Overconfidence, risk aversion and (economic) behavior of individual traders in experimental asset markets

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OVERCONFIDENCE, RISK AVERSION AND (ECONOMIC) BEHAVIOR OF INDIVIDUAL TRADERS IN EXPERIMENTAL ASSET MARKETS

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Abstract

In this paper influence of behavioral factors (overconfidence and risk aversion) on financial decision making of economic subjects is analyzed. For this purpose two kinds of experiments were conducted: asset market and risk aversion experiments. In conducted asset market sessions subjects, based on their pre-experimental overconfidence scores, were assigned to two types of markets: the least overconfident ones formed five "rational" markets and the most overconfident ones formed five "overconfident" markets. Data collected from ten experimental sessions revealed that individual performance and trade activity were overconfidence dependent. Even small variations in miscalibration among players of the same "type", comprising each of the asset markets, were sufficient to cause this effect. In the second part of experiment, post hoc assessment of risk aversion was implemented in a sample of former participants of the asset market experiment (32 persons). The presented evidence suggests that risk aversion was not among the factors that had influence on individual engagement in trade activity or performance. It was concluded that in the sample, for which risk aversion measurements were obtained, experimental market outcomes were overconfidence and not risk aversion driven.

Keywords: overconfidence, individual behavior, experiment.

JEL codes: C90, C91, D81, G11

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1 INTRODUCTION

By allowing psychological bias and emotion to affect their investment decisions, investors can do serious harm to their wealth (Baker and Nofsinger, 2002). One of such biases, inducing deviation from rational economic behavior, is overconfidence. Kahneman and Riepe (1998) emphasized the importance of overconfidence in financial decision-making and suggested that, combined with optimism, it would make individuals overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. Overconfidence in investors can result in aggressive trade (e.g. Deaves et al., 2009), portfolio undiversification (e.g. Odean, 1999), pursuit of the active portfolio management strategy (e.g. De Bondt and Thaler, 1994) and suboptimal performance (e.g. Fenton-O'Creevy et al., 2003). Another personality trait, which determines individual investment choices and strategy, is the degree of risk aversion. Some authors suggest existence of a direct link between overconfidence and risk aversion (see Russo and Shoemaker, 1992; De Long et al., 1991), namely that greater overconfidence leads to risk underestimation and excessive risk-taking by investors e.g. by engagement in aggressive trade or choice of riskier portfolios.

Interest in the topic of economic consequences of investors' overconfidence (irrationality) generated a large body of literature. Scheinkman and Xiong (2004) point out, that an issue occupying attention of researchers starting with Friedman (1953) "is whether traders with irrational beliefs will lose money trading with rational traders and eventually disappear from the market?" Consequently most of the foregoing research was focused on the analysis of the "mixed" asset market setting, where both overconfident and rational traders interacted. According to a widespread opinion, in such markets rational investors will take advantage of the overconfident ones (noise traders) and the former will eventually incur losses and die out (e.g. Hirshleifer and Luo, 2001). This proposition is supported by findings from experimental markets of this type, which present evidence that overconfident subjects, compared to rational ones, engage in more trading and face reductions to their welfare. Several articles, examining the effect of overconfidence on variation in subjects' trading activity and performance in the "mixed" market setting, which are the closest in spirit to mine are by Biais, Hilton, Mazurier, and Pouget (2005), Glaser and Weber (2007), Deaves, Lüders and Luo (2009), and Kirchler and Maciejovsky (2002). Biais et al. (2005), presented empirical evidence of the negative association between overconfidence and traders' performance; yet it had a more significant effect on males' than on females' performance. Overconfidence did not lead to increase in trading activity in their sample. In the study of Glaser and Weber (2007) overconfidence was assessed both as miscalibration score and the better than average effect. The former was found to be unrelated to trading volume, however investors who thought that they were above average traded more. Linear relationship between portfolio performance, overconfidence, and trade frequency was not detected. Results of Deaves et al. (2009) indicated that greater overconfidence has lead to increased trading activity and had a negative effect on individual trading performance. Kirchler and Maciejovsky (2002) discovered no significant difference in terms of risk attitude between their experimental markets, and concluded that any distinctions between experimental outcomes were not risk-attitude dependent.

My experiment was created with the following assumptions in mind. First, previous studies have created at least two sources of exogenous heterogeneity in their experiments by: 1) construction of "mixed" markets, consisting of both overconfident and rational traders and by 2) asymmetries in the information and/or its quality, which different types of players received from the experimenter. Conclusions of these papers were mainly based on the antagonizing principle, that one group would take advantage of the other. Second, following the examination of the instruments, which were used by previous authors to assess subjects' overconfidence, there were good reasons to suspect that overconfidence was measured inadequately and that these instruments did not offer comprehensive measure of individual miscalibration. And last but not least, to my best knowledge, there were no other experiments that tried to explore the link between individual risk aversion, overconfidence and market outcomes. The only experiment that measured both subjects' overconfidence and risk aversion was by Kirchler and Maciejovsky (2002), but they rather focused on the market-level distinctions. My paper will differ from the foregoing research in some important fashion. In contrast to the abovementioned papers in present experiment subjects, based on their pre-experimental overconfidence scores, were assigned to the two types of markets. Individuals with the lowest score formed "rational" markets and individuals with the highest score "overconfident" markets. In the course of experiment participants have interacted only with subjects of their own "type". Within each of the conducted markets, the degrees of individual overconfidence (slightly) varied. This was the only source of subjects' heterogeneity, as in my experiment participants have differed neither in terms of their initial endowments, nor in terms of information quality and access to it. Subjects' overconfidence was assessed through a specially created test, weighted for the inclusion of easy, hard and medium difficulty questions, which has also accounted for the possible gender and country biases. I have also chosen a different test format which, due to its simplicity, was clearer to subjects. None of the previous experiments made use of such test.

This paper reports the results of experiments designed to investigate the influence of behavioral factors, namely the degree of overconfidence and risk aversion, on financial decision making of economic subjects. For this purpose two kinds of experiments were conducted. The first one, whose design followed Smith, Suchanek and Williams (1988) and Deaves et al. (2009), was the asset market experiment. The second experiment was aimed at individual risk aversion measurement and followed Holt and Laury (2002) and Baker, Laury and Williams (2008). Hypotheses, tested in the context of the suggested experimental design, were formulated upon the analysis of findings from the previous research in the "mixed" market setting. Data, collected in the first part of the experiment from five overconfident and five rational markets, enabled investigation of the effect that the degree of overconfidence had on individual trading activity and performance. In the second part of experiment, post hoc assessment of risk aversion was implemented in a sample of former participants of the asset market experiment. These data were used for the determination of the importance of individual differences in risk attitude for explanation of trading behavior and outcomes.

Main findings from my experiment can be summarized as follows. The data analysis confirmed the hypothesized positive impact that overconfidence had on individual engagement in trading activity; yet, with increase in overconfidence, females have completed more stock market transactions than males. Contrary to the formulated hypothesis, data suggest that overconfidence had positive effect on gains from trade. As it was expected, individual gains were negatively affected by active involvement in trade, and low turnover players have significantly outperformed high turnover players. However, with increase in the number of market transactions males incurred smaller losses compared to females. It can be concluded that in the suggested experimental setting, where the two "types" of subjects were separated from each other, performance and trading activity were overconfidence dependent and even small variations in miscalibration among players belonging to the same "type" were sufficient to cause this effect. At the completion of subsequent risk aversion measurements thirty two former participants of the asset market experiment were found to be on average risk averse. Inconsistent with the initial proposition that overconfident subjects were more risk loving, tests detected no statistical difference between the two types of participants in terms of the average number of safe choices. Also no linear relationship between the bias score and risk aversion was detected. The presented evidence implied that, risk aversion was not among the factors which had significant influence on engagement in trading activity or performance. It can be concluded, that in the reduced sample, experimental market outcomes were overconfidence and not risk aversion driven.

Paper proceeds as follows. Section 2 gives an overview of the findings of financial overconfidence and risk aversion literature; along analysis of the similar experimental papers and discussion of the paper's contributions is presented. Section 3 lists the research hypotheses. Section 4 provides the description of experimental procedures of both experiments. Sections 5 and 6 present data analysis of, correspondingly, experimental asset market and risk aversion measurement experiment. Finally Section 7 concludes.

2 Psychological Determinants of Trading Activity and Performance

2.1 Overconfidence

Interest in the topic of economic consequences of investors' overconfidence generated a large body of literature. According to Fischoff, Slovic, and Lichtenstein (1977) most people hold unrealistic positive beliefs about their personal skills and their knowledge. Giardini et al. (2008) suggest that constant overestimation of personal talents and abilities, and chances of positive outcomes "can have important consequences, and sometimes results in suboptimal decisions". Kahneman and Riepe (1998) point out at the importance of overconfidence for financial decision taking, in that, overconfidence combined with optimism, produces overestimation of individual knowledge, exaggeration of the ability to control events, and risk underestimation. Barber and Odean (2000) indicate that overconfident investors "hold unrealistic beliefs about how high their returns will be". Thus cognitive bias of overconfidence creates various distortions in the way traders perceive objective market reality, and this can result in trade aggressiveness, portfolio undiversification, risk underestimation, pursuit of the active portfolio management strategy, and suboptimal performance (decrease in wealth, sales of the wrong assets, etc.).

Most of the research findings support the proposition that greater overconfidence leads to higher trading volume (see e.g. Deaves et al., 2009). Glaser et al (2003) showed that overconfident investors traded more aggressively, and the higher the degree of overconfidence of a trader was, the higher was her trading volume. Odean (1998) calls this outcome "the most robust effect of overconfidence". Odean (1999) analyzed the trades of 10,000 individuals with discount brokerage accounts. His results indicate that these investors reduced their returns by trading, and thus he concluded that their trading volume was excessive. Kourtidis et al., (2010) suggest that overconfidence is the fact that makes investors believe that they can predict the winners and thus makes them to engage in excessive trading activity and take too much risk. Barber and Odean (2000) analyzed a data set of trading activity of the 66,465 households for a period from 1991-1996, and found that the frequency of trading and its cost explained the poor investment performance of the households, and that overconfidence was the explanation for the high trading volume of individual investors (and the resulting poor results). In a further study Barber and Odean (2001) showed that men, who according to their analysis of psychological research findings were more overconfident, traded 45% more than women, and that trading reduced their net returns by more percentage points per year than for women (2.65 vs. 1.72).

What concerns the welfare effect of overconfidence, the evidence from research is contradictory. Some authors indicate that, in comparison to rational investors, the expected utility (De Long et al., 1991; Odean, 1998) and welfare (Fenton-O'Creevy et al., 2003; Barber and Odean, 2002; Nöth and Weber, 2003) of overconfident traders is reduced. The results of Kirchler and Maciejovsky (2002) indicate that higher degree of overconfidence is negatively correlated with earnings of participants in their experiments. Deaves et al. (2009) showed that greater overconfidence lead to higher trading volume and earnings' reduction. Likewise in the experiment of Biais et al (2004) miscalibration decreased subjects' trading performance. Overconfidence was also found to have a negative impact on trading performance in the paper by Fenton-O'Creevy et al. (2003). Barber and Odean (2000) presented evidence, that high turnover households underperformed low turnover households, in terms of investment returns, by about 7.1% annually. On the contrary, Benos (1998) reported higher earnings of overconfident investors. Kyle and Wang (1997) indicated that the expected returns of overconfident traders might outperform those of rational traders, and that this could be obtained through the aggressive trading. Also, Hirshleifer and Luo (2001) presented evidence of higher profits of overconfident traders. The third strand of literature reports no connection between overconfidence and individual gains. E.g. Glaser and Weber (2007) detected no linear relationship between gross returns (portfolio performance), trade frequency and overconfidence. Thus they concluded that underperformance of investors who trade more is transaction costs driven.

De Bondt and Thaler (1994) suggest that overconfidence explains excessive trade of portfolio managers, and active portfolio management pursuit by financial economists and pension funds. According to Lakonishok et al. (1992) overconfident subjects choose active portfolio management. Also, Mullainathan and Thaler (2000) named overconfidence as the factor, helping to explain why, even the "most professionally managed portfolios are turned-over once a year or more". They have also noticed that individual investors traded too much, and that assets sold by them tended to outperform the new, subsequently acquired, assets. De Bondt and Thaler (1994) presented evidence, that irrespective the fact that portfolio managers usually underperformed index funds, most stock portfolios were still managed actively. As well, overconfidence makes investors choosing undiversified, thus riskier, portfolios (Odean, 1998, 1999; Lakonishok, Shleifer and Vishny, 1992). Scheinkman and Xiong (2003) argue that investors who perceive prospects for the future dividends from the assets as more optimistic will "bid up the price of the asset and eventually hold the total supply" of inventories.

Some authors suggest that there is direct link between overconfidence and risk aversion. Russo and Shoemaker (1992) note that overconfidence causes risk underestimation and encourage traders to take excessive risk. Odean (1998) has shown that investors with a higher degree of overconfidence chose in general more risky portfolios than those with a lower degree of overconfidence. Evidence presented by Barber and Odean (2001) implied that overconfident investors (men) held riskier portfolios. De Long et al. (1991), who examined traders that were overconfident in the sense that they underestimated risk, found that as a result of risk underestimation, these traders held more of the risky asset. Chuang and Lee (2005) presented empirical evidence in the support of the hypothesis that overconfident investors traded more in riskier securities, since they underestimated risk. Not only risk underestimation contributes to the more aggressive trade by overconfident investors, in comparison to rational traders, it is also boosted by the fact that they overestimate the expected profit from their trading strategies (Hirshleifer and Luo, 2001).

2.2 RISK AVERSION

Risk aversion is connected to the desire of individuals to avoid uncertainty. Yet, almost every economic decision involves some sort of risk and uncertainty. Thus analysis of individual differences in risk attitudes is important in a sense, that understanding these distinctions could help in predicting real economic behavior. A commonly used approximation for modeling individuals in economic theory is that of the risk neutral economic human. However, empirical and experimental studies suggest that most people exhibit risk aversion. In the experiment of Holt and Laury (2002) about two-thirds of subjects exhibited risk aversion with low payoffs. As payoffs grew, risk aversion tended to increase as well. Binswanger (1980), who conducted his experiment with low-income farmers in Bangladesh, showed that most farmers were significantly risk averse, and that their risk aversion increased with the increase in payoffs. Demographic factors such as age, gender, education, intelligence, etc., serve as determinants of individual differences in risk attitudes.

A large body of literature addresses the topic of gender differences in risk tolerance. Holt and Laury (2002) showed that women were more risk averse in comparison to men in low-payoff decisions. Brachinger et al. (1999) and Schmidt and Traub (2002) have presented evidence that females often had higher degree of risk and loss aversion than males. Menkhoff et al. (2006) found that female fund-managers showed higher degree of risk aversion. According to Dohmen et al., (2005) at all ages women are less willing to take risks. There is as well an interaction between subject's gender and marital status. In general, married individuals are more risk-averse (Roszkowski, 1998), where married females comprise the least risk tolerant group (Yao and Hanna, 2005), and single males - the most risk tolerant; single men are followed correspondingly by married males, and single females. Households headed by females are less likely to be risk tolerant, compared to households headed by men or married couples (Sung and Hanna, 1996). As well, gender has influence on subjects' investment choices, e.g. women would invest more often in risk-free assets (Hariharan et al., 2000). Compared to single men, single women tend to hold a smaller part of their wealth in the form of risky assets (Jianakoplos and Bernasek, 1998). However, an increase in knowledge in a financial decision making context can "create a near role reversal between men and women in attitudes toward uncertainty" (Gysler et al., 2002).

The level of obtained education is importantly related to subject's risk attitude. Grable (2000) pointed out that increased risk tolerance is associated with greater levels of attained education. The results of Sung and Hanna (1996) indicated that risk tolerance in their sample increased with the schooling degree, where the lowest predicted risk tolerance (43%) was in a group of subjects who did not graduate from high school, and the highest predicted risk tolerance (71%) was obtained for those subjects who had a college degree. Better education of parents also has an important influence on individual's risk attitude: individuals whose parents are highly-educated are more willing to take risk (Dohmen et al., 2005). Educational attainments are to a large extent determined by subjects' cognitive ability. Results, concerning the relationship between cognitive ability and risk taking, are rather mixed. Frederick (2006) presented evidence, that cognitive ability was positively correlated with willingness to take risk in lotteries when outcomes included gains, and negatively – when outcomes included losses. Benjamin et al. (2005) suggested that students with lower math scores were less likely to be risk neutral. However Dohmen et al., 2007 argued that people with higher cognitive ability were significantly more risk loving.

No definite conclusion regarding the relationship between experience, age and risk attitude can be drawn. Some studies suggest that less experienced subjects are willing to take more risk (e.g. Menkhoff et al., 2006) whereas others argue that willingness to take risk increases with experience (e.g. Hong et al., 2000; Chevalier and Ellison, 1999). In the article by Hanna and Lee (1995) the predicted risk tolerance was approximately the same for all ages under 55. However, starting with 55, it decreased with an increase in age. The results of Dohmen et al., (2005) indicated that increase in subjects' age was negatively associated with their willingness to take risk. Authors note that "the impact of age implies increased financial conservatism in ageing societies" (Dohmen et al., 2005).

As in the case with overconfidence, there is some empirical evidence that risk attitude affects trading behavior. Higher propensity for risk taking manifests itself through an increase in trade frequency (Durand et al., 2006). Fellner and Maciejovsky (2007) in their experiment explored the relation between market activity and risk attitude. They concluded that higher degree of risk aversion was accompanied by lower market activity. As well, attitude to financial risk is a significant positive predictor of willingness to invest in stocks (Keller and Siergist, 2006). Camacho-Cuena, Requate and Waichman (2009) pointed out that risk attitude affected subjects' performance in the laboratory, where the probability of engagement in speculative activity increased with increment in risk tolerance. In general, females engage in market activity less actively than males, and also are more risk averse. However, according to Fellner and Maciejovsky (2007), one should be cautious in connecting gender differences (in terms of market behavior) only to risk aversion diversity. They argue that "second order characteristics", one of which is overconfidence, might influence risk attitude. Also Croson and Gneezy (2008) suggested, that differences in risk attitudes may be explained by differences in risk perception, where overconfidence can manifest itself via "reduced estimate of the riskiness of a given investment".

2.3 SIMILAR RESEARCH AND VALUE ADDED

This paper builds on several previous survey and experimental articles, which investigate the effect of the degree of overconfidence on variation in subjects' trading activity and performance (earnings), but with some new aspects in experimental design.

The approach of Biais et al. (2005) relies on the asymmetric information trading game, and focuses on determining the link between subjects' psychological characteristics and their earnings. For this purpose, their sample was broken in four quartiles in terms of overconfidence degree, and analysis of the average trading activity and profit patterns was conducted. Biais et al. (2005) showed that the association between subjects' miscalibration and their performance (trading profits) was negative, and this relation was robust across the samples. Yet the strength of the impact differed, namely overconfidence had more significant effect on males' performance, than on females'. The reported results also indicated that overconfidence did not lead to an increase in trading activity neither in the whole sample, nor in the male and female sub-samples.

Glaser and Weber (2007) empirically tested the hypothesis of theoretical models that overconfident investors trade more than the rational ones. They correlated overconfidence scores of 215 investors, who responded to their on-line questionnaire, with several measures of trading volume. In their study overconfidence was assessed both as miscalibration score and the better than average effect. Glaser and Weber (2007) discovered that miscalibration scores were unrelated to trading volume. Yet investors who thought that they were above average traded more. Although only secondary to their main interest, authors have also tested for the existence of the linear relationship between gross returns (portfolio performance), overconfidence, and trade frequency. No such connection was discovered. Also, there was no link between gender and trading volume.

Experiment of Deaves et al. (2009) was aimed at finding support for the premise that overconfidence leads to enhanced trading activity. This hypothesis was tested both at individual and market levels by regressing, previously obtained, overconfidence scores on the measure of trading activity (assessed as executed trades). In their experiment Deaves et al. (2009) conducted a limited amount of sessions where subjects were assigned, based on their overconfidence degree, to the two "high overconfidence" and the two "low overconfidence" markets. In the remaining four sessions subjects were separated by gender, while roughly maintaining average overconfidence within the markets. The reported results indicate that greater overconfidence lead to increased trading activity and that overconfidence had a negative effect on trading performance (reduced earnings). No connection between overconfidence, trading activity and gender was discovered in their sample.

Kirchler and Maciejovsky (2002) run a multi-period experimental asset market and investigate the development of overconfidence in the course of experiment. Prior to opening of the market sessions, subjects' risk aversion measurement was implemented by the methods of certainty equivalents' assessment and lottery pair's choice. Overconfidence was measured before each trading period, through the two average market trading price forecasting tasks: point prediction and interval prediction. Participants of the experiment were found to be well-calibrated in certain periods, and under- or overconfident in other periods. Higher degree of subjects' overconfidence was negatively correlated with their earnings. Between the experimental groups there was no significant difference in terms of risk aversion, thus authors concluded that any distinctions that were observed between the experimental conditions were not risk-attitude dependent.

Based on the analysis of previous research, my experiment was designed with the following assumptions in mind:

First of all, foregoing researchers have created at least two sources of exogenous heterogeneity in their experiments by: 1) construction of “mixed” markets, consisting of both overconfident and rational traders and by 2) asymmetries in the information and/or its quality, which different types of players received from the experimenter. According to Glaser et al. (2003), such heterogeneity between investors could have created a potential for trade.

Overconfident or rational subjects were not the only type of players in the market in most of the above-mentioned papers, and their conclusions were mainly based on the antagonizing principle, that one group would take advantage of the other. Thus, none of the prior experimenters have employed such market construction principle in which miscalibrated and well-calibrated subjects were separated from each other. E.g. participants of the study by Glaser and Weber (2007) operate in real markets where one cannot control for the differences in traders’ endowments, information, or for the trade between overconfident and rational traders. Although Deaves et al. (2009) run four sessions to which subjects were assigned, based on their degree of overconfidence, for the analysis purposes these data were combined with the data obtained from another treatment (four gender-based markets). Not to mention that in their experiment different overconfidence measurement methodology and market structure were employed. In my experiment subjects were assigned to the overconfident and rational markets, based on their miscalibration scores, before the start of the experimental sessions, and in the course of experiment they interacted only with subjects of their own type. Subjects with the highest score comprised “overconfident” markets, and subjects with the lowest score - “rational” markets.

A second source of exogenous heterogeneity in the previous experiments was created by supplying participants with asymmetric pieces of information, which also differed in their quality. 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. Moreover, they tried to manipulate subjects’ beliefs and make them think that their signals were more accurate than these of the other subjects. In my experiment all traders were given the same information, and no artificial belief of possessing a better information piece was created. Likewise, my participants did not differ in terms of the initial endowments[1].

Second, following the examination of the instruments, which were used in prior research to assess subjects' overconfidence, there were good reasons to suspect that overconfidence was measured inadequately and that these instruments did not offer comprehensive measure of individual miscalibration[2]. Most of the afore-named researchers followed the famous work by Russo and Schoemaker (1992) and used confidence interval elicitation tasks to measure overconfidence. However, Klayman et al. (1999) argue, that interval estimation tasks are prone to produce extreme miscalibration. E.g. in the experiment of Deaves et al. (2009) none of the subjects got close to the perfect calibration measure, and even the best calibrated participants exhibited quite high levels of overconfidence. Findings from psychological research also indicate, that overconfidence is the most pronounced for hard questions (a few persons know the right answer), and the least pronounced for the easy questions (the right answer is known to many persons). However, questions' difficulty was not assessed in the foregoing research, and the constructed scales were not pre-tested prior to their application for experimental measurements. In my experiment, a specially created test, weighted for the inclusion of easy, hard and medium difficulty questions, was used to estimate subjects' overconfidence. This instrument has also accounted for the possible gender and country biases, and, compared to some authors, included more items. Unlike previous authors, I chose another test format, which was not inherently prone to production of extreme overconfidence levels and, due to its simplicity, was clearer to subjects – multiple choice discrete propositions' task format. Prior to experimental use, the developed scale was pre-tested with students enrolled in different disciplines of social sciences. Overconfidence estimation phase was administered and financially rewarded, which increased reliability of the measurements.

And last but not least, to my best knowledge, there were no other experiments before that tried to explore the link between subjects' risk aversion, overconfidence and experimental outcomes. The only experiment that measured both subjects' overconfidence and risk aversion was by Kirchler and Maciejovsky (2002). However analysis of the individual differences among subjects in terms of risk aversion was not the aim of their research; in contrast, they focused on the existing group (market-level) differences. Dependence between

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[1] However I cannot completely avoid heterogeneity of subjects as within each of the constructed rational and overconfident markets subjects still differ from each other (even slightly) in terms of the bias scores.

[2] More information about the overconfidence measurement instrument is in the paper "Development of the Overconfidence Measurement Instrument for the Economic Experiment".

experimental outcomes, overconfidence and risk aversion was also not in their focus of interest.

3 HYPOTHESES

Hypotheses, to be tested in this article, are built on the analysis of findings from overconfidence research in financial markets, and some of them were previously tested in the "mixed" market setting, where both types of subjects (overconfident and rational) interacted.

To begin with, there is plenty of evidence that greater overconfidence leads individuals to engage in more trading activity (e.g. Odean, 1998, Deaves et al., 2009) or pursue active portfolio management (Lakonishok, Shleifer and Vishny, 1992). The mentioned findings suggest testing of the hypothesis that in my experimental setting the higher degree of subject's overconfidence is also accompanied by more active engagement in trading activity.

Hypothesis 1: Individual trading activity increases with the increase in overconfidence, measured as the bias score.

Experimental findings from the "mixed" market setting suggest that overconfident traders, who engage in trade more actively, incur losses. In other words, they are outperformed by low turnover traders (e.g. Barber and Odean, 2000). These results raise a question of whether in my experiment, where overconfident and rational traders are separated from each other, excessive trading activity still has negative impact on traders' performance.

Hypothesis 2: High turnover traders underperform low turnover traders, i.e. there is negative relationship between individual gains from trade and trading activity.

Upon analysis of the foregoing papers, it can be suspected that the final portfolio size is positively connected to the degree of overconfidence. E.g. model of Scheinkman and Xiong (2003), suggests that investors who perceive prospects for the future dividends from the assets as more optimistic will "bid up the price of the asset and eventually hold the total supply" of inventories. Likewise, some authors noted that overconfident investors chose undiversified portfolios (Odean, 1998, 1999; Lakonishok, Shleifer and Vishny, 1992). In this regard, I posit the hypothesis that the cognitive bias of overconfidence has positive influence on the asset portfolio size at the end of the experiment.

Hypothesis 3: Increase in the number of assets in trader's final inventory is accompanied by growth of her bias score.

In the experimental asset markets, where overconfident traders trade against rational traders, higher degree of traders' overconfidence reduces their welfare (e.g. Fenton-O'Creevy et al., 2003; Biais et al., 2005; Nöth and Weber, 2003; Kirchler and Maciejovsky 2002). In line with these results, it is important to explore whether in the context of suggested experimental design, subjects' market performance deteriorates with the increment in their miscalibration.

Hypothesis 4: Individual gains from trade decrease with the greater degree of overconfidence.

Foregoing research presented results, implying existence of the link between overconfidence and risk aversion, in the form of risk underestimation (e.g. Ruso and Schoemaker, 1992; Kahneman and Riepe, 1998) and increased risk taking by overconfident investors, e.g. by riskier portfolios choices (Odean, 1997, 1998; Lakonishok, Shleifer and Vishny, 1992). Risk loving individuals also engage in trading activity more actively (Durand et al., 2006) and are more willing to invest in stocks (Keller and Siergist, 2006). If, on average, participants of the experiment had the same degree of risk aversion then, their final holdings of assets would be approximately the same (e.g. Lei et al., 2001). However, as dividend value changes in a probabilistic manner from period to period, each stock is perceived as some sort of the lottery by players. More risk-averse participants, who like uncertainty 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 as many asset items as possible. Thus, I expect all stocks to be in the inventory of the more risk-loving participants at the end of experiment.

The above discussion gives justification to test three hypotheses:

Hypothesis 5: Overconfident subjects are (more) risk loving, and therefore they make more risky choices in the lottery-choice experiment.

Hypothesis 6: Trading activity is negatively dependent on the degree of risk aversion, thus more risk loving subjects engage more in trading activity.

Hypothesis 7: The number of assets in the subject's final inventory negatively depends on her degree of risk aversion: the more risk-averse a subject is, the fewer assets she has in her final portfolio.

4 EXPERIMENTAL PROCEDURE AND THE RULES OF THE GAME

This section first briefly describes the experimental procedure of the asset market experiment[3], and then it presents the risk aversion experiment.

[3] For a detailed description of the experimental procedure see the working paper "Overconfidence and Bubbles in Experimental Asset Markets".

4.1 Asset Market Experiment

Data analyzed in this article were obtained from 60 students, enrolled in social sciences at the Christian-Albrechts University of Kiel, who participated in the asset market experimental sessions that were conducted in the academic year 2008-2009. Totally ten experimental sessions were carried out, and six subjects took part in each of them. Thirty five males and 25 females, aged 19 to 28 (M = 22.73, SD = 2.06) participated in the experimental asset market. On average, one session lasted 1 hour and 40 minutes, and subjects have earned approximately 390.36 units of experimental currency (ECU)[4] (SD = 197.89) in the asset market (excluding reward for the forecasting activity). Males, on average, gained significantly more ECUs than women: 447 ECU vs. 335 ECU (Mann-Whitney Z = -2.646, $p < 0.01$, one-sided). Descriptive statistics of the group, including age, semester, the bias score, and profit are presented in the Appendix A.

Prior to conducting the asset market experiment, subjects' overconfidence was measured in the pre-experimental psychological test sessions. For that, students had to fill-in an 18-questions' general knowledge quiz ant state how confident they were that their answers were correct. Based on the difference between subject's average accuracy and her confidence, individual overconfidence was assessed. The obtained measure is called a bias score, where the negative bias score indicated underconfidence, and the positive bias score indicated overconfidence; an equal to zero bias score denoted perfect calibration. For the participation in the experimental asset markets two types of subjects were invited: those who had the lowest bias score (rational subjects) and those who had the highest bias score (overconfident subjects). Of them two types of asset markets were constructed: rational and overconfident. Thus, in the course of the experiment, subjects interacted only with traders of their own type. Yet, within each of the constructed rational and overconfident markets subjects still differ from each other (even slightly) in terms of the individual degree of overconfidence. Appendix B presents characteristics of subjects in the different experimental (sub-) groups in terms of their age, duration of studies and the bias score: all participants of the experimental sessions, and separately overconfident and rational subjects, and male and female participants.

Experiment was programmed and conducted in the computer lab with the software z-Tree (Fischbacher, 2007). Experimental design followed the pioneering work of Smith, Suchanek, and Williams (1988). Every experimental market consisted of the sequence of 15 trading periods, lasting at maximum 180 seconds, during which each trader could post her bid and ask

[4] 10.54 EUR.

price of the asset unit. Prior to the start of the experiment each subject was endowed with an equal amount of experimental assets and cash: 300 ECU and 3 experimental asset units. 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 dividend value was 0.25. An average dividend, which subjects could expect through many draws, was 2.4 ECU. Fundamental value of the stock can be obtained according to the formula $n \times 2.4$ ECU, where n stands for the number of periods remaining to the end of the session. In the first period of the experiment fundamental asset value was 36 ECU.

At the end of each trading period subjects were asked to predict the average market price in the next period, as well as to state how confident they were that this forecast was correct. Any value between 0% and 100% could be used to express subject's confidence, where 0% meant complete disbelief that the forecast was true, and 100% meant complete certainty that the forecast was correct. Participants were awarded for their predictions based on their accuracy: the closer the prediction was to the actual average market price, the higher was the reward. 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 the forecasting activity, converted at the predefined exchange rate to Euros.

4.2 RISK AVERSION EXPERIMENT

A set of experimental sessions aimed at assessment of the individual degree of risk aversion was conducted at the Christian-Albrechts University of Kiel in January, 2010. For each session former participants of the asset market experiment, described in the previous section, were recruited. Thirty two subjects took part in the experimental sessions; 16 of them were overconfident and 16 rational subjects. Nineteen males and 13 females, whose average age was 24.34 years (SD = 1.94) and who on average studied for 5.69 semesters (SD = 2.05), took part in the experiment. The duration of one experimental session was approximately 20 minutes. The part of the sessions was implemented in the computer lab; another part was paper-pen based. Computer-based experimental sessions were programmed and conducted with the software z-Tree (Fischbacher, 2007). Participants, on average, have earned 5.73 EUR (SD = 1.83), including the show-up fee of 2 EUR. Descriptive statistics of subjects in the various experimental (sub-)groups in terms of the number of taken safe choices, age, semester and the bias score are presented in Appendix C: for the whole group, and separately for rational and overconfident, and male and female subjects.

Experimental design followed the work of Holt and Laury (2002) and Baker, Laury and Williams (2008). Instructions were sent to participants in advance, and subjects were asked to read them prior to arriving to the experimental session. At the beginning of the session students received a copy of instructions, which they were sent via E-mail. The experimenter repeated the most important information concerning the experiment and participants were given time to ask questions. Then, either on their computer screen, or on the paper form, students were presented with a table of ten paired lotteries - *Option A* and *Option B*. Option A represented a "safe" choice in comparison to Option B. Safety of the options was assessed on the basis of the difference between the low payoff and the high payoff outcomes, where the small difference between the two indicated the safe option. The ten decisions had equal payoffs, however, moving down the table, the probability of the high-payoff outcome has gradually increased in steps of 10%, until it has reached 100% for the tenth decision; correspondingly, probability of the low-payoff outcome has gradually decreased in steps of 10%. Lottery payoffs in the experiment were as in the low-payoff treatment of Holt and Laury (2002) multiplied by 1.5. See Table 1 for the menu of lottery decisions that were used in the experiment, and the difference in their expected payoffs.

Table 1: The ten paired lottery-choice decisions

Option A	Option B	Difference in expected payoffs
1/10 of 3.00 EUR, 9/10 of 2.40 EUR	1/10 of 5.78 EUR, 9/10 of 0.15 EUR	1.75 EUR
2/10 of 3.00 EUR, 8/10 of 2.40 EUR	2/10 of 5.78 EUR, 8/10 of 0.15 EUR	1.24 EUR
3/10 of 3.00 EUR, 7/10 of 2.40 EUR	3/10 of 5.78 EUR, 7/10 of 0.15 EUR	0.74 EUR
4/10 of 3.00 EUR, 6/10 of 2.40 EUR	4/10 of 5.78 EUR, 6/10 of 0.15 EUR	0.24 EUR
5/10 of 3.00 EUR, 5/10 of 2.40 EUR	5/10 of 5.78 EUR, 5/10 of 0.15 EUR	-0.27 EUR
6/10 of 3.00 EUR, 4/10 of 2.40 EUR	6/10 of 5.78 EUR, 4/10 of 0.15 EUR	-0.77 EUR
7/10 of 3.00 EUR, 3/10 of 2.40 EUR	7/10 of 5.78 EUR, 3/10 of 0.15 EUR	-1.27 EUR
8/10 of 3.00 EUR, 2/10 of 2.40 EUR	8/10 of 5.78 EUR, 2/10 of 0.15 EUR	-1.77 EUR
9/10 of 3.00 EUR, 1/10 of 2.40 EUR	9/10 of 5.78 EUR, 1/10 of 0.15 EUR	-2.28 EUR
10/10 of 3.00 EUR, 0/10 of 2.40 EUR	10/10 of 5.78 EUR, 0/10 of 0.15 EUR	-2.78 EUR

Students were asked to make ten decisions and pick one *Option* for each of the lottery pairs. Only one decision was chosen at the end of the experiment to determine participant's earnings. A random number from one to ten was generated for each player individually, either through the random number generator in z-Tree program, or by rolling a ten-sided dice. The obtained number specified the decision that was used to determine subject's payment. Prior to start of the experiment, students were informed that every number had an equal probability to occur, and that they had to think carefully about each of their choices. The outcome of the selected lottery was determined by a second random number from one to ten also generated, either by the computer program, or by rolling a ten-sided dice. At the conclusion of the experiment students were paid their earnings in cash. Additionally, each of them received a show up fee of 2 EUR. English translation of instructions is included in Appendix D.

As in Holt and Laury (2002) and Baker, Laury, and Williams (2008) a total number of safe choices taken by subjects was used to assess their risk aversion. Individuals base their choice of lotteries on the difference in the expected values of the competing lotteries, and on the degree of their own risk aversion. Consequently a risk neutral person, before switching to the risky lottery, would make four safe choices; a risk-averse person would make more than four choices and a risk loving person would make less than four choices. Table 2, based on Holt and Laury (2002), classifies degrees of risk aversion, based on the number of taken safe choices in the lottery experiment.

Table 2: Risk aversion classification based on the number of safe lottery choices

Number of safe choices	Risk preference classification
0-1	Highly risk loving
2	Very risk loving
3	Risk loving
4	Risk neutral
5	Slightly risk averse
6	Risk averse
7	Very risk averse
8	Highly risk averse
9-10	Stay in bed

5 EXPERIMENTAL RESULTS

In this section the above-named hypotheses about the consequences of the cognitive bias of overconfidence on individual trading behavior and performance are tested. First, univariate and bivariate analyses are carried out. Upon it, in order to investigate these questions more thoroughly, measures of trading activity and gains from trade are regressed on several explanatory variables.

5.1 UNIVARIATE AND BIVARIATE ANALYSIS

Trading activity

Compared to other experiments where subjects had different portfolio endowments and actively used market-place to balance their portfolios, e.g. SSW (1988), in my experiment subjects had equal endowments, thus there was no need for them to use market for portfolios' balancing. Yet the empirical data suggest that average trading activity (MTA), defined as the mean of transactions (purchases and sales) conducted by an individual summed over the session divided by the number of shares outstanding in that market[5], was quite high (see Appendix A). On average, per session, traders have transacted 0.89 times the outstanding stock of shares; trading activity of some subjects equaled several times the stock. To test the hypothesis, that overconfident investors trade more, I calculate the correlation coefficient between individual average trading activity and overconfidence, expressed as the bias score. Results imply that individuals with the higher bias score engage in trading activity more actively (Pearson correlation(58) = 0.350, $p < 0.01$, one-sided; medium correlation). Traders in overconfident markets engage in trading activity significantly more often than traders in rational markets (Mann-Whitney Z = -2.610, $p < 0.01$, one-sided). There is no significant difference in transactions' frequency between female and male participants (Mann-Whitney Z = -0.105, p = 0.916, two-sided). To further analyze gender dimension in the relationship between trading activity and bias score, correlation coefficients were recalculated separately for female and male participants. 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 = 0.000, one-sided), implying that female-participants engage in trading activity more lively with increase in their bias score.

[5] 18 shares.

Now I turn to testing the proposition that high turnover traders are outperformed by low turnover traders. Normalized profits of the participants, calculated as individual gains from trade scaled by the initial portfolio value (36 ECU × 3 = 106 ECU), and corresponding to them average trading activity are presented on Figure 1. Data in the graph are arranged in the increasing order of trading activity values and are plotted with the linear trend line. The trend line implies that increase in trading activity is accompanied by decrease in individual gains. Average normalized profits equaled 3.614 times the value of the initial portfolio (SD = 1.83). In the total mass of individual earnings two values, namely 7.915 and 8.391 (in absolute value consequently 854.8 ECU and 906.2 ECU) look rather like exceptions. This observation will be taken in account, while conducting statistical tests.

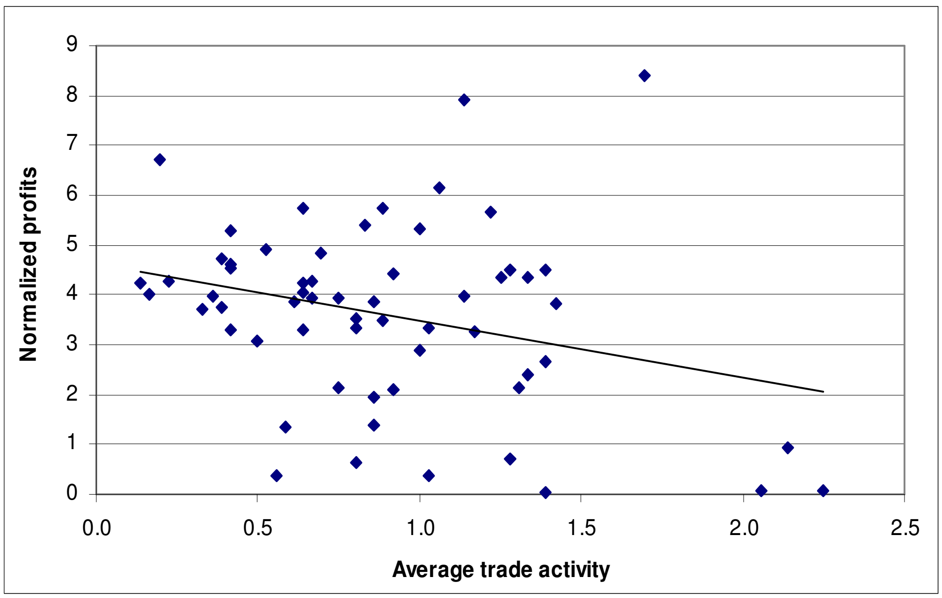

Figure 1: Normalized profits per participant

To verify the relationship between trading activity and gains from trade the sample is broken in five equal sub-samples ranked in terms of trading activity (quintiles). In Figure 2 distribution of the average total profits from trade across trading activity quintiles is presented. One can notice the pattern of reduction in earnings with growth of trading activity (with an exception of the fourth quintile). Can the hypothesis that gains are equal in turnover quintiles be rejected? The conducted Kruskal-Wallis test cannot reject this hypothesis (Kruskal-Wallis(4) = 7.562, p = 0.109, two-sided). However, as mentioned above, there are two possible outliers in the sample of individual performance, thus the analysis is repeated without these observations. For the reduced sample, proposition of gains' equality across quintiles is rejected (Kruskal-Wallis(4) = 9.351, p = 0.053, two-sided). This result serves as weak evidence that gains from trade depend on trading activity. To get more clarity on this issue, correlation coefficient between trading activity and individual earnings is estimated. The obtained coefficient is small but significant, implying that increase in trading activity is paired with poorer performance (Pearson Correlation(58) = -0.292, $p < 0.05$, one-sided). If analysis is repeated without the two outlier values, strength of the linear relationship increases to medium (Pearson Correlation(56) = -0.456, $p = 0.00$, one-sided), which suggests that increase in trading activity is moderately associated with reduction in gains from trade.

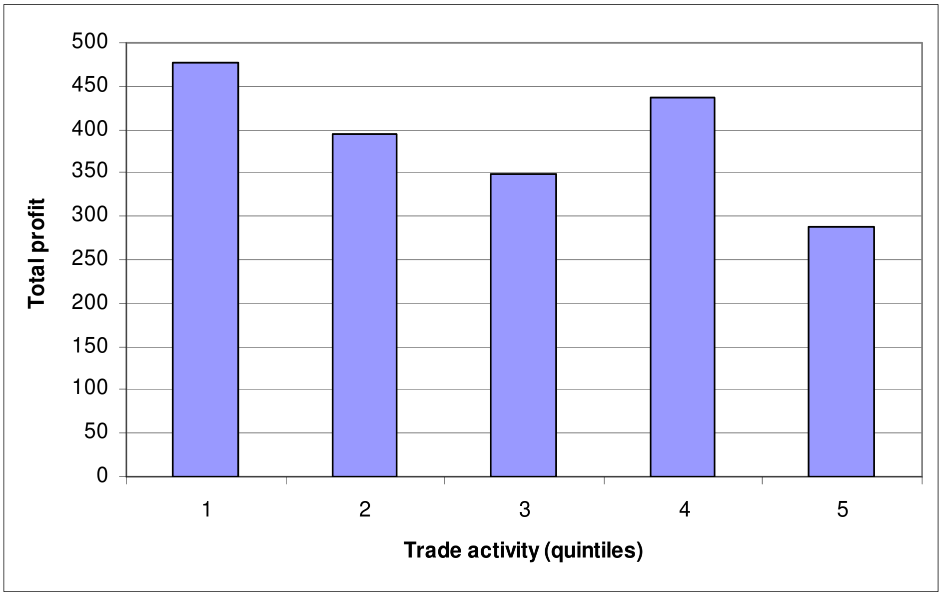

Figure 2: Distribution of individual profits across trading activity quintiles

As a next step, comparison between earnings in the subgroup, whose trading activity was lower than the median value (0.847), and subgroup, whose trading activity was higher than the median, was conducted. Although, on average the latter made 15.17% less in terms of individual earnings, a statistically significant conclusion that this group profited less from trade cannot be drawn (Mann-Whitney Z = -1.271, $p = 0.102$, one-sided). Yet, when analysis is repeated with the reduced sample (without the possible outliers)[6], results suggest that the *low trade* group outperformed on average the *high trade* group by 23.12%, and this difference is significant (Mann-Whitney Z = -1.438, $p < 0.10$, one-sided). To explore this issue further, individual gains in the lowest and the highest trading activity quartiles were compared (for descriptive statistics see Table 3(a). The conducted Mann-Whitney test revealed that traders in the lowest quartile significantly outperformed traders in the highest quartile (Z = -1.555, $p < 0.10$, one-sided) and gained on average 38% more ECUs at the end of the experiment. Without the outliers this difference is even higher – 55.7% (Mann-Whitney Z = -2.095, p <

[6] Median equals 0.819.

0.05, one-sided; see Table 3(b). This is in line with the results of Barber and Odean (2000) who showed that high turnover households were outperformed by low turnover households.

Table 3: Profit and trading activity in the lowest and highest trading activity quartiles

a: The whole sample

	1st quartile		4th quartile	
	Profit	Trade	Profit	Trade
Mean	442.69	0.363	321.13	1.515
Median	456.6	0.389	286.6	1.389
SD	145.73	0.129	260.5	0.347
Min.	42.4	0.14	4.2	1.22
Max.	726	0.56	906.2	2.25
N	15	15	15	15

b: Sample without outliers

	1st quartile		4th quartile	
	Profit	Trade	Profit	Trade
Mean	442.69	0.363	284.33	1.48
Median	456.6	0.389	286.6	1.333
SD	145.73	0.129	205.02	0.354
Min.	42.4	0.14	4.2	1.17
Max.	726	0.56	612.6	2.25
N	15	15	15	15

Gains from Trade

This subsection is devoted to the analysis of traders' performance in the experimental asset market. Subject's performance is assessed as her relative profit, which is calculated based on Hirota and Sunder (2007), as individual gains from trade (in ECUs) divided by the fundamental value of the initial portfolio of 3 stocks (36 ECU × 3 = 106 ECU) minus the cross-sectional average of this ratio. Figure 3 shows the cross-sectional distribution of players' relative profits in the two types of experimental market. The value of each marker represents one trader's relative profit. Standard deviation of individual earnings from the mean value (0) in the overconfident market sessions is 2.32 and in the rational market sessions – 1.19. Empirical evidence suggests that overconfident sessions were characterized by the larger dispersion of gains from trade, compared to the rational sessions. The conducted Siegel-Tukey test confirmed that difference in profits' variation within the two groups was statistically significant (Siegel-Tukey = 2.329, $p < 0.05$, two-sided).

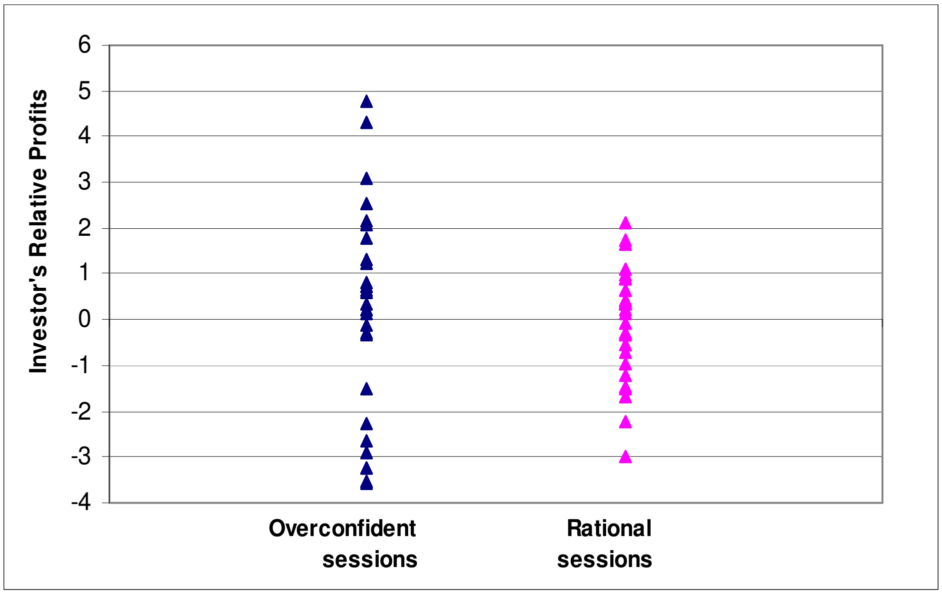

Figure 3: The cross-sectional distribution of relative profits by treatment

In the experiment by SSW (1988) better forecasters have also enjoyed higher gains from trade in the experimental market. To determine the relationship between accuracy of average price prediction and individual earnings and its' direction in my experiment several statistical tests are performed. Forecasting precision is expressed as the Total Absolute Error (TAE) of prediction and/ or the Average Absolute Error (MAE) (see Appendix A for sample values of MAE and TAE):

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

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

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

The calculated correlation coefficient between forecasting precision and relative profits detected moderate and significant negative correlation (MAE: Pearson Correlation (58)= -

0.360, $p<0.01$, one-sided; TAE: Pearson Correlation(58)= -0.365, $p<0.01$, one-sided). This is in line with previous research which suggests that increase in price prediction precision is paired with higher gains from trade in the experimental asset markets. I continue by comparing traders' accuracy in both of the groups. Subjects in the rational group committed significantly less errors, measured both as MAE and TAE (MAE: Mann-Whitney Z = -3.512, $p < 0.00$, one-sided; TAE: Mann-Whitney Z = -2.610, $p < 0.01$, one-sided). Linear relationship between overconfidence and average absolute error (MAE) is moderate and significant (Pearson Correlation(58) = 0.350, $p < 0.01$, one-sided), and between overconfidence and total absolute error (TAE) is small but significant (Pearson Correlation(58) = 0.225, $p < 0.05$, one-sided). Thus, it can be concluded that increase in the degree of overconfidence is accompanied by (moderate) reduction in accuracy of prediction.

Another factor that had negative impact on earnings was the number of assets in participants' inventory at the end of experiment. Namely there was a weak tendency for subjects with more assets in their final portfolios to have lower gains. Correlation between the final asset-holdings and relative profit is small but significant (Pearson Correlation(58) = -0.225, $p < 0.05$, one-sided). An interesting fact is that, although female subjects had fewer assets in their inventories at the end of experiment (see below), their gains from trade were significantly lower than gains of male subjects (Mann-Whitney Z = -2.646, $p < 0.01$, one-sided).

To test the proposition of Scheinkman and Xiong (2003) that more overconfident investors would hold most of the assets at the end of experiment, I first estimate the correlation between individual bias scores and the number of assets in players' final inventory. The correlation coefficient is almost equal to zero and insignificant (Pearson Correlation (28) = -0.031, $p = 0.407$, two-sided), thus providing no evidence of linear relationship between overconfidence and final portfolio size. The same is true for the rational and overconfident markets separately (overconfident: Pearson Correlation (28) = -0.097, $p = 0.306$, one-sided; rational: Pearson Correlation (28) = 0.028, $p = 0.442$, one-sided). To test for the differences in dispersion (scale) between end inventories of the two types of traders, a Siegel-Tuckey variance test was conducted, which revealed that rational and overconfident traders did not differ in terms of final portfolios' variance (Siegel-Tukey = 0.531, $p = 0.595$, two-sided). See Appendix E for distribution of the number of assets in the final inventories of all traders (a.), overconfident traders (b.), and rational traders (c.). There was significant difference in the final portfolio size of male and female players, where the latter had significantly less assets than the former at the end of experiment (Mann-Whitney Z = -3.121, $p < 0.01$, one-sided). No linear relationship between asset-holdings and the bias scores in none of the groups was detected (women:

Pearson Correlation(23) = 0.105, p = 0.309, one-sided; men: Pearson Correlation(33) = -0.126, p = 0.235, one-sided).

5.2 MULTIVARIATE ANALYSIS

Trading activity

This subsection presents results of cross-sectional regressions estimating the relationship between average trading activity of an individual (MTA) per experiment and several explanatory variables that might affect efficiency of financial decision making: the normalized bias score[7] (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 in semesters (Semester), and price forecasting precision measured as average absolute error (MAE) or total absolute error (TAE). In parenthesis error terms are shown. Equations 8 and 9, instead of average trading activity use the measure of total trading activity. All specifications of equations (see Table 4) confirm the proposition that overconfidence has explanatory power for trading activity[8].

To detect which variables significantly affect the number of average stock market transactions per person in my experiment, I start with the simplest model specification in which average trading activity (MTA) is regressed on the individual degree of overconfidence, measured as the normalized bias score (NBS). Subsequently a range of alternative specifications are estimated by adding other regressors to the model. From Equation 1 it can be seen that, as predicted, NBS has significant positive influence on trading activity: a one standard deviation increase in the bias score raises trading activity by 0.35 standard deviations[9] ($p < 0.05$, two-sided).

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[7] A sample of bias scores of the participants is normalized on an interval [0,1], where one stands for the most overconfident person.

[8] Equations 10 and 11 are discussed later in the section on "Risk Aversion Analysis: Experimental Results".

[9] In all specifications, one of the key variables of our interest, namely the normalized bias score, is measured on a scale that is not easy to interpret. Thus to assess the effect that independent variables had on a dependent variable standardized β_{std} coefficients were calculated, which allowed expressing this effect not in terms of the original units of the variables, but in standard deviation units, i.e. to see how the dependent variable changed, if the independent variable grew by one standard deviation. Standardized beta coefficients were obtained by multiplying the original beta coefficient by the ratio of the sample standard deviation of the corresponding independent variable to the sample standard deviation of the dependent variable:

$$\hat{\beta}_{std} = \left(\hat{\sigma}_j / \hat{\sigma}_y\right)\hat{\beta}_j \qquad \text{for } j = 1, \ldots, k.$$

Table 4: Trading activity (all errors are heteroskedasticity corrected)

	1	2	3	4	5	6	6a	7	8	9	10	11
C	0.660**** (0.085)	0.693**** (0.086)	0.499**** (0.102)	1.340** (0.623)	0.734**** (0.117)	1.220* (0.618)	1.301 (0.618)	1.302 (0.637)	1.318**** (0.171)	2.431* (1.239)	1.815** (0.869)	2.111** (0.836)
NBS	0.669** (0.266)	0.680** (0.268)	1.286*** (0.370)	1.237*** (0.377)	1.149*** (0.371)	0.994** (0.384)	1.052*** (0.385)	1.167*** (0.364)	1.339** (0.530)	1.985** (0.768)	0.859* (0.774)	0.854* (0.757)
Gender		-0.063 (0.119)	0.301* (0.158)	0.253$^{*, a}$ (0.160)	0.253$^{*, a}$ (0.157)	0.317$^{**, a}$ (0.163)	0.268$^{**, a}$ (0.154)	0.279* (0.160)		0.635$^{**, a}$ (0.326)	0.470 (0.269)	0.446 (0.243)
NBS*Gender			-1.074** (0.460)	-0.996** (0.481)	-0.998** (0.475)	-0.939$^{**, a}$ (0.476)	-0.956** (0.475)	-1.008** (0.480)		-1.871$^{**, a}$ (0.950)	-1.307$^{*, a}$ (0.878)	-1.329$^{*, a}$ (0.857)
Age				-0.036$^{*, a}$ (0.026)		-0.040$^{*, a}$ (0.025)	-0.041* (0.026)	-0.038$^{*, a}$ (0.027)		-0.081$^{*, a}$ (0.050)	-0.060$^{**, a}$ (0.033)	-0.067** (0.029)
Semester					-0.046** (0.019)							
MAE						0.036** (0.015)	0.027$^{**, a}$ (0.012)			0.072** (0.031)	0.040** (0.017)	
TAE								0.002$^{*, a}$ (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	60	60	32	32
adj. R2	0.11	0.10	0.16	0.17	0.17	0.23	0.25	0.19	0.11	0.23	0.15	0.23
SERegr	0.44	0.44	0.43	0.42	0.43	0.41	0.38	0.42	0.88	0.82	0.40	0.38

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

In Equation 2 it is also controlled for the role of traders' gender on variation in trading activity, and it is detected that gender has no significant influence on trading activity. Impact of overconfidence remains significant and positive: a one standard deviation increase in NBS raises trading activity by 0.356 standard deviations ($p < 0.05$, two-sided).

In Equation 3, an interaction term between overconfidence and gender is added; this increases the explained variation in trading activity. The regression results imply that, the strength of the impact of overconfidence on trade intensity varies across genders, i.e. with increase in overconfidence the rate of increment in trading activity is lower for males, than for females. For every unit increase in overconfidence when gender dummy is equal to one (i.e. a trader is a man) trading activity grows by only 0.212 units, whereas for a female subject this increase equals to 1.286 units (interaction term is significant at 5%, two-sided). This contradicts the result of Barber and Odean (2001) that men traded more than women. Yet, Deaves et al. (2009) found no interaction between gender and overconfidence in their sample. They noted that, after controlling for overconfidence, there was no difference in trading activity between genders. Also in the paper of Glaser and Weber (2007) gender was not significantly related to the trading volume measures.

In addition to previous regressors, in Equation 4 it is tested for the explanatory power of subjects' experience, namely age, for trading activity. Results indicate that a one standard deviation increment in age decreases trading activity by -0.162 standard deviations ($p < 0.1$, one-sided). Overconfidence and gender interaction term is significant at 5% level (two-sided) and for every unit increase in NBS for male subjects there is growth in trading activity of 0.241 units; in contrast, for female subjects increase of 1.237 units in trading activity is observed.

In Equation 5, I control for another subjects' experience proxy, such as duration of studies in semesters. Negative impact of subjects' experience on the number of average market transactions persists: a one standard deviation increase in semester variable decreases trading activity by -0.207 standard deviations ($p < 0.05$, two-sided). Interaction term between gender and overconfidence is negative and significant at 5% level (two-sided), and for every unit increase in NBS for male subjects there is growth in trading activity of 0.150 units; in contrast, for female subjects increase of 1.340 units in trading activity is observed.

To test if forecasting errors boost trading activity, in Equation 6 it is controlled for individual average absolute error (MAE) in forecasting. Analysis reveals that the more an individual is mistaken about future asset prices, the more actively she engages in trading activity: a one standard deviation increase in MAE raises trading activity by 0.291 standard deviations ($p < 0.05$, two-sided). Other significant control variables are interaction term between participants' overconfidence and gender, and age: a one standard deviation increment in age reduces trading activity by -0.184 standard deviations ($p < 0.1$, one-sided); interaction term is negative and significant at 5% level (one-sided), and for every unit increase in NBS for male subjects there is growth in trading activity of 0.055 units; in contrast, for female subjects increase of 0.994 units in trading activity is observed.

After analysis of the residuals, one possible outlier was detected and, after exclusion of it, the regression was re-run. Equation 6a indicates that increase in forecasting error by one standard deviation increases trading activity by 0.231 standard deviations ($p < 0.1$, one-sided). Increase in age by one standard deviation reduces trading activity by -0.201 standard deviations ($p < 0.1$, two-sided). Interaction term between gender and overconfidence is negative and significant at 5% level (two-sided), and for every unit increase in NBS for male subjects there is growth in trading activity of 0.095 units; in contrast, for female subjects increase of 1.052 units in trading activity is observed. Exclusion of the outlier resulted in increase in the explained variation in trading activity and reduction of the regression error, implying that model without the outlier better represents the data.

In Equation 7 forecasting imprecision is assessed as total absolute error (TAE). The goodness of fit of the regression model deteriorates and regression error increases; the direction of the relationship between the variables remains as in Equation 6: a one standard deviation increment in age reduces trading activity by -0.173 standard deviations ($p < 0.1$, one-sided); a one standard deviation increase in forecasting error, measured as TAE, raises trading activity by 0.168 standard deviations ($p < 0.1$, one-sided); interaction term is negative and significant at 5% (two-sided), and for every unit increase in NBS for male subjects there is growth in trading activity of 0.159 units; in contrast, for female subjects increase of 1.167 units in trading activity is observed.

In Equations 8 and 9 instead of average trading activity another dependent variable namely total trading activity (TTA) is used. Total trading activity is defined as the sum of all trade contracts (purchases and sales) per fifteen periods divided by the number of shares outstanding in that market (i.e. 18 shares in each of the markets). Replacement of the dependent variable does not bring about any substantial changes in relationships between regressors and the dependent variable. The goodness of fit of the models does not improve, yet the error term doubles.

Results, presented in Table 4, lead to the following conclusions 1) subject's experience has a significant negative effect on her engagement in trading activity, 2) impact of overconfidence on trade is positive, however, holding all other factors constant, with increase in overconfidence men engage in stock market transactions less than women, 3) forecasting errors, that induce false future price expectations, force subjects to involve in trading activity 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. I will come back 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 was obtained.

Gains from Trade

Many theoretical and empirical works predict reduction in welfare, which is faced by overconfident traders. In this subsection I describe the results of the cross-sectional regressions, estimating the relationship between subjects' performance, assessed as relative profit, and several explanatory variables: the normalized bias score (NBS), gender dummy (this variable takes value 1 if subject is male), average trading activity (Trading activity), an interaction term between gender and trading activity (Gender*Trading activity), price forecasting precision measured as average absolute forecasting error (MAE) or total absolute forecasting error (TAE), subject's experience expressed as age (Age) or duration of studies in semesters (Semester), and the number of assets in the final inventory (End assets). In parenthesis the error terms are shown. For the specifications of the estimated models see Table 5.

I start again with the simplest model specification and, by adding other regressors to the model, test which variables significantly affect relative profit from trade of participants in my experiment. In Equation 1 it is tested for the influence of subject's degree of overconfidence and gender on gains from trade. The normalized bias score has no significant effect on performance, while gender has significant impact on individual profit: male students enjoy higher earnings in comparison to their female counterparts ($p < 0.01$, two-sided).

In addition to previous regressors in Equation 2 it is controlled for the impact of active trade engagement on variations in relative profit. From the results, one can see that this influence is negative and significant: a one standard deviation increase in trading activity reduces performance by -0.325 standard deviations ($p < 0.05$, two-sided). The effect of overconfidence on gains from trade is positive, yet insignificant. Males have earned significantly more ECUs compared to females ($p < 0.01$, two-sided).

To analyze, whether strength of the effect that active trade engagement has on performance varies across female and male participants, an interaction term between gender and trading activity is introduced in Equation 3. Adding this regressor increases the explained variation in relative profits. Results indicate that with increase in the average number of market transactions, the rate of decrease in gains varies across genders, and is lower for male subjects. For every unit increase in trading activity for male traders there is reduction in earnings by -0.206 units, whereas for female traders earnings decrease by -2.655 units (interaction term is significant at 5%, two-sided). Overconfidence is a factor that has significant positive effect on earnings: for a one standard deviation increase in NBS there is growth in relative profit by 0.210 standard deviations ($p < 0.1$, one-sided).

In Equation 4, impact of forecasting errors on relative profit is analyzed. As in the work by SSW (1988), forecasting errors have negative and significant consequences for gains from trade: a one standard deviation increase in average absolute error (MAE) reduces relative profit by -0.221 standard deviations ($p < 0.1$, one-sided). Subjects' relative profits significantly increase with the increment in the degree of overconfidence ($p < 0.1$, two-sided). For every unit increase in trading activity for male traders there is reduction in earnings by -0.074 units, whereas for female subjects earnings decrease by -2.314 units (interaction term is significant at 5%, two-sided

In Equation 5 forecasting imprecision is assessed as total absolute error (TAE). TAE has negative effect on relative profit, which is comparable to the effect obtained in Equation 4; however there is increase in the goodness of fit of the model and decrease in the error term. A one standard deviation increment in TAE reduces individual earnings by -0.277 standard deviations ($p < 0.05$, one-sided). Growth in the degree of overconfidence has positive and significant effect on performance: a one standard deviation increase in NBS raises gains by 0.253 standard deviations ($p < 0.1$, two-sided). For every unit increase in trading activity for male traders there is reduction in earnings by -0.130 units, whereas for female subjects earnings decrease by- 2.360 units (interaction term is significant at 5%, two-sided

In Equation 6 one more regressor is added, and it is tested for the explanatory power of subjects' experience, proxied by age, for relative profit. From the estimation outcome one can see that age has no significant effect on individual earnings. A one standard deviation increment in forecasting error, measured as TAE, reduces relative profit by -0.293 standard deviations ($p < 0.05$, one-sided). Growth in the degree of overconfidence has positive and significant effect on performance: a one standard deviation increase in NBS raises gains by 0.241 standard deviations ($p < 0.1$, two-sided). For every unit increase in trading activity for male traders there is reduction in earnings by -0.112 units, whereas for female subjects earnings decrease by -2.124 units (interaction term is significant at 5%, two-sided).

Table 5: Gains from trade (all errors are heteroskedasticity corrected)

	1	2	3	4	5	6	7	8	9	10	11
C	-0.776* (0.423)	0.108 (0.539)	1.159*** (0.377)	1.626*** (0.498)	1.525*** (0.442)	-1.030 (2.881)	-0.029 (2.702)	-0.035 (2.700)	1.790** (0.788)	1.465**** (0.417)	1.624**** (0.399)
NBS	0.065 (1.085)	0.932 (1.037)	1.577$^{*, a}$ (1.045)	1.995* (1.069)	1.896* (0.987)	1.805* (0.957)	1.440$^{*, a}$ (0.919)	1.436$^{*, a}$ (0.919)	1.549$^{*, a}$ (1.013)	1.474$^{*, a}$ (0.936)	1.628* (0.899)
Gender	1.293*** (0.442)	1.212*** (0.395)	-1.012 (0.812)	-1.064* (0.813)	-0.950 (0.770)	-0.692 (0.760)	-0.431 (0.740)	-0.429 (0.740)	-0.695 (0.820)	-0.564 (0.738)	-0.577 (0.746)
Trading activity (average)		-1.276** (0.520)	-2.655**** (0.488)	-2.314**** (0.568)	-2.360**** (0.564)	-2.124*** (0.661)	-2.122**** (0.559)		-2.366**** (0.567)	-2.255**** (0.469)	-2.402**** (0.446)
Trading activity*Gender			2.449** (0.996)	2.240** (0.986)	2.229** (0.977)	2.013** (0.977)	2.237** (0.978)	1.120** (0.489)	2.362** (1.023)	2.370** (0.969)	2.555*** (0.947)
MAE				-0.108$^{*, a}$ (0.069)							
TAE					-0.012$^{**, a}$ (0.006)	-0.013$^{**, a}$ (0.007)	-0.008$^{*, a}$ (0.006)	-0.008$^{*, a}$ (0.006)	-0.007 (0.006)	-0.008$^{*, a}$ (0.005)	-0.011*** (0.004)
Age						0.104 (0.118)	0.061 (0.109)	0.061 (0.109)			
End assets							-0.136$^{**, a}$ (0.073)	-0.136$^{**, a}$ (0.073)	-0.118$^{*, a}$ (0.085)	-0.143** (0.071)	-0.153** (0.069)
Semester									-0.067 (0.105)		
Trading activity (total)								-1.061**** (0.280)			
N	60	60	60	60	60	60	60	60	54	60	59
adj. R2	0.09	0.17	0.26	0.28	0.32	0.32	0.38	0.38	0.32	0.39	0.47
SERegr	1.75	1.67	1.58	1.55	1.51	1.51	1.45	1.45	1.49	1.44	1.34

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

Equation 7 analyzes the effect of the final portfolio size on gains from trade. The number of assets in the final inventory is a significant determinant of reduction in relative profit: a one standard deviation increase in final portfolio size decreased earnings by -0.301 standard deviations ($p < 0.1$, one-sided). A one standard deviation increment in forecasting error, measured as TAE, reduces relative profit by -0.189 standard deviations ($p < 0.05$, one-sided). Growth in the degree of overconfidence has positive and significant effect on performance: a one standard deviation increase in NBS raises gains from trade by 0.192 standard deviations ($p < 0.1$, one-sided). For every unit increase in trading activity for male traders there is growth in earnings by 0.115 units, whereas for female subjects earnings decrease by -2.366 units (interaction term is significant at 5%, two-sided).

In Equation 8, instead of average trading activity another dependent variable, namely total trading activity (TTA), is used. This specification, compared to Equation 7, results in no changes to the goodness of fit of the model and standard error of regression. A one standard deviation increment in forecasting error, measured as TAE, reduces earnings by -0.189 standard deviations ($p < 0.1$, one-sided). Subjects' relative profit deteriorates with growth in the size of their final portfolio: a one standard deviation increase in the end inventory reduces individual earnings by -0.301 standard deviations ($p < 0.05$, one-sided). Increment in the degree of overconfidence has positive and significant effect on performance: a one standard deviation increase in NBS raises gains from trade by 0.192 standard deviations ($p < 0.1$, one-sided). For every unit increase in trading activity for male traders there is growth in earnings by 0.059 units, whereas for female subjects earnings decrease by -2.122 units (interaction term is significant at 5%, two-sided).

In Equation 9, I control for another subjects' experience proxy, such as duration of studies in semesters. As in the case with age variable, this relationship is also insignificant. Forecasting error, measured TAE, has no significant effect on gains from trade. Subjects' relative profit deteriorates with growth in the size of their final portfolio: a one standard deviation increase in the end inventory reduces individual earnings by -0.260 standard deviations ($p < 0.1$, one-sided). Increment in the degree of overconfidence has positive and significant effect on performance: a one standard deviation increase in NBS raises gains from trade by 0.207 standard deviations ($p < 0.1$, one-sided). For every unit increase in trading activity for male traders there is reduction in earnings by -0.004 units, whereas for female subjects earnings decrease by -2.122 units (interaction term is significant at 5%, two-sided).

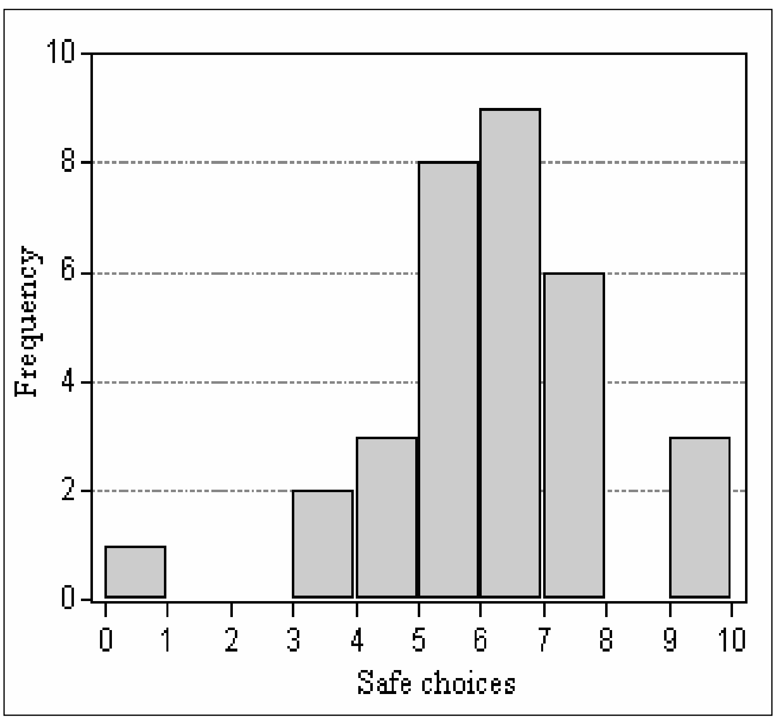
The insignificant experience variables (age and semester) are removed from Equation 10. This specification, compared to Equations 7 and 9, is characterized by better fit of the regression model and reduction of the regression error. A one standard deviation increment in forecasting error, measured as TAE, decreases earnings by -0.175 standard deviations ($p < 0.1$, one-sided). Subjects' gains deteriorate with growth in the size of their final portfolio: a one standard deviation increase in the end inventory reduces individual earnings by -0.315 standard deviations ($p < 0.05$, one-sided). Increment in the degree of overconfidence has positive and significant effect on performance: a one standard deviation increase in NBS raises gains from trade by 0.197 standard deviations ($p < 0.1$, one-sided). For every unit increase in trading activity for male traders there is growth in earnings by 0.115 units, whereas for female subjects earnings decrease by -2.255 units (interaction term is significant at 5%, two-sided).

After analysis of the residuals, one possible outlier was detected and, after exclusion of it, the regression was re-run. Equation 11 indicates that a one standard deviation increment in forecasting error, measured as TAE, decreases earnings by -0.249 standard deviations ($p < 0.01$, two-sided). Subjects' relative profit deteriorates with growth in the size of their final portfolio: a one standard deviation increase in the end inventory reduces individual earnings by -0.335 standard deviations ($p < 0.05$, two-sided). Increment in the degree of overconfidence has positive and significant effect on performance: a one standard deviation increase in NBS raises gains from trade by 0.218 standard deviations ($p < 0.1$, two-sided). For every unit increase in trading activity for male traders there is growth in earnings by 0.153 units, whereas for female subjects earnings decrease by -2.402 units (interaction term is significant at 1%, two-sided). Exclusion of the outlier resulted in increase in the explained variation in relative profit and reduction of the regression error, implying that model without the outlier better represents the data.

Results presented in Table 5 suggest that 1) overconfidence degree has a significant positive effect on individual earnings, 2) impact of active trade engagement on relative profit is negative, however, holding all other factors constant, with increase in the number of market transactions males incur smaller losses, or even some yield, in comparison to females, 3) forecasting errors, that induce false future price expectations and "cause mistakes in financial decision making" (Biais et al., 2005), produce losses, 4) the number of assets in the final inventory of the subject is a significant determinant of reduction in gains from trade. 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.

6 RISK AVERSION ANALYSIS: EXPERIMENTAL RESULTS

Experimental results present evidence that on average subjects were risk averse with 5.66 taken safe choices (SD = 1.82). 28.13% of the group has made six safe choices, 25% has made five safe choices, and 18.75% has made seven safe choices. As Table 2 suggests, risk preferences of the participants can be classified correspondingly as risk averse, slightly risk averse and very risk averse. In general, 71.88% of choices have fallen in the interval of [5, 7] safe options (see Figure 4). Rational subjects have taken on average 5.81 safe choices (SD = 1.42), and overconfident subjects 5.50 safe choices (SD = 2.19). Subjects' demographics (age, semester, gender) had no significant impact on their risk aversion. No linear relationship between participants' age, their duration of studies (semester), and the number of safe choices was found (age: Spearman's Rho(30) = 0.091, p = 0.310, one-sided; semester: Spearman's Rho(26) = -0.159, p = 0.205, one-sided). Men have taken on average 5.68 safe choices (SD = 2.00), and women 5.62 safe choices (SD = 1.61). Difference in the average number of safe choices taken by both genders is insignificant (Mann-Whitney Z = -0.452, p = 0.652, two-sided). In Appendix C descriptive statistics of the experiment are presented: the number of safe choices taken by participants, their age, semester and the bias score.



Safe choices	Percentage of group
0	3.13%
1	0.00%
2	0.00%
3	6.25%
4	9.38%
5	25.00%
6	28.13%
7	18.75%
8	0.00%
9	9.38%

Figure 4: Distribution of safe choices in the group

Now, I turn to the examination of the relationship between overconfidence and risk aversion. It was hypothesized that overconfident subjects would be more risk loving, i.e. they would make less safe choices. Statistical tests detected no significant difference between two groups of players, neither in terms of the average number of safe choices (Mann-Whitney $Z = 0.320$, $p = 0.749$, two-sided), nor in their variation (Siegel Tukey test = 0.465, $p = 0.642$, two-sided). Correlation coefficient between risk aversion, measured as the number of safe choices, and individual bias score implies no linear relationship between them (Spearman's Rho(30) = -0.095, $p = 0.303$, one-sided). Additionally two regressions were run, where subjects' degree of overconfidence was regressed on the number of safe choices they made, their gender, and either their age (Equation 1) or duration of their studies in semesters (Equation 2) (see Appendix F). In Equation 1, no significant regressors were identified for predicting individual overconfidence; the goodness of fit measure indicates very poor fit. From inspection of Equation 2 it can be seen that a one standard deviation increase in duration of studies reduces overconfidence by -0.0064 standard deviations ($p < 0.1$, two-sided), however this impact is almost negligible. Other regressors are insignificant. The presented evidence implies that, in this sample, the number of safe choices has no explanatory power for subject's overconfidence.

The next step is to analyze the relationship between risk aversion and some experimental outcomes: the number of assets in the final inventory of the subject, intensity of the engagement in trading activity and gains from trade. It has been predicted that greater degree of subject's risk aversion will have stronger negative effect on her trading activity and the number of assets in her final inventory. This prediction is based on the assumption that risk-averse subjects would perceive each stock as a lottery and try to sell them in the initial periods of the game. No linear relationship was detected, neither between the final portfolio size and risk aversion (Spearman's Rho(30) = -0.001, $p = 0.498$, one-sided), nor between gains from trade and risk aversion (Spearman's Rho(30) = 0.031, $p = 0.433$, one-sided). The correlation coefficient between the number of safe choices and active trade engagement was negative, yet insignificant (Spearman's Rho(30) = -0.100, $p = 0.294$, one-sided). To clarify more precisely the impact of risk aversion on trading activity, I run two regression models – Equation 10 and Equation 11 (see Table 4) – whose specifications are the same as of Equations 6 and 7, with the variable measuring the number of safe choices added.

From inspection of Equation 10 it can be seen that the degree of risk aversion, measured as the number of safe choices, has no significant effect on the intensity of individual engagement in trading activity. Other relations between the variables remain similar to the observed in

Equation 6: 1) a one standard deviation increase in MAE raises trading activity by 0.348 standard deviations ($p < 0.05$, two-sided); 2) a one standard deviation increment in age reduces trading activity by -0.266 standard deviations ($p < 0.05$, one-sided); 3) interaction term between gender and overconfidence indicates that for every unit increase in NBS for male subjects there is reduction in trading activity by -0.448 units; in contrast, for female subjects increase of 0.859 units in trading activity is observed ($p < 0.1$, one-sided). In the model tested in Equation 11 also no significant influence of subjects' risk aversion on their engagement in trading activity was detected. Other relations between the variables remain similar to the observed in Equation 7: 1) a one standard deviation increase in TAE raises trading activity by 0.433 standard deviations ($p < 0.05$, two-sided); 2) a one standard deviation increment in age reduces trading activity by -0.300 standard deviations ($p < 0.05$, two-sided); 3) interaction term between gender and overconfidence indicates that for every unit increase in NBS for male subjects there is reduction in trading activity by -0.475 units; in contrast, for female subjects increase of 0.854 units in trading activity is observed ($p < 0.1$, one-sided).

It can be concluded that, in this sample, differences in experimental market outcomes between the traders were overconfidence and not risk aversion driven.

7 CONCLUSIONS

The aim of this article was to investigate the influence of behavioral factors, namely the degree of overconfidence and risk aversion, on financial decision making of economic subjects. For this purpose two kinds of experiments were conducted. The first one, whose design followed Smith, Suchanek and Williams (1988), was the asset market experiment, whereas the second was aimed at individual risk aversion measurement. Hypotheses, which were tested in the context of the suggested experimental design, were built on exploration of findings from the foregoing overconfidence research in financial markets. The presented evidence builds on individual traders' decisions.

The usual finding from experimental literature testing for the impact of overconfidence on variation in subjects' trading activity and performance (earnings) in market settings where both overconfident and rational traders are present, is that the former engage in more trading activity (Odean, 1998; Deaves et al., 2009) and face welfare reductions (e.g. Biais et al., 2005; Kirchler and Maciejovsky, 2002) compared to the latter. In contrast to these works, in the present experiment subjects, based on their pre-experimental overconfidence scores, were assigned to the two types of markets – rational and overconfident – and in the course of experiment they could interact only with participants of their own "type" (rational or overconfident). Within each of the conducted markets, the degree of overconfidence varied (even slightly) from participant to participant, and this part of experiment was built upon the assumption, that this was the only source of individual heterogeneity.

The design of experimental sessions, where all participants had identical initial endowments and information access, did not create preconditions for the active use of market-place for portfolio balancing purposes; correspondingly (almost) no trade should have occurred. However, the empirical data suggest that average trading activity was rather high and some traders demonstrated trading activity that equaled several times the outstanding market inventory. The results of data analysis supported the hypothesis that individuals with higher degree of overconfidence engaged in trading activity more actively. Yet, holding all other factors constant, with increase in overconfidence men have completed fewer stock market transactions than women. This contradicts the result of Barber and Odean (2001) that men trade more than women. On the other hand Deaves et al. (2009) found that after controlling for overconfidence there was no difference in trading activity between males and females. Also in Glaser and Weber (2007) gender was not significantly related to the trading volume measures. Other control variables, which had significant effect on the number of stock market transactions per person, were: errors in predicting average asset market prices and subjects' experience, measured as their age or duration of study. Namely, forecasting errors, inducing false future price expectations, forced subjects to engage in trading activity more actively, whereas experience had significant negative impact on their involvement in trading activity.

Statistical data suggest that, contrary to the formulated hypothesis, overconfidence had positive effect on gains from trade. Other factors that significantly affected variation of relative profits were: trading activity, gender, forecasting errors and the final portfolio size. As it was expected, active engagement in trade had negative consequences on individual gains. High turnover players were significantly outperformed by low turnover players, namely participants in the lowest trading activity quartile gained on average 38% more ECUs than participants in the highest quartile. However, holding all other factors constant, with increase in the number of market transactions males incurred smaller losses, or even some yield, compared to females. In line with the previous research, forecasting errors, bringing about mistakes in financial decision making, were associated with losses. The number of assets in trader's final inventory, which was found to be not overconfidence dependent, proved to be a significant determinant of reduction in gains from trade. A curious fact is that, although females held fewer assets in their portfolios than males, their gains were significantly lower.

Based on the above-mentioned findings, it can be concluded that also in the setting, where two "types" of subjects were separated from each other, performance and trading activity were overconfidence dependent and even small variations in miscalibration among players belonging to the same "type" were sufficient to evoke this effect.

At the completion of subsequent risk aversion measurements in the reduced sample, consisting of sixteen rational and sixteen overconfident former asset market experiment participants, the collected data revealed that subjects on average were risk averse. Inconsistent with the proposition that overconfident subjects would be more risk loving, statistical tests detected no significant difference between the two types of traders in terms of the average number of safe choices. The presented evidence implied that, neither the number of safe choices, nor demographics (age, gender, and semester) had explanatory power for the individual degree of overconfidence. Prior to the experiment it was expected that risk aversion would have negative effect on participant's trading activity and her final portfolio size. However, no significant relationship between these variables was detected. Other factors, which were found to influence trading activity in the complete sample, remained significant. Hence, it can be concluded that in the reduced sample, differences in experimental market outcomes between the traders were overconfidence and not risk aversion driven.

For future research in the area of psychological motivation of asset market experiment participants' behavior it would be beneficial to establish the origin of differences between rational and overconfident traders' economic behavior. Investment decisions in this experiment are based on beliefs concerning the likelihood of the two kinds of independent uncertain events: 1) the size of the dividend at the end of the period, and 2) the probability to resell the asset at a higher price (finding a "greater fool"). Research is called for to examine, whether overconfident traders generate subjective probabilities of occurrence of these events, which significantly deviate from the objective ones, namely by optimistically overestimating probabilities of favorable to them outcomes (e.g. maximum dividend value) and almost neglecting unfavorable ones. Another possible extension could be the assessment and control of personality characteristics other than overconfidence and risk aversion. E.g. students' intelligence assessed as their IQ score, their attitude towards deception and manipulation aimed at personal gain attainment (Machiavellianism), psychological traits such as extraversion, openness, neuroticism and etc.

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APPENDIX A: DESCRIPTIVE STATISTICS (ASSET MARKET EXPERIMENT).

	N	M	SD	Min.	Max.
Profit	60	390.36	197.89	4.20	906.20
Relative profit	60	0.00	1.83	-3.58	4.78
Profit / initial portfolio value	60	3.61	1.83	0.04	8.39
Bias score	60	11.20	12.08	-5.89	43.50
Age	60	22.77	2.13	19.00	28.00
Semester	54	3.39	2.10	1.00	12.00
End assets	60	3.00	4.04	0.00	18.00
MAE	60	7.24	3.76	1.79	20.64
TAE	60	55.33	42.40	5.00	202.00
Trading activity (average)	60	0.89	0.47	0.14	2.25

Appendix B: Bias Score, Age, Semester for Different Experimental Samples

		Whole Sample			
	N	M	SD	Min	Max
Bias score	60	11.20	12.08	-5.89	43.50
Age	60	22.77	2.13	19.00	28.00
Semester	60	3.39	2.10	1.00	12.00
		Overconfident Traders			
	N	M	SD	Min	Max
Bias score	30	21.33	8.26	10.17	43.50
Age	30	22.83	1.88	19.00	27.00
Semester	30	2.96	1.37	1.00	5.00
		Rational Traders			
	N	M	SD	Min	Max
Bias score	30	1.06	4.02	-5.89	6.78
Age	30	22.70	2.38	19.00	28.00
Semester	30	3.81	2.60	1.00	12.00
		Male Participants			
	N	M	SD	Min	Max
Bias score	35	12.08	11.91	-4.72	43.50
Age	35	22.51	1.85	19.00	27.00
Semester	35	3.19	1.71	1.00	7.00
		Female Participants			
	N	M	SD	Min	Max
Bias score	25	9.96	12.45	-5.89	38.89
Age	25	23.12	2.45	19.00	28.00
Semester	25	3.68	2.59	1.00	12.00

Appendix C: Risk Aversion Experiment Sample

Whole Sample					
	N	M	SD	Min	Max
Safe choices	32	5.66	1.82	0.00	9.00
Age	32	24.34	1.94	20.00	29.00
Semester	29	5.69	2.05	3.00	9.00
Bias score	32	11.09	10.49	-3.72	35.00
Overconfident Traders					
	N	M	SD	Min	Max
Safe choices	16	5.50	2.19	0.00	9.00
Age	16	24.00	1.97	20.00	27.00
Semester	16	4.93	1.33	3.00	7.00
Bias score	16	20.17	6.48	10.17	35.00
Rational Traders					
	N	M	SD	Min	Max
Safe choices	16	5.81	1.42	3.00	9.00
Age	16	24.69	1.92	22.00	29.00
Semester	13	6.08	1.89	3.00	9.00
Bias score	16	2.01	3.10	-3.72	6.06
Male Participants					
	N	M	SD	Min	Max
Safe choices	19	5.68	2.00	0.00	9.00
Age	19	23.95	1.84	20.00	27.00
Semester	17	5.47	1.62	3.00	8.00
Bias score	19	11.95	10.02	-2.39	35.00
Female Participants					
	N	M	SD	Min	Max
Safe choices	13	5.62	1.61	3.00	9.00
Age	13	24.92	2.02	21.00	29.00
Semester	11	5.45	1.86	3.00	9.00
Bias score	13	9.84	11.45	-3.72	30.50

APPENDIX D: TRANSLATED INSTRUCTIONS OF THE RISK AVERSION EXPERIMENT

INSTRUCTIONS

In this experiment you are to make ten decisions. Each decision is a choice between two paired lotteries - "Option A" and "Option B" such as those presented below:

Decision	Option A	Option B	Your Choice
1	3.00 EUR with 10% chance, 2.40 EUR with 90% chance	5.78 EUR with 10% chance, 0.15 EUR with 90% chance	A ○ ○ B
⋮	⋮	⋮	⋮
10	3.00 EUR with 100% chance	5.78 EUR with 100% chance	A ○ ○ B

You will make ten choices but only one of them will be used in the end of the experiment to determine your earnings. Each decision has an equal chance of being used in the end.

How one of the decisions is going to be chosen? We will use a random number generator in the computer which will generate a number between 1 and 10. The generated number is the number of decision that will be used to determine your payment. Each number has an equal probability to occur, so you have to think carefully about EACH of the Decisions!

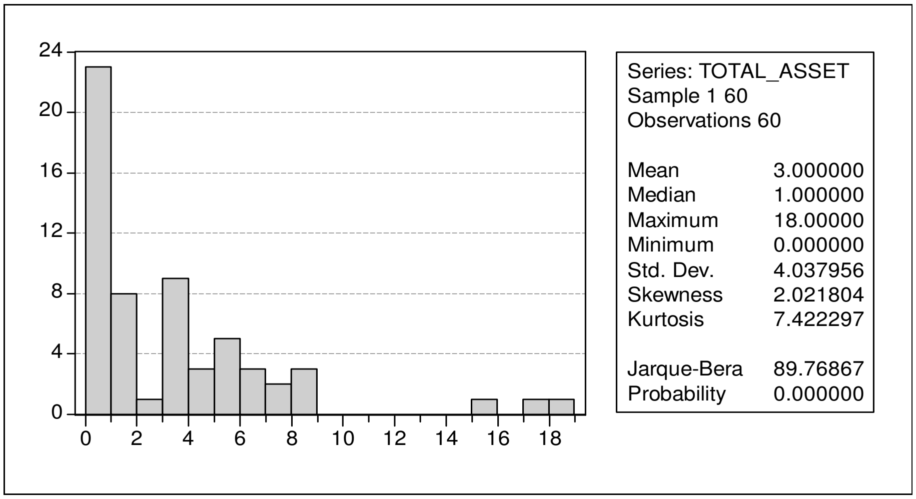
How payment for a lottery of your choice is determined? After one of the decisions has been randomly selected, the computer will generate another random number. This random number determines your earnings for the Option (A or B) that you previously selected for the decision being used. E.g. if you choose Option A in the first decision row shown above, you will have a 10% chance of earning 3.00 EUR and a 90% chance of earning 2.40 EUR. Similarly Option, B offers a 10% chance of earning 5.78 EUR and a 90% chance of earning 0.15 EUR.

What is the sequence of your actions? For each decision row you will have to choose between Option A and Option B by clicking on one of the "circles" on the right side of the screen. You will make ten choices. You may choose A for some decision rows and B for other rows and you may change your decisions and make them in any order. You have 15 minutes make your choices. When you are finished, press the “Submit” button. After you have pressed this button you can no longer change your choices. Then a random number generator will choose a number of the decision that will be used for payment. A second random number will determine the outcome of the lottery you chose.

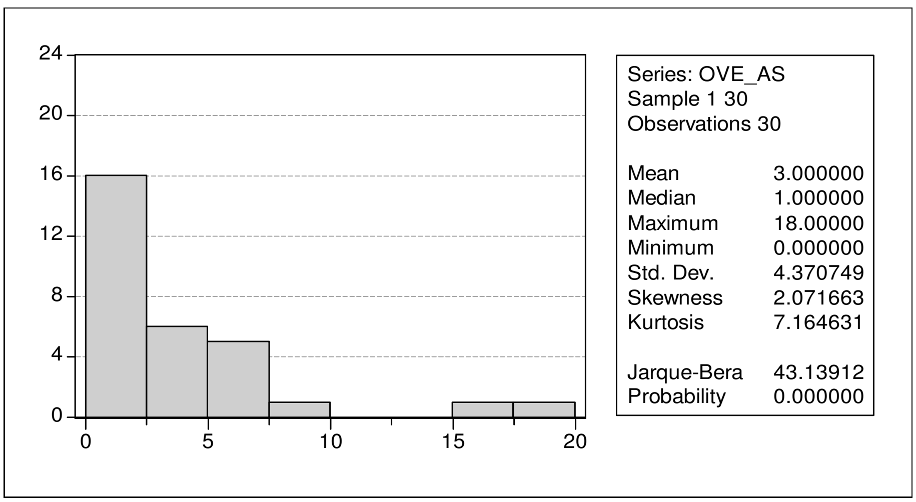
Important: please do not talk with anyone! Raise your hand if you have a question.

APPENDIX E: FINAL INVENTORIES DISTRIBUTION IN

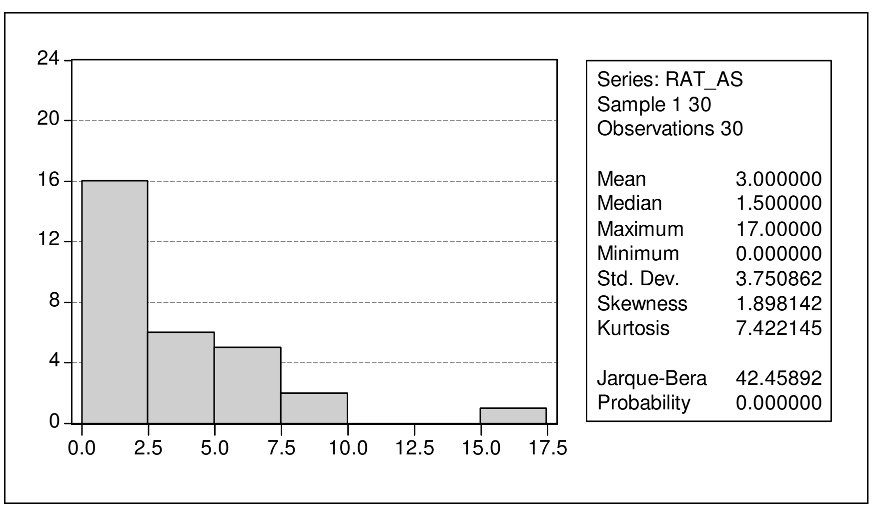
a. The whole sample



b. Overconfident markets sample



c. Rational markets sample



APPENDIX F: REGRESSION OF OVERCONFIDENCE ON RISK AVERSION AND OTHER FACTORS

	1	2
C	0.956* (0.522)	0.690*** (0.215)
Safe choice	-0.011 (0.021)	-0.017 (0.019)
Gender	0.021 (0.080)	0.067 (0.084)
AGE	-0.023 (0.021)	
Semester		-0.051* (0.026)
N	32	28
R2	0.065	0.182
SEreg	0.22	0.21

*** - 0.01,

* - 0.1