investors overconfidence can result in trade aggressiveness (Glaser et al. 2004; Deaves et al. 2009), portfolio undiversification (Odean 1999), pursuit of the active portfolio management strategy (De Bondt and Thaler 1994) and suboptimal performance (Fenton-O'Creevy et al. 2003; Barber and Odean 2000, 2001). Moreover, overconfident investors underestimate risks (Russo and Shoemaker 1992; Croson and Gneezy 2008) and thus take more risks in comparison to rational traders (Glaser et al. 2004; Lakonishok et al. 1992).

Most of the foregoing empirical and experimental research was focused on the analysis of the "mixed" markets where both more and less overconfident (rational) traders interact (cf. Glaser and Weber 2007; Menkhoff et al. 2013). Moreover experimental work of this type also supplied different kinds of players with asymmetric information (e.g. Biais et al. 2005; Kirchler and Maciejovsky 2002), to test the hypothesis that overconfident subjects were "fooled in" to trade more actively by the belief in the better quality of their information, and that less overconfident (rational) subjects took advantage of it. However Deaves et al. (2009) demonstrated that

overconfidence induced trade increase also in the markets with asymmetric information that consisted of only one type of players (more or less overconfident). This finding raises a question: is it actually asymmetric information or overconfidence that produces trade increase. To disentangle these effects, we expand on the work of Deaves et al. (2009) and test the experimental hypotheses in “pure” markets but remove the informational asymmetries. To analyze the possible ways how individual overconfidence might translate in differences in individual behavior we also control for individual risk aversion and future price expectations.

Based on their pre-experimental overconfidence scores, our subjects were divided in two groups: the most overconfident and the least overconfident; for our convenience these participants are subsequently called rational and overconfident. Of them five “overconfident” and five “rational” markets were constructed. At the completion of the market experiment, a sample of former participants was invited for risk aversion measurement. Our main results can be summarized as follows: In the setting with no informational asymmetries and where the two “types” of subjects were separated, performance and trading activity were overconfidence dependent only for females. More overconfident subjects were significantly worse at price forecasting, and mistakes in price predictions were paired with losses. Finally, differences in individual outcomes were overconfidence and not risk aversion driven.

Paper proceeds as follows. Section 2 presents a brief review of related research and contribution of this paper. Section 3 lists the research hypotheses. Section 4 provides the description of experimental design. Section 5 describes the results. Finally Section 6 concludes.

2. Related research

This paper builds on several previous experiments that investigate the effect of overconfidence on subjects’ trading activity and performance in the context of the asymmetric information trading game: Biais et al. 2005, Kirchler and Maciejovsky 2002, and Deaves et al. 2009.

The study of Biais et al. (2005) focused on determining the link between subjects’ psychological characteristics and their earnings in the experimental financial markets. They presented evidence of the negative association between overconfidence and traders’ performance; yet it had a more significant effect on males’ performance. In their sample overconfidence did not lead to increased individual trading activity. Kirchler and Maciejovsky (2002) run experimental asset market to investigate the development of the market-level overconfidence in the course of experiment. Prior to opening of the market sessions, subjects’ risk aversion measurement was implemented. In their study overconfidence was negatively correlated with individual earnings.

They found no difference between different experimental groups in terms of risk aversion, and concluded that any distinctions between the outcomes were not risk-attitude dependent. Both Biais et al. (2005) and Kirchler and Maciejovsky (2002) constructed “mixed” markets, consisting of both more and less overconfident (rational) traders, and assumed that the latter group was more accurate in perceiving the uncertainty of their private signals and took advantage of the former, who overestimated the precision of their signals.

Experiment of Deaves et al. (2009), which tested the impact of overconfidence and gender on trading activity, utilized “pure” market setting. Namely they run four sessions to which subjects were assigned based on their degree of overconfidence: two high and two low overconfidence markets. To discover the impact of gender, they also run four sessions to which subjects were assigned based on their gender. In their experiment overconfidence led to enhanced trading activity and had negative effect on trading performance. No connection between overconfidence, trading activity and gender was detected.

Based on the analysis of the previous research our experimental design, presented in the Section 4, was created with the following considerations in mind:

As already mentioned, in all three experiments participants were supplied with asymmetric pieces of information. E.g. in the experiment of Kirchler and Maciejovsky (2002) half of the participants had no information about the dividend distribution, and the other half had complete information. Subjects of Biais et al. (2005) received three different types of private signals: bullish, bearish, and neutral. Deaves et al. (2009) also supplied their participants with signals of different quality and tried to manipulate subjects’ beliefs to make them think that their signals were more accurate than these of the other subjects. In our opinion, this approach does not allow disentangling the effect of overconfidence on trade increase from the effect of informational asymmetries.

Following the examination of instruments used in prior research to assess subjects’ miscalibration, there were good reasons to suspect that these instruments did not offer comprehensive measurement of individual overconfidence. First, following the work by Russo and Schoemaker (1992), the abovementioned authors used interval elicitation tasks to assess overconfidence. Yet Klayman et al. (1999) argue that interval estimation tasks are prone to produce extreme overconfidence levels. Second, findings from psychological research indicate that overconfidence is most pronounced for hard questions (the right answer is known to a few persons) and least pronounced for the easy questions (the right answer is known to many persons) (cf. Lichtenstein et al. 1982). However, items’ difficulty was not assessed in the

foregoing research, and utilized scales were not pre-tested prior to their application for experimental measurements.

3. Hypotheses

Empirical and experimental findings obtained from “mixed” market setting suggest that overconfident traders engage in trade more actively and as a consequence incur losses (cf. Barber and Odean 2001; Glaser et al. 2004), i.e. they are outperformed by low turnover traders (cf. Barber and Odean 2000). Taken together, these results generate two hypotheses:

Hypothesis 1: Individual trading activity increases with an increase in overconfidence.

Hypothesis 2: Relationship between individual gains and trading activity is negative.

In empirical studies and experimental markets where overconfident and rational traders interact, higher degree of traders’ overconfidence reduces their welfare (e.g. Barber and Odean 2001; Nöth and Weber 2003; Biais et al. 2005; Kirchler and Maciejovsky 2002). In line with these results, we advance a hypothesis:

Hypothesis 3: Individual gains decrease with the greater degree of overconfidence.

Empirical evidence suggests that risk attitude affects trading behavior. Higher risk propensity is accompanied by an increase in trade frequency (Durand et al. 2008; Markiewicz and Weber 2013) and higher risk aversion manifests itself through lower market activity (Fellner and Maciejovsky 2007). Risk loving individuals are found to be more willing to invest in stocks (Keller and Siergist 2006) and engage in speculative activity (Camacho-Cuena et al. 2012). With the above discussion in mind, and based on the finding by some of the previous authors that more active traders were also more overconfident (e.g. Barber and Odean 2001; Glaser et al. 2004) we suggest testing the following hypotheses:

Hypothesis 4: Overconfident subjects are (more) risk loving.

Hypothesis 5: Trading activity is negatively dependent on the degree of risk aversion.

If on average subjects had the same degree of risk aversion then their final holdings of assets would be approximately the same (cf. Lei et al. 2001). However, as dividend value changes in a probabilistic manner from period to period, each stock could be perceived as some sort of the lottery by players. Participants who like risk less would try to sell their assets at the early stages of the experiment; on the contrary, more risk-loving subjects would try to acquire more asset items.

Hypothesis 6: The size of the final portfolio negatively depends on individual risk aversion.

Finally, we want to analyze one possible way how individual overconfidence might translate in higher trading volume and possible losses. Since individual overconfidence is negatively associated with accuracy, we want to test whether more overconfident subjects are less successful (accurate) in price forecasting task. Moreover, could these errors induce false future price expectations and cause mistakes in financial decisions, which result in more active trading and eventually in losses. E.g. in the experiment by Smith et al. (1988) better forecasters have indeed enjoyed higher gains from trade in the experimental market.

Hypothesis 7: More overconfident subjects are less accurate in their price forecasts.

Hypothesis 8: Less accuracy in price forecasts leads to more trading activity.

Hypothesis 9: Less accuracy in price forecasting leads to lower individual gains.

4. Experimental design

4.1. Overconfidence measurement

The under- or overconfidence of potential participants was measured in three pre-experimental psychological test sessions. For that purpose a specially created instrument was used. This instrument asked subjects to complete a quiz consisting of 18 general knowledge questions and state how confident they were in the correctness of each answer. For this purpose any number from 33% (complete uncertainty) to 100% (complete certainty) could be used. Each question had three alternative answers, only one of which was right. Subjects competed for the three prizes based on test accuracy. Individual overconfidence was assessed as the difference between subject's mean confidence and accuracy across all questions. The obtained measure is called a bias score (BS). The positive BS indicates overconfidence, and the negative BS underconfidence; a zero-BS indicates perfect calibration. For the participation in the experimental asset markets the least overconfident and the most overconfident subjects were invited. Of them two types of markets were constructed (rational and overconfident), and in the course of the experiment subjects interacted only with other subjects of their own type. A brief note on the creation of the overconfidence measurement instrument follows.²

In comparison to previous experiments several steps were taken to improve overconfidence measure. Instead of confidence intervals another test format was chosen, namely discrete propositions with multiple-choice alternatives. Then the instrument was balanced for the hard-easy effect, controlling for gender and country bias. For that a pilot study was performed to

assess difficulty of the 50 initial items, selected from the German quiz-page <http://wissen.de>. Each question had three alternative answers, only one of which was right. Questions' difficulty was assessed based on the group accuracy: 0-33% accuracy hard questions, 34-66% medium difficulty, 67-100% easy questions. Second, based on the analysis of the pilot-test outcomes, a final test was constructed from 18 questions of the three difficulty levels: six hard, six medium and six easy items. Instrument was again pre-tested with the second group of participants, and its reliability was assessed via Cronbach's alpha: $\alpha_{confidence} = 0.79$ and $\alpha_{bias\ score} = 0.68$.

4.2. Asset market experiment

The experiment was conducted using 60 students of social sciences from the Christian-Albrechts University of Kiel. Thirty five males and 25 females, aged 19 to 28 participated in ten computerized market sessions. Experiment was programmed with the software z-Tree (Fischbacher 2007). One session lasted approximately 1 hour and 40 minutes, and subjects earned on average 390.36 units of experimental currency (10.54 EUR) (excluding reward for forecasting). Overconfidence statistics of the group are presented in the Table 1.

Insert Table 1 about here

Experimental procedure was based on the pioneering work of Smith et al. (1988). Prior to the start of the experiment each subject was endowed with 300 experimental currency units (ECU) and 3 experimental asset units. Experimental market consisted of the sequence of 15 trading periods, lasting at maximum 180 seconds, during which each trader could trade in experimental assets. At the end of the trading period, each asset in participants' inventory paid a dividend with possible values of 0.0, 0.8, 2.8, or 6.0 ECU; probability of each value $p = 0.25$. 2.4 ECU was an average dividend, which subjects could expect through many draws. Thus fundamental value of one asset unit equaled $n \times 2.4$ ECU, where n is the number of periods remaining to the end of the session. Additionally, at the end of each trading period subjects were asked to predict the average market price in the next period and state confidence in their prediction. Any value between 0% (disbelief that the forecast was true) and 100% (certainty that the forecast was correct) could be used to express subjects' confidence. Participants were awarded for their predictions based on their accuracy: if forecast fell within 10% of the real price it earned 3 ECU; forecasts within 25% and 50% of the real price earned consequently 1 ECU and 0.5 ECU. Gains from the forecasting task were not added to subjects' working capital, but paid to them at the end of the experiment. At the termination of the experiment each participant was paid in cash the amount of money, which was based on her final working capital and total gains from forecasting.

4.3. Risk aversion measurement

Individual risk aversion was assessed several months after the completion of the experimental asset market. Of the 32 repeatedly recruited subjects 16 were overconfident ($OVE = 20.17$, $SD = 6.48$) and 16 rational ($OVE = 2.01$, $SD = 3.10$). Risk aversion measurement took at most 20 minutes and participants earned on average 5.73 EUR ($SD = 1.83$), including the show-up fee of 2 EUR. Risk aversion measurement procedure was based on the method of Holt and Laury (2002). Subjects made a choice between paired lotteries: Option A and B. Option A was a “safe” choice and paid either 3 EUR or 2.40 EUR; Option B was a “risky” choice and paid either 5.78 EUR or 0.15 EUR. There were ten decisions to take and each of them had equal payoffs. However, the probability of the high-payoff (low-payoff) outcome increased (decreased) in steps of 10%, until it reached 100% (0%) for the tenth decision. Total number of safe choices was used to assess individual risk aversion (cf. Holt and Laury 2002).

5. Experimental results

5.1. Univariate and bivariate analysis

Trading activity

Experimental data suggest that average trading activity (MTA), defined as the mean of transactions (purchases and sales) conducted by an individual over the session and divided by the number of shares outstanding in the market (18), was quite high. On average per session traders transacted 0.89 times the outstanding stock of shares ($SD = 0.47$). More overconfident investors engaged in trading activity more actively (Pearson correlation(58) = 0.350, $p < 0.01$, one-sided; medium correlation). No significant linear relationship between overconfidence and trading activity was found for males (Pearson correlation(33) = 0.118, $p = 0.249$, one-sided). Yet, for females the correlation coefficient is high and significant (Pearson correlation(23) = 0.635, $p = 0.00$, one-sided), i.e. with an increase in the bias score female participants engaged more actively in trading.

To test the proposition that high turnover traders are outperformed by low turnover traders, normalized profits of the participants were calculated as individual gains scaled by the initial portfolio value ($36 \text{ ECU} \times 3 = 106 \text{ ECU}$). These profits and corresponding to them average trading activity, are presented on Figure 1. Average normalized profits equaled 3.61 times the value of the initial portfolio ($SD = 1.83$).³ Correlation coefficient between trading activity and individual earnings is small but significant, implying that increased trading is paired with poorer

performance (Pearson Correlation(58) = -0.292, $p < 0.05$, one-sided); exclusion of the two outlier values increased this linear relationship (Pearson Correlation(56) = -0.456, $p = 0.00$, one-sided).

Insert Figure 1 about here

The sample was further broken in five equal sub-samples, ranked in terms of trading activity (quintiles). Individual earnings of the lowest trading quintile and the highest trading quintile were compared. Mann-Whitney test detected that the latter were significantly outperformed by the former ($Z = -1.555$, $p < 0.10$, one-sided), who earned on average 38% more ECUs at the end of the experiment. Without the two outliers this difference increased to 55.7% (Mann-Whitney $Z = -2.095$, $p < 0.05$, one-sided). This is in line with the results of Barber and Odean (2000), who revealed that high turnover households were outperformed by low turnover households.

Gains from trade

Individual performance was assessed as relative profit calculated based on Hirota and Sunder (2007) as gains from trade divided by the fundamental value of the initial portfolio of 3 stocks ($36 \text{ ECU} \times 3 = 106 \text{ ECU}$) minus the cross-sectional average of this ratio. Figure 2 depicts the cross-sectional distribution of subjects' relative profits in the two types of markets. The value of each marker represents one trader's relative profit. Overconfident markets were characterized by significantly larger dispersion of gains ($SD = 2.32$) in comparison to rational sessions ($SD = 1.19$) (Siegel-Tukey = 2.329, $p < 0.05$, two-sided).

Insert Figure 2 about here

To determine the relationship between accuracy of average price prediction and individual earnings several statistical tests were performed. Forecasting precision was expressed as the Total Absolute Error (TAE) of prediction (Equation 1) and the Average Absolute Error (MAE) of prediction (Equation 2):

$$\text{Total Absolute Error (TAE)}_i = |\text{Sum}(P_t - F_{it})| = |\text{Sum}(P_t) - \text{Sum}(F_{it})| \quad (1)$$

$$\text{Average Absolute Error (MAE)}_i = \text{Sum} |(P_t - F_{it})| / 15 \quad (2)$$

Here, F_{it} is the forecast of subject i for the period t , and P_t is the average price in period t .

Correlation between forecasting precision and relative profits was negative and significant (MAE: Pearson Correlation (58) = -0.360, $p < 0.01$, one-sided; TAE: Pearson Correlation(58) = -0.365, $p < 0.01$, one-sided). Statistically significant linear relationship between overconfidence and forecasting precision was detected (MAE: Pearson Correlation(58) = 0.350, $p < 0.01$, one-sided; TAE: Pearson Correlation(58) = 0.225, $p < 0.05$, one-sided). It can be concluded that

increased overconfidence was paired with reduction in accuracy of prediction. Based on the analysis of the average absolute forecasting error females were significantly less accurate than males in their predictions (MAE: Mann-Whitney $Z = -1,957$, $p < 0.05$, one-sided); however no difference was found upon analysis of the absolute total forecasting error (TAE: Mann-Whitney $Z = -1,035$, $p = 0.15$, one-sided).

Another factor that had negative impact on earnings was the number of assets in participants' final inventory (Pearson Correlation(58) = -0.225 , $p < 0.05$, one-sided). There was significant difference in the final portfolio size of males and females, where the former had significantly less assets than the latter (Mann-Whitney $Z = -3.121$, $p < 0.01$, one-sided).

5.2. Multivariate Analysis

Trading activity

This subsection presents results of cross-sectional regressions estimating the relationship between the average trading activity of an individual (MTA) and several explanatory variables that might affect efficiency of financial decision making: the normalized bias score⁴ (NBS), gender dummy (this variable takes value 1 if subject is male), an interaction term between the bias score and gender (NBS*Gender), subject's experience expressed as age (Age) or duration of studies (Semester), and price forecasting precision measured as average absolute error (MAE) or total absolute error (TAE). In parenthesis error terms are shown. We start with the simplest model specification; subsequently a range of alternative specifications are estimated by adding other regressors to the model. For the specifications of the estimated models see Table 2⁵.

Insert Table 2 about here

Results, presented in Table 2, led to the following conclusions 1) holding all other factors constant, impact of overconfidence on trade was positive for female participants, i.e. with an increase in overconfidence females engaged in more stock market transactions than males, and 2) forecasting errors, that induced false future price expectations, forced subjects to engage in trading more actively. Modest success in explaining variation in trading activity in the sample by means of selected models suggests that other unobserved factors that were not included in the regression, also have impact on the average number of market transactions by an individual participant. We return to this issue in the section on risk aversion analysis, where the regression model is re-estimated for a sample of participants whose risk aversion measures were obtained.

Gains from trade

This subsection presents results of cross-sectional regressions estimating the relationship between subjects' performance, assessed as relative profit, and several explanatory variables: the normalized bias score (NBS), gender dummy (takes value 1 if subject is male), average trading activity (Trading activity), an interaction term between gender and trading activity (Gender*Trading activity), subject's age (Age), the number of assets in the final inventory (End assets), and price forecasting precision measured as average absolute forecasting error (MAE) or total absolute forecasting error (TAE). In parenthesis the error terms are shown. We start again with the simplest model specification and, by adding other regressors, test which variables affect individual profit from trade. For the specifications of the estimated models see Table 3.

Insert Table 3 about here

Results presented in Table 3 suggest that 1) contrary to the formulated hypothesis overconfidence had no significant (direct) effect on individual earnings, 2) holding all other factors constant, impact of trading activity on relative profit was more negative for female participants than males, i.e. with an increase in the number of market transactions males incurred smaller losses or even some yield in comparison to females, 3) forecasting errors, that induced false future price expectations and "caused mistakes in financial decision making" (Biais et al. 2005), produced losses, 4) the number of assets in the final inventory was a significant determinant of reduction in gains. In general, the described specifications succeeded quite well in explaining variation in relative profits in the sample. Yet, the amount of unexplained variation suggests that other unobserved factors that were not included in the regression also were at play.

5.3. Risk aversion measurement: Experimental results

On average subjects were found to be risk averse with 5.66 safe choices (SD = 1.82). In general, 71.88% of choices have fallen in the interval of [5, 7] safe options. Rational subjects made on average 5.81 safe choices (SD = 1.42), and overconfident subjects 5.50 safe choices (SD = 2.19). It was hypothesized that overconfident subjects were more risk loving. Statistical tests detected no significant difference between the two groups of players (Mann-Whitney $Z = 0.320$, $p = 0.749$, two-sided). Correlation coefficient between risk aversion and individual overconfidence implies no linear relationship between them (Spearman's $Rho(30) = -0.095$, $p = 0.303$, one-sided). The presented evidence suggests that risk aversion, measured in a lottery type task, had no explanatory power for subject's overconfidence. It was predicted that greater risk aversion had stronger negative effect on individual trading activity and the size of her final portfolio. However, no linear relationship was detected between these variables (portfolio size: Spearman's

Rho(30) = -0.001, $p = 0.498$, one-sided; gains: Spearman's Rho(30) = 0.031, $p = 0.433$, one-sided). Correlation between the number of safe choices and average trading activity of an individual was negative, yet insignificant (Spearman's Rho(30) = -0.100, $p = 0.294$, one-sided). Also inspection of Equation 8 and 9 (see Table 2) revealed no significant effect of risk aversion on the frequency of trading. It can be concluded that in this sample differences in experimental market outcomes between the traders were overconfidence and not risk aversion⁶ driven.

6. Conclusions

The aim of this paper was to investigate the influence of the degree of overconfidence and risk aversion on financial decision making of economic subjects. For this purpose asset market experiment based on Smith et al. (1988) was conducted. Based on pre-experimental overconfidence measurement subjects were assigned to the two types of markets: the first consisting of more overconfident subjects and the second of less overconfident (rational) subjects. This experiment was followed by post hoc risk aversion measurement in the sample of former participants.

Our results supported the hypothesis that more overconfident individuals engaged in trading activity more actively only for female participants. The hypothesis that active engagement in trade had negative impact on individual gains was also supported only for female subjects. Contrary to the formulated hypothesis, overconfidence had no significant effect on profits. However data revealed that forecasting errors, which were significantly correlated with overconfidence, forced subjects to engage in trading more actively. In line with previous research (cf. Smith et al. 1988), forecasting errors were associated with losses. It can be concluded that in the setting with no informational asymmetries and "pure" markets, performance and trading activity were overconfidence driven only for female participants. As a possible explanation for that we suggest lower forecasting accuracy by female subjects⁷.

At the completion of risk aversion measurement it was found that subjects on average were risk averse. Statistical tests detected no difference between the two types of traders in terms of the number of safe choices. No linear relationship between individual risk aversion and overconfidence, trading activity or final portfolio size was detected. It can be concluded that in the reduced sample differences in experimental outcomes were overconfidence and not risk aversion driven.

Acknowledgements

I acknowledge a German Academic Exchange Office (DAAD) scholarship.

References

- Baker, K.H. and Nofsinger, J.R. (2002) 'Psychological biases of investors.' *Financial Services Review*, Vol. 11, pp. 97–116.
- Barber, B.M. and Odean, T. (2000) 'Trading is hazardous to your wealth: the common stock investment performance of individual investors.' *Journal of Finance*, Vol. 55, pp. 773–806.
- Barber, B.M. and Odean, T. (2001) 'Boys will be boys: gender, overconfidence, and common stock investment.' *Quarterly Journal of Economics*, Vol. 116, pp. 261–292.
- Biais, B., Hilton, D., Mazurier, K., and Pouget, S. (2005) 'Judgmental overconfidence, self-monitoring and trading performance in an experimental financial market.' *Review of Economic Studies*, Vol. 72, pp. 287–312.
- Camacho-Cuena, E., Requate, T., and Waichman, I. (2012) 'Investment Incentives under Emission Trading: An Experimental Study.' *Environmental and Resource Economics*, Vol. 53, pp. 229–249.
- Croson, R. and Gneezy, U. (2008) 'Gender differences in preferences.' *Journal of Economic Literature*, Vol. 47, pp. 1–27.
- Deaves, R., Lüders, E., and Luo, G.Y. (2009) 'An experimental test of the impact of overconfidence and gender on trading activity.' *Review of Finance*, Vol. 13, pp. 555–575.
- De Long, J.B., Shleifer, A., Summers, L.H., and Waldmann, R.J. (1991) 'The survival of noise traders in financial markets.' *The Journal of Business*, Vol. 64, pp. 1–19.
- Durand, R.B., Newby, R., and Sanghani, J. (2008) 'An intimate portrait of the individual investor.' *Journal of Behavioral Finance*, Vol. 9, pp. 193–208.
- Fellner, G. and Maciejovsky, B. (2007) 'Risk attitude and market behavior: evidence from experimental asset markets.' *Journal of Economic Psychology*, Vol. 28, pp. 338–350.
- Fenton-O'Creevy, M., Nicholson, N., Soane, E., and Willman, P. (2003) 'Trading on illusions: unrealistic perceptions of control and trading performance.' *Journal of Occupational and Organizational Psychology*, Vol. 76, pp. 53–68.

- Fischbacher, U. (2007) 'z-Tree: Zurich toolbox for ready-made economic experiments.' *Experimental Economics*, Vol. 10, pp. 171–178.
- Glaser, M., Nöth, M., and Weber, M. (2004) 'Behavioral finance', in Koehler, D. J. and Harvey N. (Eds.), *Blackwell Handbook of Judgment and Decision Making*, Wiley-Blackwell, Oxford, Malden, pp. 527–546.
- Glaser, M. and Weber, M. (2007) 'Overconfidence and trading volume.' *The Geneva Risk and Insurance Review*, Vol. 32, pp. 1–36.
- Hirota, S. and Sunder, S. (2007) 'Price bubbles sans dividend anchors: evidence from laboratory stock markets.' *Journal of Economic Dynamics & Control*, Vol. 31, pp. 1875–1909.
- Holt, C.A. and Laury, S.K. (2002) 'Risk aversion and incentive effects.' *American Economic Review*, Vol. 92, pp. 1644–1655.
- Kahneman D., and Riepe, M.W. (1998). Aspects of investor psychology.' *Journal of Portfolio Management*, Vol. 24, pp. 52–65.
- Keller, C. and Siergist, M. (2006) 'Investing in stocks: the influence of financial risk attitude and values-related money and stock market attitudes.' *Journal of Economic Psychology*, Vol. 27, pp. 285–303.
- Kirchler, E. and Maciejovsky, B. (2002) 'Simultaneous over- and underconfidence: evidence from experimental asset markets.' *Journal of Risk and Uncertainty*, Vol. 25, pp. 65–85.
- Klayman, J., Soll, J.B., Gonzáles-Vallejo, C., and Barlas, S. (1999) 'Overconfidence: it depends on how, what, and whom you ask.' *Organizational Behavior and Human Decision Processes*, Vol. 79, pp. 216–247.
- Kyle, A. and Wang, F. A. (1997) 'Speculation duopoly with agreement to disagree: can overconfidence survive the market test?' *Journal of Finance*, Vol. 52, pp. 2073–2090.
- Langer, E. (1975) 'The illusion of control. ' *Journal of Personality and Social Psychology*, Vol. 32, pp. 311–328.
- Lakonishok, J., Shleifer, A., and Vishny, R.W. (1992) 'The impact of institutional trading on stock prices.' *Journal of Financial Economics*, Vol. 32, pp. 23–43.
- Lei, V., Noussair, C.N., and Plott, C.R. (2001) 'Nonspeculative bubbles in experimental asset markets: lack of common knowledge of rationality vs. actual irrationality.' *Econometrica*, Vol. 69, pp. 831–859.

- Lichtenstein, S., Fischhoff, B., and Phillips, L.D. (1982) 'Calibration of probabilities: the state of the art to 1980', in Kahneman, D., Slovic, P., and Tversky, A. (Eds.), *Judgment under Uncertainty: Heuristics and Biases*, Cambridge University Press, New York, pp. 306–334.
- Markiewicz, L. and Weber, E.U. (2013) 'DOSPERT's gambling risk-taking propensity scale predicts excessive stock trading.' *Journal of Behavioral Finance*, Vol. 14, pp. 65–78.
- Menkhoff, L., Schmeling, M., and Schmidt, U. (2013) 'Overconfidence, experience, and professionalism: An experimental study.' *Journal of Economic Behavior & Organization*, Vol. 86, pp. 92–101.
- Michailova, J., and Katter, J.K.Q. (2013). Thoughts on quantifying overconfidence in economic experiments. MPRA Working Paper No. 44399.
- Moore, D.A. and Healy, P.J. (2008) 'The trouble with overconfidence.' *Psychological Review*, Vol. 115, pp. 502–517.
- Nöth, M. and Weber, M. (2003) 'Information aggregation with random ordering: Cascades and overconfidence.' *The Economic Journal*, Vol. 113, pp. 166–189.
- Odean, T. (1999. Do investors trade too much?' *American Economic Review*, Vol. 89, pp. 1278–1298.
- Russo, J.E. and Schoemaker, P.J.H. (1992) 'Managing overconfidence.' *Sloan Management Review*, Vol. 33, pp. 7–17.
- Taylor, S.E. and Brown, J.D. (1988) 'Illusion and well-being: A social psychological perspective on mental health.' *Psychological Bulletin*, Vol. 103, pp. 193–210.
- Scheinkman, J.A. and Xiong, W. (2003) 'Overconfidence and speculative bubbles.' *Journal of Political Economy*, Vol. 111, pp. 1183–1219.
- Smith, V.L., Suchanek G.L., and Williams A.W. (1988) 'Bubbles, crashes, and endogenous expectations in experimental spot asset markets.' *Econometrica*, Vol. 56, pp. 1119–1151.

Endnotes

1. However according to Moore and Healy (2008) the item-confidence paradigm, used to assess overconfidence in most of the economic experiments, as well as in this one, measures both overprecision and overestimation.

2. For a detailed description of the test construction procedure refer to Michailova and Katter (2013).
3. Two values, namely 7.92 and 8.39, are possible outliers.
4. A sample of bias scores of the participants is normalized on an interval [0,1].
5. Equations 8 and 9 are discussed in subsection “Risk aversion measurement: Experimental results”.
6. Measured in the lottery type task.
7. Based on the MAE.

Figure 1 Normalized profits per participant

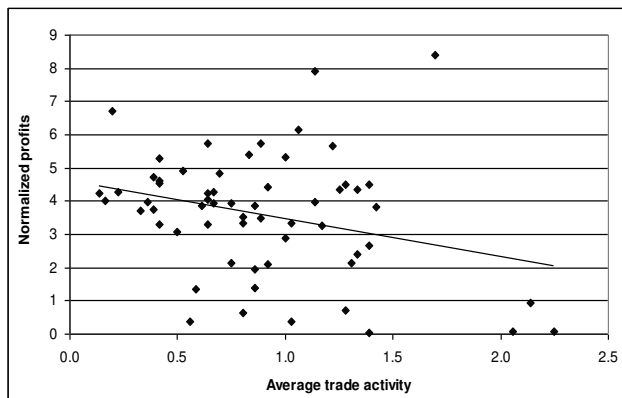


Figure 2 The cross-sectional distribution of relative profits by treatment

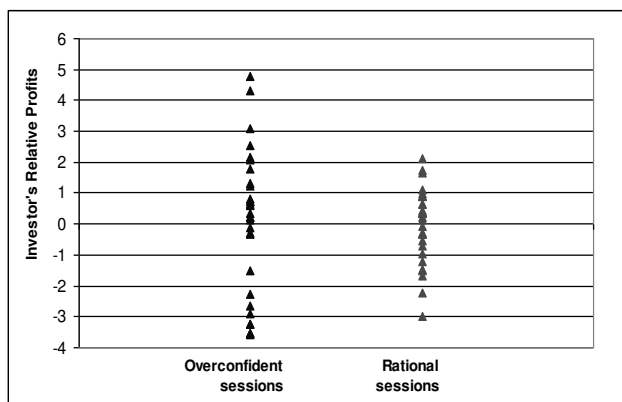


Table 1 Bias scores of experimental (sub-)samples.

	OBS	Mean	SD	Min	Max
All	60	11.20	12.08	-5.89	43.50
Overconfident	30	21.33	8.26	10.17	43.50
Rational	30	1.06	4.02	-5.89	6.78

Table 2 Trading activity (errors are corrected for heteroschedasticity (eq. 1-9) and for correlation within session clusters (eq. 1-7))

	1	2	3	4	5	6	6a	7	8	9
C	0.659 ^{****} (0.083)	0.692 ^{****} (0.089)	0.498 ^{****} (0.086)	1.338 [*] (0.711)	0.734 ^{****} (0.141)	1.218 [*] (0.711)	1.299 [*] (0.726)	1.300 [*] (0.699)	1.815 ^{**} (0.869)	2.111 ^{**} (0.836)
NBS	0.671 ^{****} (0.132)	0.682 ^{****} (0.131)	1.285 ^{****} (0.224)	1.236 ^{****} (0.237)	1.147 ^{****} (0.205)	0.993 ^{****} (0.272)	1.050 ^{****} (0.245)	1.166 ^{****} (0.234)	0.859 [*] (0.774)	0.854 [*] (0.757)
Gender		-0.062 (0.097)	0.301 ^{***} (0.109)	0.253 ^{**} (0.109)	0.252 [*] (0.128)	0.317 ^{***} (0.107)	0.267 ^{***} (0.093)	0.278 ^{***} (0.091)	0.470 (0.269)	0.446 (0.243)
NBS*Gender			-1.069 ^{***} (0.340)	-0.991 ^{***} (0.342)	-0.993 ^{***} (0.323)	-0.934 ^{**} (0.357)	-0.951 ^{***} (0.337)	-1.003 ^{***} (0.342)	-1.307 ^{*, a} (0.878)	-1.329 ^{*, a} (0.857)
Age				-0.036 (0.029)		-0.040 (0.028)	-0.041 (0.028)	-0.038 (0.029)	-0.060 [*] (0.033)	-0.067 ^{**} (0.029)
Semester					-0.046 ^{**} (0.020)					
MAE						0.036 ^{**} (0.014)	0.027 ^{***} (0.008)		0.040 ^{**} (0.017)	
TAE								0.002 [*] (0.001)		0.004 ^{**} (0.002)
Safe choices									-0.023 (0.026)	-0.033 (0.026)
N	60	60	60	60	54	60	59	60	32	32
adj. R2	0.11	0.10	0.16	0.17	0.17	0.23	0.25	0.19	0.15	0.23
SERegr	0.44	0.44	0.43	0.42	0.43	0.41	0.38	0.42	0.40	0.38

**** 0.001; *** 0.01; ** 0.05; * 0.1. ^a one-sided test..

Table 3 Gains from trade (errors are corrected for heteroschedasticity and for correlation within session clusters)

	1	2	3	4	5	6	7	8	8a
C	2.838 (0.297)	3.717 (0.338)	4.770 ^{****} (0.265)	2.994 (4.101)	4.052 (3.366)	3.771 (3.409)	5.128 ^{****} (0.303)	5.075 ^{****} (0.344)	5.235 ^{****} (0.401)
NBS	0.065 (0.722)	0.931 (0.979)	1.574 [*] (0.892)	1.499 (1.022)	1.179 (1.026)	1.467 (1.059)	1.483 (1.038)	1.470 (0.929)	1.625 (0.981)
Gender	1.293 ^{**} (0.564)	1.213 ^{**} (0.513)	-1.013 [*] (0.598)	-0.837 (0.603)	-0.447 (0.468)	-0.471 (0.456)	-0.589 (0.519)	-0.562 (0.581)	-0.575 (0.642)
Trade activity (average)		-1.271 ^{***} (0.420)	-2.654 ^{****} (0.399)	-2.503 ^{****} (0.641)	-2.333 ^{****} (0.601)	-2.081 ^{****} (0.607)	-2.216 ^{****} (0.389)	-2.253 ^{****} (0.361)	-2.401 ^{****} (0.346)
Trade activity * Gender			2.454 ^{**} (1.006)	2.313 ^{**} (0.986)	2.458 ^{**} (1.019)	2.265 ^{**} (1.025)	2.393 ^{**} (1.058)	2.372 ^{**} (1.047)	2.557 ^{**} (0.869)
Age				0.072 (0.164)	0.033 (0.131)	0.056 (0.135)			
End assets					-0.169 [*] (0.087)	-0.152 [*] (0.090)	-0.158 [*] (0.086)	-0.143 ^{*, a} (0.089)	-0.153 [*] (0.085)
MAE						-0.071 [*] (0.037)	-0.064 [*] (0.036)		
TAE								-0.008 [*] (0.004)	-0.011 ^{**} (0.005)
N	60	60	60	60	60	60	60	60	59
AdjR2	0.09	0.17	0.26	0.25	0.36	0.36	0.37	0.38	0.47
SERegr	1.75	1.67	1.58	1.59	1.46	1.46	1.45	1.44	1.34

**** 0.001; *** 0.01; ** 0.05; * 0.1.

^a one-sided test.