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Overconfidence, risk aversion and individual financial decisions in experimental asset markets

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ABSTRACT

Prior experiments revealed that investors' overconfidence can result in excessive trade and negative wealth effects. However, in most of these studies, informational asymmetries were part of the experimental design, and therefore no clear conclusion on whether the obtained results were driven by overconfidence or informational asymmetries could be made. The article addresses this issue by analysing individual financial decisions based on the study of Michailova and Schmidt, who ran an asset markets experiment with no informational asymmetries. Additionally, the study controls for differences in individual risk aversion. The data revealed that, in this setting, individual trading activity and performance were influenced by overconfidence only for female participants. Mistakes in future price forecasting, which were negatively correlated with overconfidence, partially accounted for this result. Risk aversion was uncorrelated with overconfidence and had no influence on experimental outcomes.

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1. Introduction

By allowing psychological bias to affect their investment decisions, investors can do serious harm to their wealth (Baker & Nofsinger, 2002, p. 98). Overconfidence – a widely observed empirical phenomenon – is one of the biases that have potential importance for financial decision-making (Kahneman & Riepe, 1998). The overconfidence bias manifests itself in several effects: miscalibration, better-than-average effect and illusion of control. Moore and Healy (2008) suggest referring to these three facets of overconfidence as, correspondingly, overprecision, overplacement and overestimation. Miscalibration is defined as the overestimation of precision of one's knowledge (see Lichtenstein, Fischhoff, & Phillips, 1982). People's inclination to have unrealistically positive views of the self with regard to skills or personal traits embodies itself as the better-than-average effect (see Taylor & Brown, 1988). Illusion of control is an unwarranted belief in having the ability to control one's fate: e.g.

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probability of personal success (see Langer, 1975). In this paper, we use miscalibration as the operationalisation of overconfidence.

Interest in the topic of economic consequences of investors' overconfidence generated a large body of literature. Research findings suggest that investors' overconfidence can result in trade aggressiveness (Deaves, Lüders, & Luo, 2009; Glaser, Nöth, & Weber, 2004), portfolio nondiversification (Odean, 1999), pursuit of the active portfolio management strategy (De Bondt & Thaler, 1984) and suboptimal performance (Barber & Odean, 2000, 2001; Fenton-O'Creevy, Nicholson, Soane, & Willman, 2003). Moreover, overconfident investors tend to underestimate risks and, as a result, take more risks in comparison to rational traders (Croson & Gneezy, 2008; Glaser et al., 2004; Lakonishok, Shleifer, & Vishny, 1992; Russo & Schoemaker, 1992).

Previous experimental studies investigate the effect of overconfidence on investors' trading activity and performance in the context of experimental asset markets with *asymmetric information* (see Biais, Hilton, Mazurier, & Pouget, 2005; Deaves et al., 2009; Kirchler & Maciejovsky, 2002). Biais et al. (2005) and Kirchler and Maciejovsky (2002) employed mixed market structure in which both more and less overconfident traders interacted. Their expectation was that less overconfident subjects would take advantage of the more overconfident ones. Deaves et al. (2009), on the contrary, employed pure market structure, in which all players in the market were either of low or high overconfidence. Additionally, as mentioned above, in all these experiments, participants were supplied with asymmetric pieces of information. For example, in Kirchler and Maciejovsky (2002), half of the participants had no information about the dividend distribution, and the other half had complete information. We believe that such an approach raises the question of whether differences which were discovered in individual performance in these experiments were a result of varying degrees of subjects' overconfidence or were merely the effect of informational asymmetries. The main aim of our paper is to disentangle these two effects and study the impact of overconfidence on individual economic behaviour in pure experimental asset markets with no informational asymmetries. For that we analyse the data obtained in the experimental study by Michailova and Schmidt (2016). This study (1) employs the classic experimental market design of Smith, Suchanek, and Williams (1988) and (2) assigns subjects to markets based on their overconfidence (pure market setting), yet it also (3) removes informational asymmetries. To capture the possible channels through which overconfidence might influence experimental decisions, we also control for individual risk aversion and future price expectations.

In this paper, we test the following hypotheses:

Empirical and experimental findings obtained from a mixed market setting suggest that a higher degree of traders' overconfidence reduces their welfare (Barber & Odean, 2001; Biais et al., 2005; Kirchler & Maciejovsky, 2002; Nöth & Weber, 2003). This might be due to the fact that overconfident traders engage in trade more actively and, as a consequence (of this active trade), incur losses (Barber & Odean, 2001; Glaser et al., 2004), i.e. they are outperformed by low turnover traders (Barber & Odean, 2000). Thus, our first aim is to test whether these relationships also hold in the pure market under a no informational asymmetries experimental setting.

By its very definition, overconfidence occurs when individual confidence systematically exceeds individual accuracy (Bar-Hillel, 2001; Moore & Healy, 2008), thus there is a negative relationship between overconfidence and accuracy. Therefore, we suggest that

more overconfident subjects are also less accurate (successful) in the price forecasting task. Moreover, these errors in prediction induce false future price expectations and cause mistakes in financial decisions, resulting in more active trading and, eventually, in losses. For example, in the experiment by Smith et al. (1988), better forecasters have indeed enjoyed higher gains from trade in the experimental market.

There is copious empirical and experimental evidence that higher risk propensity is accompanied by an increase in trade frequency, and on the contrary, higher risk aversion manifests itself in lower market activity (Durand, Newby, & Sanghani, 2008; Fellner & Maciejovsky, 2007; Markiewicz & Weber, 2013; Robin, Straznicka, & Villevall, 2012). Overconfidence, however, is a factor that induces active engagement in trading (see above). This sparks our interest in which of the two effects has the dominant impact on the trading activity in the experimental market: risk aversion or overconfidence.

Finally, we analyse the dependence between the size of the final experimental portfolio and individual risk aversion. Since the dividend value of assets in our experiment changes in a probabilistic manner from period to period, each stock could be perceived as some sort of a lottery by players. Therefore, we expect participants who dislike risk to try to sell their assets at the early stages of the experiment; on the contrary, more risk-loving subjects would try to acquire more asset items.

The paper proceeds as follows: Section 2 provides a description of the experimental procedures used by Michailova and Schmidt (2016), Section 3 presents an analysis of results and Section 4 concludes.

2. Experimental design

2.1. Overconfidence measurement

Individual overconfidence of potential participants of experimental asset market was measured in three pre-experimental sessions using the procedure of Michailova and Katter (2014). First, subjects were asked to complete a general knowledge quiz consisting of 18 questions and state how confident they were in the correctness of each answer. For this purpose any number from 33% (complete uncertainty) to 100% (complete certainty) could be used. Each question had three alternative answers, only one of which was right (see Appendix 1). In each pre-experimental session, subjects competed for three monetary prizes based on their accuracy in answering the quiz questions.

Then, overconfidence was calculated for each subject separately as the difference between the average confidence in correctness of their answers and the average actual accuracy. The obtained measure is called a bias score (BS) (Equation 1):

$$\text{bias score} = \text{average \% confidence} - \text{average \% correct} \quad (1)$$

The positive BS indicates overconfidence, and the negative BS indicates underconfidence; a zero BS indicates perfect calibration. Only subjects who had the highest and lowest overconfidence scores were invited to participate in the market experiment. Among them, two types of markets were constructed: low overconfidence and high overconfidence. Over the course of the experiment, subjects interacted only with subjects of their own type, i.e. either low overconfidence or high overconfidence subjects. It is important to mention that subjects were aware neither that the knowledge quiz was a precursor of another experiment nor that their results in the quiz were linked to their grouping in the experimental asset market.

Table 1. Overconfidence (bias) scores of experimental participants.

	N	Mean	SD	Min	Max
All	60	11.20	12.08	-5.89	43.50
High overconfidence	30	21.33	8.26	10.17	43.50
Low overconfidence	30	1.06	4.02	-5.89	6.78

Source: Author's calculations.

2.2. Asset market experiment

The main experiment was conducted using 60 students of social sciences from the Christian-Albrechts University of Kiel. Thirty-five males and 25 females, aged 19 to 28, participated in 10 computerised market sessions. The overconfidence (bias) scores of these subjects are presented in Table 1. The experiment was programmed with the software *z-Tree* (Fischbacher, 2007). On average, subjects earned 10.54 EUR for their participation in the experiment (excluding reward for forecasting).

The experimental procedure was based on the pioneering work of Smith et al. (1988). Prior to the start of the experiment, each subject was given 300 experimental currency units (ECU) and 3 experimental asset units. The experimental market consisted of the sequence of 15 trading periods, lasting a maximum 180 seconds, during which each trader could trade in experimental assets. At the end of the trading period, each asset in the participants' inventory paid a dividend with possible values of 0.0, 0.8, 2.8 or 6.0 ECU; the probability of each value was $p = 0.25$. Thus, the average dividend which subjects could expect through many draws was 2.4 ECU. The fundamental value (FV) of one asset unit equalled $n \times 2.4$ ECU, where n was the number of periods remaining at the end of the session.¹

Additionally, at the end of each trading period, subjects were asked to predict the average market price in the next period and state their confidence in their prediction. Any value between 0% (disbelief that the forecast was correct) and 100% (certainty that the forecast was correct) could be used to express subjects' confidence. For the forecasting task, participants were awarded based on the accuracy of their forecast: if their forecast fell within 10% of the real price, it earned 3 ECU; forecasts within 25% and 50% of the real price therefore earned 1 ECU and 0.5 ECU. Gains from the forecasting task were not added to subjects' working capital, but were accumulated in a separate account. At the end of the experimental session, each participant was paid in cash the amount of money that was based on (1) their final working capital and (2) total gains from forecasting. Appendix 2 presents the summary statistics of demographic variables and variables describing participants' behaviour in the experimental asset market.

2.3. Risk aversion measurement

Individual risk aversion was assessed a few months after the completion of the experimental asset market. Of the 32 repeatedly recruited subjects, 16 were former participants of the high overconfidence markets (OVE = 20.17, SD = 6.48) and 16 of the low overconfidence markets (OVE = 2.01, SD = 3.10). Holt and Laury's (2002) lottery-choice task was employed for the risk aversion measurement. This task required subjects to make 10 choices between two paired lotteries: Option A and Option B. The possible payoff for Option A was either 3 EUR or 2.40 EUR and for Option B 5.78 EUR or 0.15 EUR (see Table 2).

Table 2. Holt and Laury (2002) lottery-choice decisions.

Option A	Option B
1/10 of 3 EUR, 9/10 of 2.40 EUR	1/10 of 5.78 EUR, 9/10 of 0.15 EUR
2/10 of 3 EUR, 8/10 of 2.40 EUR	2/10 of 5.78 EUR, 8/10 of 0.15 EUR
3/10 of 3 EUR, 7/10 of 2.40 EUR	3/10 of 5.78 EUR, 7/10 of 0.15 EUR
4/10 of 3 EUR, 6/10 of 2.40 EUR	4/10 of 5.78 EUR, 6/10 of 0.15 EUR
5/10 of 3 EUR, 5/10 of 2.40 EUR	5/10 of 5.78 EUR, 5/10 of 0.15 EUR
6/10 of 3 EUR, 4/10 of 2.40 EUR	6/10 of 5.78 EUR, 4/10 of 0.15 EUR
7/10 of 3 EUR, 3/10 of 2.40 EUR	7/10 of 5.78 EUR, 3/10 of 0.15 EUR
8/10 of 3 EUR, 2/10 of 2.40 EUR	8/10 of 5.78 EUR, 2/10 of 0.15 EUR
9/10 of 3 EUR, 1/10 of 2.40 EUR	9/10 of 5.78 EUR, 1/10 of 0.15 EUR
10/10 of 3 EUR, 0/10 of 2.40 EUR	10/10 of 5.78 EUR, 0/10 of 0.15 EUR

Source: Author's calculations.

A total number of choices A was used to assess individual risk aversion: a risk-neutral person would make four A choices and then switch to Option B; a risk-averse person would make more than four A choices and a risk-loving person would make fewer than four A choices (see Holt & Laury, 2002).

3. Experimental results

3.1. Univariate and bivariate analysis

We assume independence across subjects and start this section by analysing the trading activity of experimental participants. Generally individual average trading activity, defined as the mean of transactions (purchases and sales) conducted by an individual over the session and divided by the number of shares outstanding in the market (18), was quite high: on average per session, traders had transacted 0.89 times the outstanding stock of shares (SD = 0.47). An increase in traders' overconfidence was accompanied by an increase in their trading activity (Pearson correlation (58) = 0.350, $p < 0.01$, one-sided), which is consistent with the hypothesis that more overconfident investors engage in trade more actively. When we analysed the relationship between trading activity and individual overconfidence for females and males separately, we found no significant linear relationship between the two variables of interest for males (Pearson correlation (33) = 0.118, $p = 0.249$, one-sided). However, with an increase in overconfidence, female participants engaged in trading more actively (Pearson correlation (23) = 0.635, $p = 0.00$, one-sided). Nevertheless, there was no difference in the frequency of transactions between female and male participants (Mann-Whitney $Z = -0.105$, $p = 0.916$, two-sided).

To test the proposition that high-turnover traders would be outperformed by low-turnover traders, normalised profits per participant were calculated as individual gains scaled by the initial portfolio value ($36 \text{ ECU} \times 3 = 106 \text{ ECU}$). These profits and their corresponding average trading activity are presented in Figure 1. Data in the graph are arranged in the increasing order of trading activity values and are plotted with the linear trend line, which demonstrates that increases in trading activity were accompanied by decreases in individual gains.

Average normalised profits of all participants equalled 3.61 times the value of the initial portfolio (SD = 1.83).² The correlation coefficient between trading activity and individual earnings was small but significant, implying that increased trading is paired with poorer performance (Pearson correlation (58) = -0.292, $p < 0.05$, one-sided). Exclusion of the

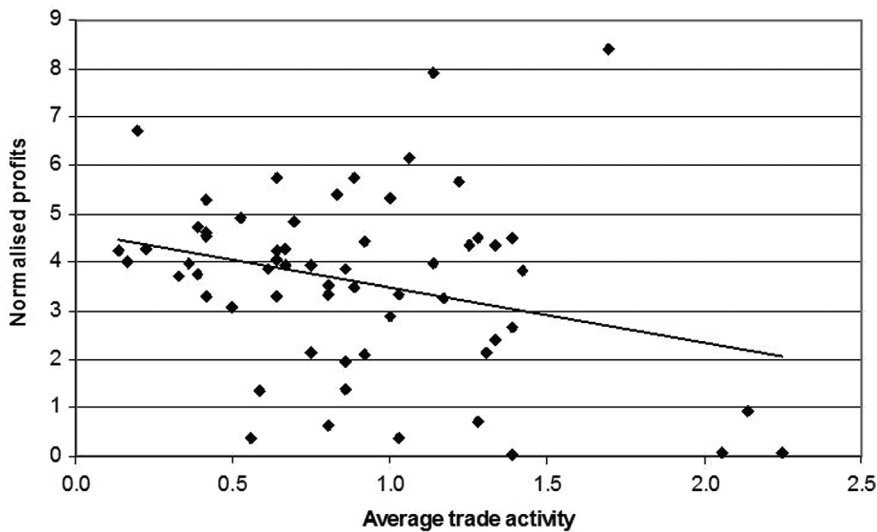


Figure 1. Normalised profits per participant. Source: Author's calculations.

two possible outlier values substantially increased the strength of this linear relationship (Pearson correlation (56) = -0.456 , $p = 0.00$, one-sided).

The sample was further broken into four equal sub-samples, ranked in terms of trading activity (quartiles) (see Figure 2). Individual earnings in the lowest and the highest trading activity quartiles were compared. The Mann-Whitney test detected that traders from the latter quartile were significantly outperformed by traders in the former, who earned on average 38% more ECUs at the end of the experiment ($Z = -1.555$, $p < 0.10$, one-sided); without the two possible outliers, this difference increased to 56% (Mann-Whitney $Z = -2.095$, $p < 0.05$, one-sided). Therefore, our hypothesis was supported. This finding is in line with Barber and Odean (2000), who revealed that high-turnover households were outperformed by low-turnover households.

To determine the relationship between accuracy of average price prediction and individual earnings, we first calculated precision of price predictions, which was expressed as the Average Absolute Error (Equation 2):

$$\text{Average Absolute Error(AAE)}_i = \text{Sum} \left| (P_t - F_{it}) \right| / T \quad (2)$$

where, F_{it} is the forecast (prediction) of subject i for the period t , P_t is the average real price in period t , and T is the total number of periods in experimental session ($T = 15$).

As we hypothesised, a statistically significant linear relationship between overconfidence and errors in market price predictions was detected (Pearson correlation (58) = 0.350 , $p < 0.01$, one-sided). Thus, increased overconfidence was indeed paired with reduction in accuracy of prediction. Furthermore, correlation between errors in future price predictions and individual profits was negative and significant (Pearson correlation (58) = -0.36 , $p < 0.01$, one-sided). Interestingly, we find that female participants were significantly less accurate than males in their price predictions³ (Mann-Whitney $Z = -1.957$, $p = 0.05$, two-sided).

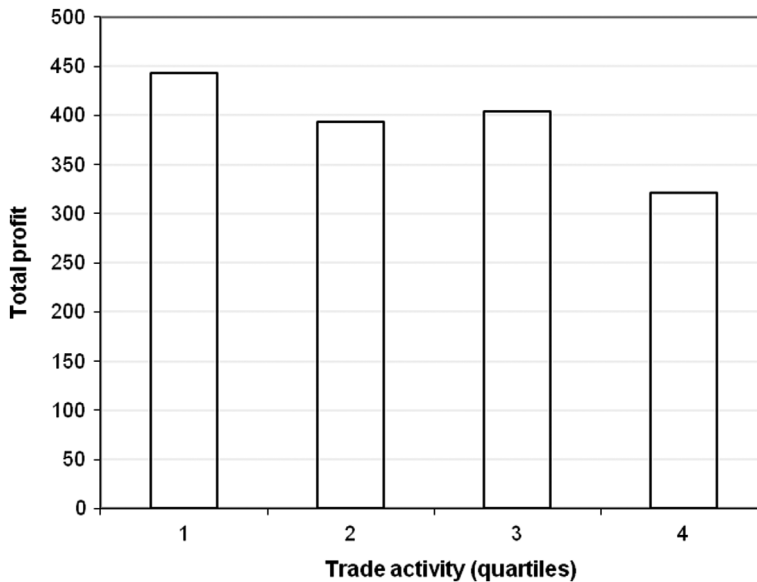


Figure 2. Distribution of individual profits across trading activity quartiles. Source: Author's calculations.

Another factor that had a negative impact on individual earnings was the number of assets in participants' final inventory (Pearson correlation (58) = -0.225, $p < 0.05$, one-sided).

3.2. Multivariate analysis

Trading activity

This subsection presents the results of cross-sectional regressions estimating the relationship between the average trading activity of an individual and several explanatory variables that might affect the efficiency of financial decision-making (the standard error terms are shown in parentheses): the normalised bias score⁴ (NBS), gender dummy (this variable takes the value 1 if the subject is male), an interaction term between the bias score and gender (NBS*Gender); subjects' experience expressed as age (Age) or duration of studies (Semester); and price-forecasting precision measured as average absolute error (AAE). We assume that observations across individuals are independent and start with the simplest model specification in which average trading activity is regressed on individual degree of overconfidence (NBS). Subsequently, a range of alternative specifications are estimated by adding other regressors to the model. For the specifications of the estimated models, see Table 3.⁵

The results, presented in Table 3, led to the following conclusions: (1) holding all other factors constant, the impact of overconfidence on trade was positive for female participants, i.e. with an increase in overconfidence, females engaged in more market transactions than males, and (2) forecasting errors that induced false future price expectations forced subjects to engage in trading more actively. Modest success in explaining variation in trading activity in the sample by means of selected models suggests that other unobserved factors that were not included in the regression also have an impact on the average number of market transactions by an individual participant. We return to this issue in the section on risk

Table 3. Trading activity (errors are corrected for heteroscedasticity and for correlation within session clusters).

	1	2	3	4	5	6	6a	7
C	0.659**** (0.083)	0.692**** (0.089)	0.498**** (0.086)	1.338* (0.711)	0.734**** (0.141)	1.218* (0.711)	1.299* (0.726)	1.815** (0.869)
NBS	0.671**** (0.132)	0.682**** (0.131)	1.285**** (0.224)	1.236**** (0.237)	1.147**** (0.205)	0.993**** (0.272)	1.050**** (0.245)	0.859* (0.774)
Gender		-0.062 (0.097)	0.301*** (0.109)	0.253** (0.109)	0.252* (0.128)	0.317*** (0.107)	0.267*** (0.093)	0.470 (0.269)
NBS*Gender			-1.069*** (0.340)	-0.991*** (0.342)	-0.993*** (0.323)	-0.934** (0.357)	-0.951*** (0.337)	-1.307* ^a (0.878)
Age				-0.036 (0.029)		-0.040 (0.028)	-0.041 (0.028)	-0.060* (0.033)
Semester					-0.046** (0.020)			
AAE						0.036** (0.014)	0.027*** (0.008)	0.040** (0.017)
Safe choices								-0.023 (0.026)
N	60	60	60	60	54	60	59	32
adj. R2	0.11	0.10	0.16	0.17	0.17	0.23	0.25	0.15
SERegr	0.44	0.44	0.43	0.42	0.43	0.41	0.38	0.40

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

^aone-sided test.

Source: Author's calculations.

aversion analysis, where the regression model is re-estimated for a sample of participants whose risk aversion measures were obtained.

Gains from trade

This subsection presents the results of cross-sectional regressions estimating the relationship between subjects' performance in the experiment and several explanatory variables (the standard error terms are shown in parentheses): the normalised bias score (NBS), gender dummy (takes value 1 if the subject is male), average trading activity (Trading activity), an interaction term between gender and trading activity (Gender*Trading activity), subject's age (Age), the number of assets in the final inventory (End assets), and price forecasting precision measured as average absolute forecasting error (AAE). Individual performance was assessed as relative profit, calculated based on Hirota and Sunder (2007) as gains from trade divided by the FV of the initial portfolio of three stocks (36 ECU \times 3 = 106 ECU) minus the cross-sectional average of this ratio. We assume that observations across individuals are independent and start again with the simplest model specification, in which relative profit is regressed on the individual degree of overconfidence (NBS) and gender; subsequently, a range of alternative specifications are estimated by adding other regressors to the model. For the specifications of the estimated models, see Table 4.

The results presented in Table 4 suggest that (1) contrary to the formulated hypothesis, overconfidence had no significant (direct) effect on individual earnings; (2) holding all other factors constant, the impact of trading activity on relative profit was more negative for female than male participants, i.e. with an increase in the number of market transactions, males incurred smaller losses or even yielded gains in comparison to females; (3) forecasting errors that induced false future price expectations and caused mistakes in financial decision-making (Biais et al., 2005) produced losses; and (4) the number of assets in the final inventory was a significant determinant of reduction in gains. In general, the

Table 4. Gains from trade (errors are corrected for heteroscedasticity and for correlation within session clusters).

	1	2	3	4	5	6	7
C	2.838 (0.297)	3.717 (0.338)	4.770*** (0.265)	2.994 (4.101)	4.052 (3.366)	3.771 (3.409)	5.128*** (0.303)
NBS	0.065 (0.722)	0.931 (0.979)	1.574* (0.892)	1.499 (1.022)	1.179 (1.026)	1.467 (1.059)	1.483 (1.038)
Gender	1.293** (0.564)	1.213** (0.513)	-1.013* (0.598)	-0.837 (0.603)	-0.447 (0.468)	-0.471 (0.456)	-0.589 (0.519)
Trading activity		-1.271*** (0.420)	-2.654*** (0.399)	-2.503*** (0.641)	-2.333*** (0.601)	-2.081*** (0.607)	-2.216*** (0.389)
Trading activity * Gender			2.454** (1.006)	2.313** (0.986)	2.458** (1.019)	2.265** (1.025)	2.393** (1.058)
Age				0.072 (0.164)	0.033 (0.131)	0.056 (0.135)	
End assets					-0.169* (0.087)	-0.152* (0.090)	-0.158* (0.086)
AAE						-0.071* (0.037)	-0.064* (0.036)
N	60	60	60	60	60	60	60
AdjR2	0.09	0.17	0.26	0.25	0.36	0.36	0.37
SERegr	1.75	1.67	1.58	1.59	1.46	1.46	1.45

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

Source: Author's calculations.

described specifications succeeded quite well in explaining the 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 were also present.

3.3. Risk aversion measurement: experimental results

On average, the subjects were found to be risk averse ($M = 5.66$; $SD = 1.82$), and choices of even 71.88% of the participants fell at the interval of [5, 7] safe options. Men took on average 5.68 safe choices ($SD = 2.00$) and women 5.62 safe choices ($SD = 1.61$). The difference in the average number of safe choices taken by both genders is insignificant (Mann-Whitney $Z = -0.452$, $p = 0.652$, two-sided); this is in line with previous research findings (e.g. Holt & Laury, 2002; Michailova, Tyszka, & Pfeifer, 2016). The correlation coefficient between risk aversion and individual overconfidence implies no linear relationship between them (Spearman's $Rho(30) = -0.095$, $p = 0.303$, one-sided). The presented evidence suggests that risk aversion, measured in a lottery-type task, had no explanatory power over subjects' overconfidence.

We predicted that risk aversion had a negative effect on individual trading activity and the size of the final portfolio. However, no linear relationship between these variables was detected (trade: Spearman's $Rho(30) = -0.100$, $p = 0.294$, one-sided; portfolio size: Spearman's $Rho(30) = -0.001$, $p = 0.498$, one-sided). An additional inspection of Equation 7 (see Table 3) revealed no significant effect of risk aversion on the frequency of trading. Although we had no specific hypothesis formulated, we have also checked whether there was a linear relationship between individual gains and risk aversion. This relationship was also found to be insignificant (Spearman's $Rho(30) = 0.031$, $p = 0.433$, one-sided). It can be concluded that, in this sample, differences between the traders in experimental outcomes were driven by overconfidence and not risk aversion.

4. Conclusions

The aim of this paper was to investigate the influence of the degree of overconfidence and risk aversion on the financial decision-making of economic subjects. To address this research question, we use data from the asset market experiment and post hoc risk aversion measurement by Michailova and Schmidt (2016).

Our results suggest that, although generally the genders did not differ in their trading frequency, for female participants, an increase in overconfidence was paired with an increase in trading activity, which resulted in losses. This relationship did not hold for male participants, for whom more active trading in some instances even yielded gains. Surprisingly, overconfidence had no direct wealth effects for female or male participants. However, we found support for the proposition that overconfidence had significant negative influence on forecasting accuracy that in turn forced subjects to engage in trading more actively. Moreover, in line with previous research (see Smith et al., 1988), forecasting errors were associated with losses. Females in our experiment generated significantly less accurate predictions of future market prices than males, which was in line with the findings by Eckel and Füllbrunn (2015). Unlike them, our measure of forecasting accuracy did not allow us to make any conclusions about the direction (underestimation or overestimation) of mistakes in the price forecasts. Nevertheless, we conclude that, in the setting with no informational asymmetries and pure markets, trading activity and performance were driven by overconfidence only for female participants, and this suggests lower forecasting accuracy by female subjects as a possible explanation for this finding. Finally, we found no evidence of the existence of the relationship between the individual risk aversion (estimated using the Holt and Laury task) and overconfidence, trading activity or final portfolio size. Therefore, we conclude that, in the reduced sample, differences in the experimental outcomes were driven by overconfidence and not risk aversion.

Our research suggests that there is indeed a difference between economic behaviour and the financial results of more and less overconfident traders in experimental asset markets, and this difference might be gendered. As one of the possible explanations for these findings, mistakes in predicting future market prices were suggested. However, our study does not allow us to directly determine and analyse channels through which overconfidence influences the economic behaviour of experimental participants, which we believe should be the next step in future research.

Evidence presented in this paper could be of benefit to policy-makers: our results indicate that psychological bias of overconfidence could be harming investors' wealth, which in turn can have negative macroeconomic consequences and harm sustainable economic development (Dubauskas, 2016; Kulišauskas & Galinienė, 2015; Laužikas & Krasauskas, 2013; Peker, Tvaronavičienė, & Aktan, 2014; Stasytytė, 2015; Tvaronavičienė, 2014). Therefore, we suggest that governments should invest in increasing individual financial literacy, which will help to mitigate the impact of overconfidence on investment decisions and to achieve sustainable management of individual finances (Ciemleja, Lace, & Titko, 2014; Dubauskas, 2016; Kalyugina, Strielkowski, Ushvitsky, & Astachova, 2015; Njaramba, Chigeza, & Whitehouse, 2015). Moreover, it could also direct individuals towards more socially responsible investing (Slapikaitė, Tamošiūnienė, & Mackevičiūtė, 2015).

Notes

1. The FV of one asset unit at the beginning of experimental session is therefore 36 ECU (= 15×2.4 ECU).
2. Two values, namely 7.92 and 8.39, are possible outliers.
3. $AAE_{female} = 8.48$ (SD = 4.51); $AAE_{male} = 6.36$ (SD = 2.88).
4. A sample of bias scores of the participants is normalised on an interval [0,1].
5. Equation 7 is discussed in subsection 'Risk aversion measurement: experimental results'.

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Appendix 1.

Michailova and Katter (2014) overconfidence measurement questions (correct answer is underlined).

What is the name for an instant camera?	Canon camera	<u>Polaroid camera</u>	Minolta camera
What is a rollmop made of?	<u>herring</u>	pork	salmon
What is a hot chili sauce?	<u>Tabasco</u>	Curacao	Macao
What is the name of Eskimo snow shelter?	wigwam	<u>igloo</u>	tipi
What enterprise belongs to Bill Gates?	Intel	<u>Microsoft</u>	Dell Computers
What is the Islamic month of fasting called?	Sharia	<u>Ramadan</u>	Imam
Where do flounders usually live?	among the reeds	amongst coral reefs	<u>on the sea bed</u>
What country does the Nobel Prize winner in Literature Gabriel García Márquez come from?	Spain	Venezuela	<u>Colombia</u>
What artistic movement does anacreontics belong to?	<u>Rococo</u>	Romanticism	Realism
How many letters are there in the Russian alphabet?	40	33	26
What is the name of the Greek Goddess of Wisdom?	<u>Pallas Athena</u>	Nike	Penelope
What is ascorbic acid?	apple vinegar	vitamin A	<u>vitamin C</u>
'Tosca' is an opera by...?	<u>G. Puccini</u>	G. Verdi	A. Vivaldi
What is the most abundant metal on Earth?	<u>iron</u>	<u>aluminium</u>	copper
What is a word to describe an uninformed person?	Ignatius	<u>ignorant</u>	ideologue
Who was the first person to fly around the Eiffel Tower in an airship?	<u>Santos-Dumont</u>	Count Zeppelin	Saint-Exupéry
What language does the term 'Fata Morgana' come from?	Arabic	Swahili	<u>Italian</u>
How long does it take for a hen to hatch an egg?	<u>21 days</u>	14 days	<u>28 days</u>

Source: Author's calculations.

Appendix 2.

Summary statistics.

	N	Mean	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
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
AAE	60	7.24	3.76	1.79	20.64
Trading activity (average)	60	0.89	0.47	0.14	2.25

Source: Author's calculations.