Simultaneous over- and underconfidence: Evidence from experimental asset markets*

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Abstract

In this paper we investigate individual overconfidence within the context of an experimental asset market. Overall, 72 participants traded one risky asset on six markets of 12 participants each. Our results indicate that participants are not generally prone to overconfidence. A comparison of two different measures of overconfidence, (i) subjective confidence intervals and (ii) differences between objective accuracy and subjective certainty, lead to a different classification of behavior in our data-set. We observe well-calibration as well as over- and underconfidence.

Keywords: Overconfidence; Behavioral finance; Investment decisions; Experimental economics; Decision making

JEL-Classification: C90; D40

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1. Introduction

Psychological evidence on individual decision biases and heuristics challenges the prescriptive predictions of standard economic theory. Most of the evidence, however, is based on questionnaire studies involving only hypothetical decision tasks with no financial consequences to the decision maker. In this paper we investigate the overconfidence bias within the context of a decision environment in which we (i) allow for competition and learning and (ii) in which participants do not make hypothetical decisions, but are paid for their effort and according to their decisions. Since competition and learning are main features of market institutions, an experimental asset market is employed for our study on overconfidence.[1] More precisely, we focus on the correspondence of two different measures of overconfidence, namely subjective confidence intervals and the comparison of objective accuracy to subjective certainty, in order to investigate whether overconfidence is a general valid phenomenon.

The remainder of this paper is organized as follows: In this section empirical evidence on the overconfidence bias and on unrealistic optimism is discussed. Section 2 deals with the hypotheses, and section 3 is concerned with the experimental design and procedure. Section 4 presents and discusses the results, and in section 5 we summarize our results and draw the main conclusions.

1.1 Overconfidence

Overconfidence is considered the most robust finding in the psychology of judgment (e.g., De Bondt and Thaler, 1995). It refers to the systematic overestimation of the accuracy of one's decisions, and has been observed in many professionals, for instance in clinical psychologists (Oskamp, 1965), engineers (Kidd, 1970), entrepreneurs (Cooper, Woo and Dunkelberg, 1988), investment bankers (Stael von Holstein, 1972), lawyers (Wagenaar and Keren, 1986), managers (Russo and Schoemaker, 1992), negotiators (Neale and Bazerman, 1990), and physicians and nurses (Christensen-Szalanski and Bushyhead, 1981). In addition, empirical results indicate a gender effect: Females were found to be less overconfident than men (Pulford and Colman, 1997).

Overconfidence was found to be strongest for questions of moderate to extreme difficulty (Fischhoff, Slovic and Lichtenstein, 1977; Griffin and Tversky, 1992; Lichtenstein, Fischhoff and Phillips, 1982; Soll, 1996; Yates, 1990), and seems to increase with the personal importance of the task (Frank, 1935). Schraw and Roedel (1994) showed in an experimental investigation that overconfidence is due largely to test difficulty, and Juslin (1993; 1994) found that overconfidence is eliminated when test items are selected randomly. However this result could not be confirmed by Brenner, Koehler, Liberman and Tversky (1996). Stone (1994) reported that self-efficacy judgments made in cognitively complex tasks are biased toward overestimates of personal ability, such as overconfidence.

When easy judging tasks are involved, empirical results indicate that individuals may even be underconfident (Klayman, Soll, Gonzalez-Vallejo and Barlas, 1999; Pulford and Colman, 1997). Subbotin (1996) investigated the effect of outcome feedback on over- and

[1] Related recent experiments investigating overconfidence in financial decision making are the studies on market entry by Camerer and Lovallo (1999), on investment decisions by Dittrich, Güth and Maciejovsky (2001), on illusion of expertise by Fellner, Güth and Maciejovsky (2001), and on task difficulty and financial incentives by Hölzl and Rustichini (2001).

underconfident judgments in a general knowledge task. His results indicate that outcome feedback reduces the bias and improves calibration of underconfident judgments, but has no effect in the case of overconfident judgments. People were also found to be more confident of their predictions in fields where they have self-declared expertise (Heath and Tversky, 1991).

Plous (1995) compared interval overconfidence with respect to individual tasks and to group tasks. The results indicate that 3-4 person nominal groups, who were not allowed to interact, were found to be more accurate in their judges than individuals. Yet, comparing individual judges to judges made by interacting group members indicate that such groups did not perform substantially better than individuals, although participants frequently had the impression they would. There is also evidence of stability of overconfidence across domains. West and Stanovich (1997) report a positive correlation between participants' degrees of overconfidence in their performance on a general knowledge task and on a motor skill task, and Bornstein and Zickafoose (1999) report stability between the domains of eyewitness memory and general knowledge. Perfect and Hollins (1996) found that participants were equally overconfident in both domains, their performance in an eyewitness task and in a general knowledge task. However, the authors did not assess the stability of overconfidence on an individual level.

Overconfidence has been explained by selective information searching strategies (e.g., Hoch, 1985; Klayman, 1995; Koriat, Lichtenstein and Fischhoff, 1980), by motivational factors (e.g., Babad 1987; Kunda, 1990; Langer, 1975; Larrick, 1993), by imperfections in learning (e.g., Erev, Wallsten and Budescu, 1994; Ferrell, 1994; Soll, 1996), and for instance by the experimenters' tendency to choose harder-than-normal questions (e.g., Gigerenzer, Hoffrage and Kleinbölting, 1991; Juslin, 1993, 1994).

Overconfidence can also be defined with respect to subjective confidence intervals. When investors are asked to generate price forecasts p_{lo} and p_{hi}, so that there is only an x% chance that the future price will be lower than their price prediction p_{lo}, and an x% chance that the future price will be higher than their price prediction p_{hi}, the observed intervals are often too narrow. Whereas, the expected price predictions should create a confidence interval with a range of (100 - 2x)%, the observed intervals actually only cover some of the predicted range. In a study conducted by Lichtenstein, Fischhoff and Phillips (1982), subjects were asked to create a subjective confidence interval of 98% width. The actual proportion of intervals that failed to include the true answer, however, equaled 42% rather than 2%. Subjects in the study of Yaniv and Foster (1997) had to create a subjective confidence interval of 95% width, and observed intervals of 55% width. Subjective confidence intervals were thus too narrow as they excluded the correct answers far too often.

Exceptions to overconfidence are reported (i) for tasks where predictability is high, (ii) for tasks where swift and precise feedback about the accuracy of the judgments is provided, and (iii) for highly repetitive tasks (Kahneman and Riepe, 1998). Correspondingly, expert bridge players (Keren, 1987), race-track bettors (Dowie, 1976; Hausch, Ziemba and Rubinstein, 1981), and meteorologists (Murphy and Winkler, 1984) were found to be well-calibrated in their predictions.

However, there are also studies which challenge the validity of the conclusion that individuals are *generally* overconfident. Erev, Wallsten and Budescu (1994) showed that both over- as well as underconfidence can be obtained from the same set of data, indicating that the results are actually moderated by the research method used. Also the results of Juslin, Winman and Olsson (2000) indicate that the overconfidence bias depends on the selective attention to particular data sets. Klayman, Soll, Gonzalez-Vallejo and Barlas (1999) emphasize that overconfidence depends on how the experimenter asks his/her questions, what he/she asks, and whom he/she asks.

1.2 Unrealistic optimism

Empirical evidence suggests that individuals do not only overestimate the accuracy of their knowledge, but also tend to be unrealistically optimistic about their future (Weinstein, 1980). Weinstein (1984) conducted a study on 405 students to examine their perceptions of susceptibility to health and safety risks. Whereas subjects were generally unbiased about hereditary risk factors and were even somewhat pessimistic about environmental risk factors, they were excessively optimistic in their views of their own actions and psychological attributes. Weinstein (1987) found that hazards most likely to elicit unrealistic optimism are those associated with the belief that if the problem has not yet occurred, it is unlikely to occur in the future. Unrealistic optimism also increases with the perceived preventability of a hazard and decreases with perceived frequency and personal experience. Questionnaire responses from teachers in a study by Weinstein (1988) reveal a strong tendency among subjects to believe that they would experience less difficulty than the average first-year teacher in 33 different teaching tasks. Studies have also been conducted on unrealistic optimism with regard to the likelihood of car accidents (Robertson, 1977; Rutter, Quine and Albery, 1998), the likelihood of lung cancer for smokers (Reppucci, Revenson, Aber and Reppucci, 1991), and the likelihood of getting divorced (Baker and Emery, 1993).

The classic study on unrealistic optimism was conducted by Weinstein (1980). In his study 258 students estimated how much their own chances of experiencing 42 events differed from the chances of their classmates. Overall, subjects rated their own chances to be above average for positive events and below average for negative events. Thus, the results indicate a clear differentiation between positive and negative events. Subjects expected good things to happen to them more often than to their peers, and bad things to happen to them less often. For instance, subjects thought themselves to be 41.5% more likely than their peers to earn a good starting salary, and 38.4% less likely to have a heart attack before the age of 40.

Optimism seems also to be linked to an illusion of control. Even for purely chance events, people sometimes show optimistic biases (Irwin, 1953; Langer and Roth, 1975; Marks, 1951). Not only do individuals consider themselves to be better than the average person, they also see themselves in a better light than others see them (Taylor and Brown, 1988). Individuals judge positive traits to be overwhelmingly more characteristic of self than negative attributes (Alicke, 1985; Brown, 1986). There is also empirical evidence indicating that positive personality information can be recalled much more quickly than negative information (Kuiper and Derry, 1982). Most people also show poorer recall for information related to failure than to success (Silverman, 1964), and tend to recall their task performance as more positive than it actually was (Crary, 1966). Individuals were also found to credit themselves for past success, and blame external factors for failures (Fischhoff, 1982; Langer and Roth, 1975), and neglect reference groups in their decisions (Kahneman and Lovallo, 1993).

1.3 Overconfidence and unrealistic optimism within the context of financial decision making

"The combination of overconfidence and optimism is a potent brew, which causes people to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events" (Kahneman and Riepe, 1998, p. 54). Cornett, Mehran and Tehranian (1998) investigated whether financial markets are overly optimistic about the prospects of firms that issue equity. The authors compared the performance of all voluntary and all involuntary common stock offerings by publicly traded commercial banks in the U. S. during the period from June 1983 through December 1991, and observed that voluntary issuers earned significantly negative two-day abnormal returns on announcements of the issue, while involuntary issuers did not. Also, during the three years after the stock issue, the banks that voluntarily issued stock experienced an average matched adjusted return of - 14.44%. Because the firms generally experienced improvements in profitability prior to the offering, the market was overly optimistic about the prospects of the issuing firms. However, as market participants saw and evaluated the actual post-issue performance of the banks, they adjusted the stock price accordingly.

Odean (1999) analyzed trading records for 10,000 accounts at a large discount brokerage house. The results indicate that investors bought securities that have experienced greater absolute price changes over the previous two years than the ones they sold. They bought similar numbers of winners and losers, but they sold far more winners than losers. Thus, on average, the stocks investors purchased actually underperformed those they sold. It may be that those who bought previous winners believed that securities would follow trends, whereas those who bought previous losers believed they would revert. In addition, Odean (1999) showed that the observed trading volume, as implied by overconfidence, was excessive. Thus, investors clearly traded too much.

In a further study, Barber and Odean (2000) analyzed investment behavior of private households. The authors found that of 66,465 households with accounts at a large discount broker in the period from 1991 to 1996, those that traded most earned an annual return of 11.4%, while the market return was 17.9%. High turnover households underperformed the low turnover households. The excessive trading volume of the high turnover households cost them about 6.8% relative to the returns earned by low turnover households. In addition, the results indicate that the average household turns over about 75% of its common stock portfolio annually. Barber and Odean (2000) conjecture that the high trading volume is due to overconfidence. Overconfident investors are assumed to overestimate the value of their private information, and this causes them to trade too actively and, consequently, to earn below average returns.

Overconfidence has not only been investigated in field data, but has also been analytically modeled. Benos (1998), for instance, models overconfidence by assuming that some risk neutral investors overestimate the precision of their private information. These overconfident traders compete in market orders with another group of informed traders who have rational expectations. The results indicate that biased traders may make higher individual profits than traders with rational expectations. Overconfident traders were also found to increase market depth, price variability, informativeness, and trading volume in the presence of a risk neutral market maker.

In the model of Odean (1998), a market is examined in which price-taking traders, a strategic-trading insider, and risk-averse market makers are overconfident. Overconfidence is defined as the overestimation of the precision of private knowledge. The results indicate that overconfident traders increase trading volume and market depth, and lower their expected utilities. Overconfident traders hold undiversified portfolios. The effect of overconfidence on volatility and price quality depends on who in the market is overconfident. In addition, overconfident traders can cause the market to underreact to the information of rational traders.

Gervais and Odean (1999) developed a multi-period market model that describes both the process by which traders learn about their ability, and how a bias in this learning *can* create overconfidence by causing traders to take too much credit for their successes. Success is measured by how well a trader forecasts dividends. The model predicts that overconfident traders will increase their trading volume and thereby lower their expected profits. Volatility increases with the number of past successes a trader has had. Investors are shown to be most overconfident early in their careers. With experience, self assessment becomes more realistic and overconfidence more subdued. In contrast to other models that assume that biased traders stay in the market by earning above-average returns, the model by Gervais and Odean (1999) is based on biased traders who earn, on average, lower profits. In their model, overconfidence does not lead to greater profits, but greater profits do lead to overconfidence.

The studies discussed above support the conjecture that overconfidence influences individual behavior in financial decision making. Empirical results indicate that individual investors overestimate the precision of private knowledge, generate confidence intervals which are too narrow, and are overly optimistic about future events, even uncontrollable ones. Markets were found to be overly optimistic about the prospects of firms that issued equity, and the trading volume of individual investors was found to be too high, leading to suboptimal net returns.

However, there are also studies which challenge the validity of the conclusion that individuals are *generally* overconfident. Erev, Wallsten and Budescu (1994) showed that both overconfidence as well as underconfidence can be obtained from the same set of data, indicating that the results are actually moderated by the research method used and thus are not a general phenomenon. Also the results of Juslin, Winman and Olsson (2000) indicate that the overconfidence bias depends on the selective attention to particular data sets. Klayman, Soll, Gonzalez-Vallejo and Barlas (1999) emphasize that overconfidence depends on (i) how the experimenter asks his/her questions, (ii) what he/she asks, and (iii) whom he/she asks. First, in studies that used two-choice questions, observed biases were few, whereas studies that used confidence-range judgments were found to trigger more overconfident responses. Second, no relation between the amount of overconfidence and the difficulty of the domain of the questions was observed. However, empirical evidence indicates that domains differ in the extent to which they elicit under- and overconfidence, respectively. Third, consistent individual differences in the degree of overconfidence were found, indicating that individuals generally differ in their proneness to biased responses.

2. Hypotheses

In this paper we investigate four hypotheses: The first two hypotheses deal with two different measures of overconfidence, in order to investigate whether overconfidence is a general valid phenomenon or whether it is moderated by the method used. The third hypothesis deals with the relation between individual experience and overconfidence, and the fourth hypothesis is concerned with the relation between trading volume and individual earnings.

Overconfident traders overestimate the precision of their price predictions by placing too much weight on their own (private) signal, and by misinterpreting the variance of actually observed outcomes. Thus, if individuals create confidence intervals, they set the upper and lower boundaries falsely. In our experiment we ask participants at the beginning of each trading period to create a subjective confidence interval of 98% width, that is they have to set the upper boundary such that the observed average trading price will be *higher* than the boundary only in 1% of the time, and the lower boundary such that the observed average trading price will be *lower* than the boundary in 1% of the time. If participants in our market are overconfident with respect to their created confidence intervals, we expect that the created confidence intervals are too narrow.

Hypothesis 1: Subjective confidence intervals are too narrow, as they exclude the observed trading prices far too often.

Overconfidence cannot only be defined based on subjective confidence intervals, but also on the comparison between subjective certainty of having made accurate decisions and the objective outcome of the decision. In our experiment participants are asked at the beginning of each trading period to predict the next average trading price and to state on a scale (ranging from 1=not certain to 9=certain) how certain they are that their price predictions are correct. If participants in our market are overconfident, we expect that their subjective certainty of having made accurate decisions exceeds the objective accuracy of their decisions.

Hypothesis 2: Traders are overconfident with respect to the accuracy of their price predictions, as their subjective certainty of having made accurate decisions exceeds the objective accuracy.

Overconfidence was found to be particularly pronounced in decisions under uncertainty, implying that experts may even be more prone to overconfidence than novices in certain tasks (Griffin and Tversky, 1992). Since predicting asset prices on a financial market is a decision task involving uncertainty, we expect that overconfidence is more likely in late trading periods, when traders are experienced. More precisely, we expect that with experience participants place more and more weight on their own (private) signal, leading them to be more likely to being prone to overconfidence. In turn, we expect that participants in the beginning of trading are more cautious, are less certain of having made accurate predictions, and create wider confidence intervals. However, as participants gain more experience across trading periods, we expect them to increasingly place more weight on their predictions, overestimate the accuracy of their predictions, and lower the boundaries of the confidence intervals. Thus, we hypothesize that overconfidence will be particularly pronounced in late market periods, when traders have already gained experience, and that overconfidence will be lowest at the beginning of trading.

Hypothesis 3: The degree of overconfidence is highest in late trading periods and lowest in early trading periods.

The models of Benos (1998) and Odean (1998) suggest that due to investor overconfidence traders will trade too much. Since investors overestimate their own (private) signal and inappropriately consider the signals of other market participants, traders have differing beliefs about the likely performance of assets, resulting in a multiplicity of trading opportunities. The models further predict that overconfident traders do not only trade too much, but more importantly also trade when the expected earnings are negative, leading them to have lower total utility. Thus, we expect that trading volume is negatively correlated with individual earnings, indicating that the higher the trading volume, the lower the earnings will be.

Hypothesis 4: Trading volume is negatively correlated with individual earnings.

3. The experiment

3.1 Participants

Overall, 72 participants, all students either at the University of Vienna or at the Vienna University of Economics and Business Administration, participated in six experimental asset markets. Participants earned on average a remuneration of ATS 209.82, approximately $14 in May 2000 when the experiment was conducted, the standard deviation was ATS 161.93 (about $11). The time required to conduct the experiment was about 2 hours and 15 minutes. Twenty-one females and 51 males, aged 18 to 29 (M = 21.51, SD = 2.33), participated in the experiment. Fifty-nine participants were students of economics, whereas the remaining 13 participants were enrolled in other social science disciplines.

3.2 Experimental design

The experiment was conducted in a 2 x 3 factorial design in order to investigate the interaction of differently informed participants within *one* market. The independent variables were (i) dividend information (complete information about dividend payments, no information) and (ii) the public signal subjects received about the market participants' average price predictions (precise public signal, vague public signal, no public signal). Both variables were between-subjects factors.

Participants were randomly assigned to the experimental conditions. Half of the participants received complete information about the dividend distribution (market insiders), whereas the other market participants got no information (market outsiders).

In addition, participants received exactly one of three public signals: a precise public signal, a vague public signal, and no public signal. In the first experimental condition (precise public signal), participants received information about their individual prediction of the average market price in the next trading period s_i and a precise public signal informing them about the corresponding average prediction of all market participants $\bar{s}_i$, including themselves ($\bar{s}_i = \sum_{i=1}^{n} s_i$).

In the second experimental condition (vague public signal), participants also had information about their individual prediction of the average market price in the next trading period s_i, but obtained only a vague public signal $\hat{s}_i$, indicating current market mood on a seven-step scale, ranging from a very optimistic market mood to a very pessimistic market mood. The vague public signal $\hat{s}_i$ was defined as the relative deviation of one's individual price prediction s_i from the average prediction $\bar{s}_i$ ($\hat{s}_i = \frac{\bar{s}_i - s_i}{\bar{s}_i}$). If the individual price prediction was lower than the average price prediction, participants were informed that the market mood was optimistic. If individual price prediction was higher than the average price prediction, participants were informed that the market mood was pessimistic with respect to their own prediction (see Table 1).

Table 1: Market mood scale (vague public signal)

Relative deviation of subject's price prediction from the average price prediction $\hat{s}_i$	Market mood
$\hat{s}_i <- 0.49$	Very pessimistic market mood
$- 0.49 \leq \hat{s}_i < - 0.29$	Pessimistic market mood
$- 0.29 \leq \hat{s}_i <- 0.09$	Slightly pessimistic market mood
$- 0.09 \leq \hat{s}_i < 0.10$	Sideward moving market mood
$0.10 \leq \hat{s}_i < 0.30$	Slightly optimistic market mood
$0.30 \leq \hat{s}_i < 0.50$	Optimistic market mood
$\hat{s}_i > 0.49$	Very optimistic market mood

In the third experimental condition (no public signal), participants received information only about their individual prediction of the average market price in the next trading period s_i, but no information about the predictions of the other market participants.

3.3 Experimental procedure

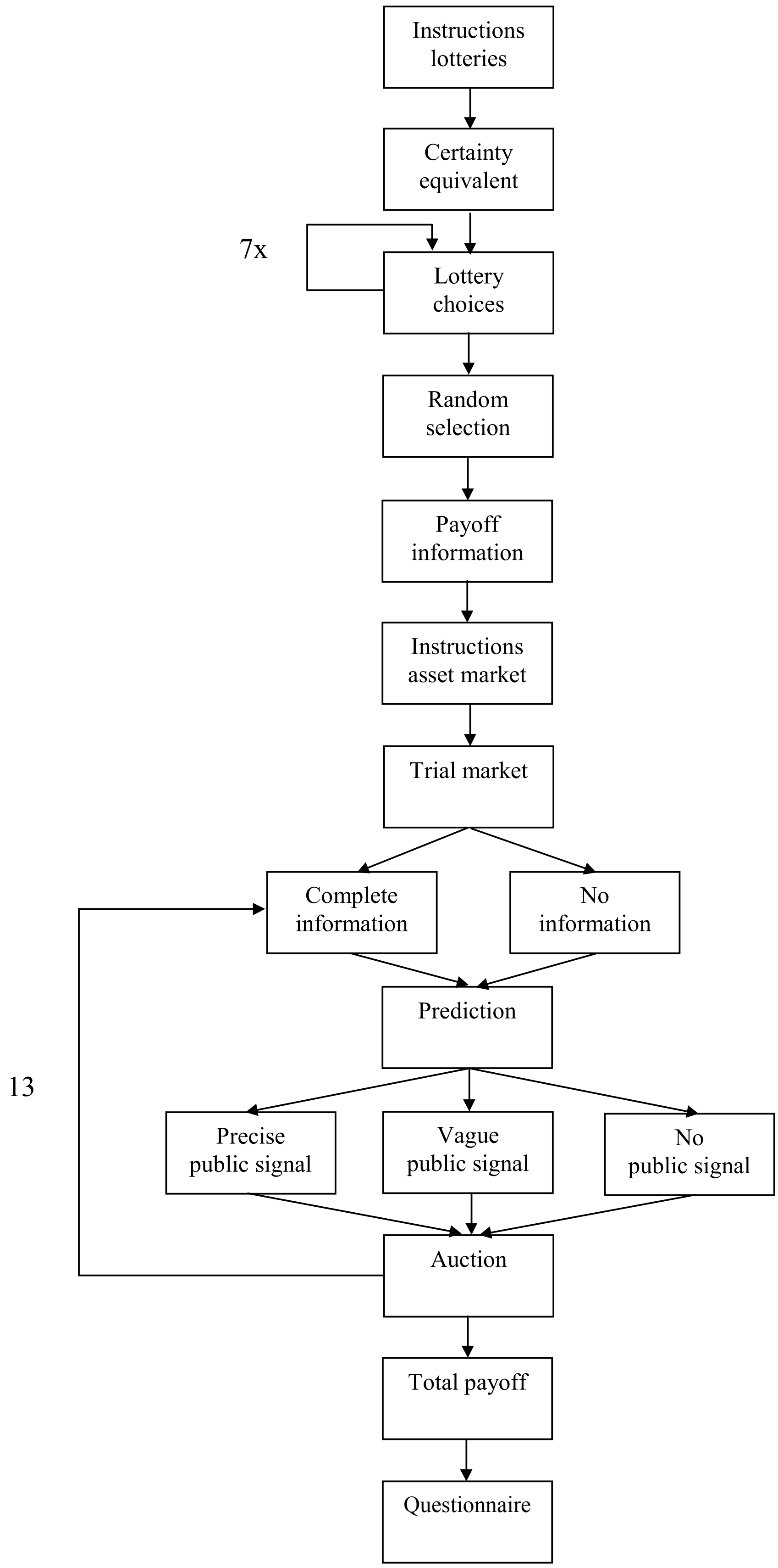
The experiment consisted of three phases. In the first phase, subjective propensity towards risk was measured experimentally by the methods of certainty equivalents and by lottery choices in order to control for differences in individual risk attitude. In the second phase, the experimental asset market was opened and assets were traded. In the third and last phase, participants were asked to fill out a short questionnaire. The complete experiment was conducted on computers using the software z-Tree (Zurich Toolbox for Readymade Economic Experiments, Fischbacher, 1998). The exact sequence of events in the experiment is shown in Figure 1.

Phase 1: After brief instructions, participants were asked (i) to reveal their certainty equivalent for a lottery that offers a payoff of 100 Experimental Guilders with a probability of p = .50, and zero Experimental Guilders[2] otherwise; and (ii) to make seven decisions among risky lotteries. As a control for order effects, the lotteries were systematically varied.

The certainty equivalent allows the experimenter to infer whether participants are risk averse, risk neutral, or risk seeking, whereas the lotteries were constructed in a way that allows the experimenter only to distinguish between risk aversion and risk neutrality. A certainty equivalent that is lower than the expected value of the lottery, which is 50 Experimental Guilders, indicates risk aversion, whereas a certainty equivalent equal to the expected value indicates risk neutrality, and finally a certainty equivalent above the expected value indicates risk proneness. Also, the seven decisions among lotteries can be used to infer risk attitude. However, since each lottery has the same expected value in each of its two components, namely the certain payoff and the risky payoff, the design only allows to distinguish between risk aversion (certain payoff) and risk neutrality (risky payoff).

[2] The exchange rate for Experimental Guilders was 10 to 1, that is 10 Experimental Guilders equal 1 Austrian Schilling.

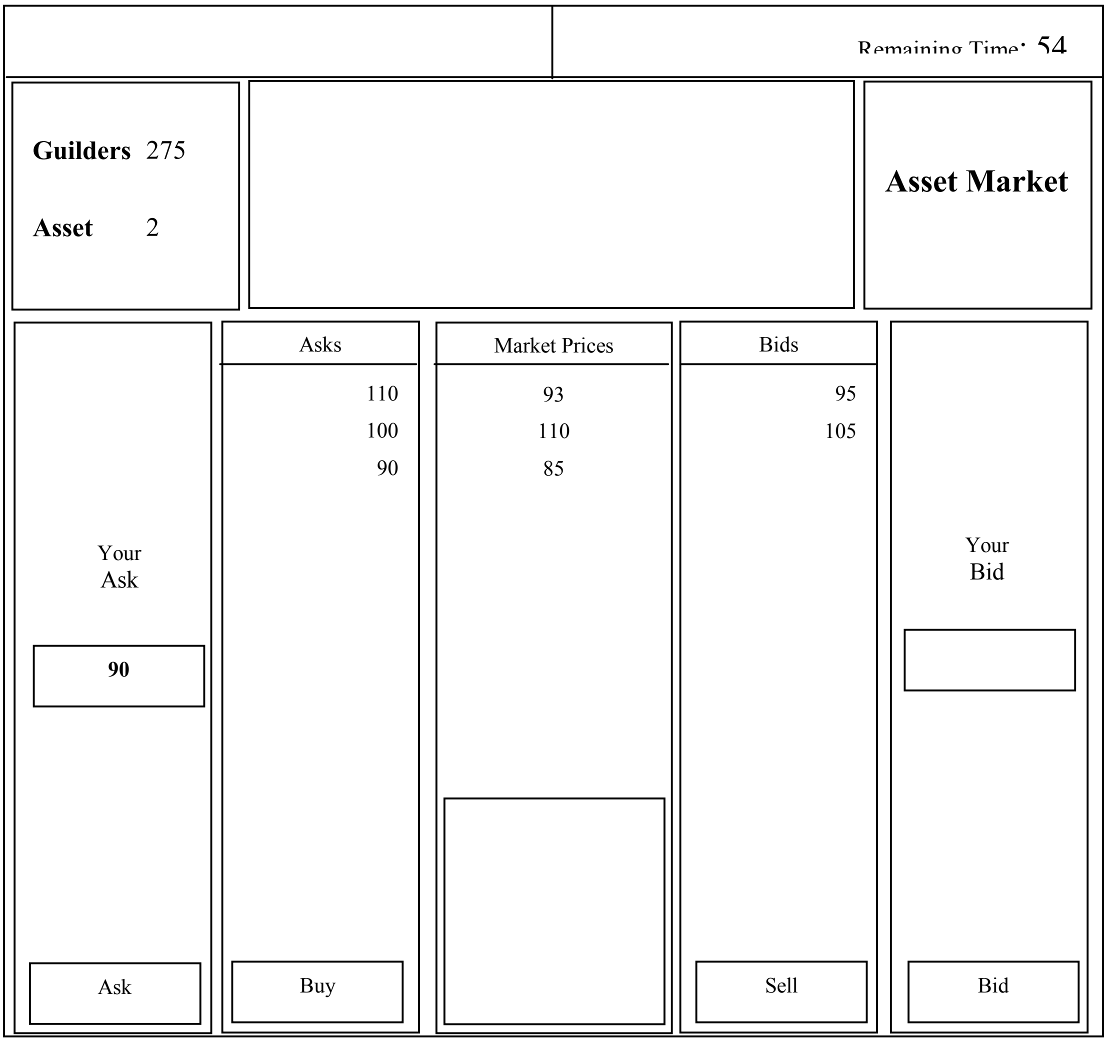
Figure 1: Sequence of events in the experiment



One of the seven decisions was randomly selected in order to determine the individual payoff, which was then added to the total payoff earned in the auction. The time required for conducting phase 1 was about 15 to 20 minutes.

Phase 2: After receiving instructions about the experimental asset market, subjects participated in two trial periods of six minutes in order to become familiar with the selling and buying procedures on the market. After the trial periods, the asset market was opened. Overall, six market sessions were run with 12 participants each on a computerized asset market. The computer screen for the auction is shown in Figure 2. Each market participant was entitled (i) to submit bids and asks, (ii) to accept standing bids and asks, whereas only improving offers, i.e. higher bids and lower asks, respectively, were allowed, or (iii) to stay aloof. Bids and asks were automatically ranked, indicating the most favorable offer. Information about trading history, provided as a chronological list of contracts, was common knowledge.

Figure 2: The screen of the auction



The experiment was performed as a continuous anonymous double auction. Participants were endowed with 250 Experimental Guilders plus five risky assets. Dividends were randomly determined according to p_d, and were paid out at the end of each period (see Table 2). In order to reveal possibly divergent dynamics in price and the intrinsic value of the asset, a monotonously falling expected value of the dividend was stipulated, implying consistently falling asset prices across trading periods. Participants were informed that the market would be open for at least 12 periods and at most 15 periods. The probability that the market would end after the 12^{th}, 13^{th}, and 14^{th} period was 33%. Participants were also informed that at the end of the final market period the liquidation value of the asset would be zero. To ensure comparability between sessions, the last market period was randomly chosen once for all six sessions before the experiment was actually conducted. According to the random selection, it was determined that each session would end after the 13^{th} period. Each period lasted for 180 seconds.

Table 2: Dividend payments in Experimental Guilders

Periods	Dividends	Probability (p_d)	Expected value
1-3	0, 11, 27, 45, 59	.20	28.40
4-6	0, 19, 35, 53	.25	26.75
7-9	0, 13, 21, 33, 49	.20	23.20
10-12	0, 11, 29, 43	.25	20.75
13	0, 7, 19, 27, 39	.20	18.40

Before the market was opened, participants (i) either received information about the distribution of dividends in the next market period or received no such information, were asked (ii) to predict the next average market price, to create a subjective confidence interval of 98% width, to state how certain they were that their predictions were accurate on a nine-step scale, ranging from 1=not certain to 9=certain, and (iii) were given one of three public signals. The time required for conducting phase 2 was about 80 to 90 minutes.

Phase 3: Participants were asked to fill out a computerized post-experimental questionnaire with items designed to check how well they understood the experiment and to determine the effort they had put into arriving at accurate decisions. The time required for conducting phase 3 was about 15 to 20 minutes.

4. Experimental results

4.1 Descriptive data analysis

Participants earned on average 2,012.50 Experimental Guilders on the asset market (SD = 1,881.51), without the payoff of the lottery decisions. In each of the 13 market periods an average of 44.9 contracts were concluded by the groups of 12 market participants (SD = 15.07, ranging from a minimum of 7 contracts to a maximum of 89 contracts). The average market price was 79.94 Experimental Guilders (SD = 53.22).

As can be seen from Figure 3, the observed average market prices differ substantially from the expected market prices based on the intrinsic or fundamental value of the asset. However, over periods with increasing experience and learning, the observed average market prices come close to the expected prices. In period 9, the observed and the expected prices intersect, and for the next two trading periods the observed average trading prices overshoot the expected ones. Prices are above the expected value, but then sharply decrease and tend to converge to the expected value again. Thus, the results on the average trading prices indicate - as in other experimental studies on trading behavior in asset markets - that with experience and repetition, learning takes place that ensures that market prices will converge to the equilibrium prediction (for a survey on the experimental literature on asset market behavior see e.g., Sunder, 1995).

Figure 3: Observed average market prices and expected market prices

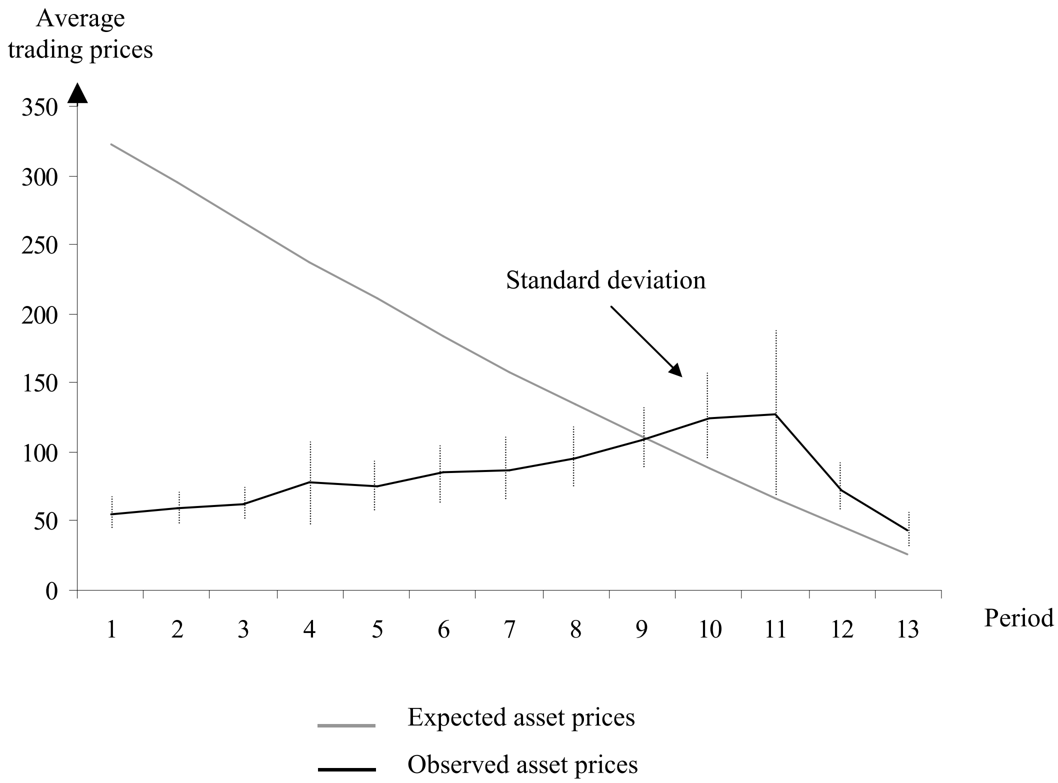


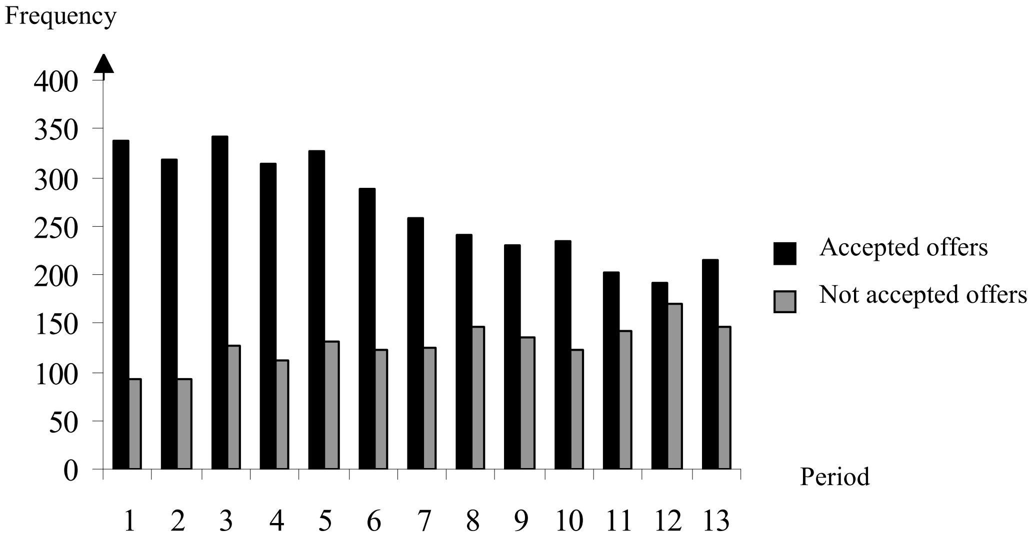
Figure 4 indicates that across the trading periods, the number of concluded contracts decrease ($\chi^2 = 129.16$, $p < .001$), while the number of offers not accepted by other market participants increase ($\chi^2 = 43.69$, $p < .001$). Whereas 78.37% of all submitted offers are accepted in the first trading period, only 53.04% of them are accepted in the 12th, and 59.50% are accepted in the 13th trading period by other market participants ($\chi^2 = 127.05$, $p < .001$). Of course, one can argue that the number of accepted offers may have decreased because prices increased over trading periods. However, if one compares the average prices of not accepted offers in period 1 with the corresponding prices of not accepted offers in period 13, one can see that prices in fact decrease over time to a statistically significant degree ($M_1 = 61.57$, $SD_1 = 34.11$; $M_{13} = 51.62$, $SD_{13} = 34.76$; $F(1; 460) = 6.13$, $p < .05$), nevertheless the number of contracts concluded did not increase, but in fact decreased.

To control for differences in individual risk attitude, we investigated in a next step whether individual risk attitude differs between sessions and between experimental conditions with respect to the elicitation methods of certainty equivalents and lottery decisions. The average certainty equivalent revealed by the participants is 43.42 (SD = 37.63), indicating a slight degree of risk aversion.[3] Certainty equivalents do not differ significantly between the six sessions ($F(5; 66) = 1.88$, $p = .11$). An index for risk attitude ranging from 0=risk neutrality to 7=risk aversion is computed out of the seven decisions among lotteries. Subjects' average risk attitude amounts to 3.26 (SD = 1.91), indicating that in 3.26 cases the secure rather than the risky alternative in the lottery is chosen. Again no statistically significant difference between the six sessions is observed ($F(5; 66) = 0.43$, $p = .83$). Neither for the kind of public signal

[3] Eleven participants exhibit risk proneness, as their certainty equivalents exceed 50. However, these participants do neither earn more or less than others on the market ($F(1; 70) = 0.76$, $p = .39$).

subjects received nor for the information condition is there a statistically significant difference between the groups with respect to the certainty equivalent ($F(2; 69) = 2.26$, $p = .11$; $F(1; 70) = 2.40$, $p = .13$) nor with respect to the lottery decisions ($F(2; 69) = 0.36$, $p = .70$; $F(1; 70) = 2.42$, $p = .12$). Thus, it can be expected that any differences observed in the experiment between experimental conditions are not caused by different underlying risk attitudes.

Figure 4: Frequency of accepted and not accepted offers across trading periods



In a next step, we investigated whether there are any differences in individual accuracy between experimental conditions. The results indicate that objective accuracy, defined as the absolute value of the difference between participants' price predictions and the actual average trading prices, neither differs between dividend information-conditions ($F(1; 934) = 0.34$, $p = .56$) nor between public signal-conditions ($F(1; 933) = 2.18$, $p = .11$). Thus, our findings suggest that information dissemination between differently informed market participants takes place.[4] Differently informed traders exchange their knowledge on the market by submitting offers and concluding contracts, whereby formerly private information becomes public information.[5]

Questionnaire data reveals that the subjects understood the instructions and that their decisions were well considered. Participants agree to the statement that the instructions are clear and easy to understand ($M = 7.11$, $SD = 2.24$, all items are nine-step items ranging from 1=I do not agree to 9=I fully agree), and they also agree that they have carefully considered their buying offers ($M = 5.82$, $SD = 2.34$) and their selling offers ($M = 6.00$, $SD = 2.21$).

4.2 Subjective confidence intervals and individual experience

We hypothesized that traders would be prone to overconfidence, and that their subjective confidence intervals would be too narrow, as they exclude the observed trading prices far too often (Hypothesis 1). We also hypothesized that individual overconfidence would increase

[4] Recent experimental analyses of information dissemination are provided by Kirchler, Maciejovsky and Weber (2001), Maciejovsky (2001) as well as by Maciejovsky, Helmenstein, Kirchler, Haumer and Hofmann (2001).

[5] Thus, in order to exploit any information advantage on a market one has to reveal that information, whereby it becomes publicly known, and the former advantage vanishes.

with experience (Hypothesis 3). Thus, we expected that the degree of overconfidence is highest in late trading periods and lowest in early trading periods.

In each trading period, participants were asked to make price predictions that (i) *would not* be exceeded with a probability of 99% (upper boundary) and that (ii) *would be* exceeded with a probability of 99% (lower boundary). Instead of the expected range of 98% for the confidence intervals, the observed subjective confidence intervals covered only a range of 75.3%. Figure 5 displays the frequency of instances where the observed average trading prices lie *outside* the generated confidence intervals. If participants are well-calibrated in their predictions, then only up to 1.44 confidence intervals (2% out of 72 observations) would be insufficiently wide. If the number of outliers is, however, higher, then participants can be classified as over-confident.

Figure 5: Frequency of calibrated confidence intervals and of those with insufficient width

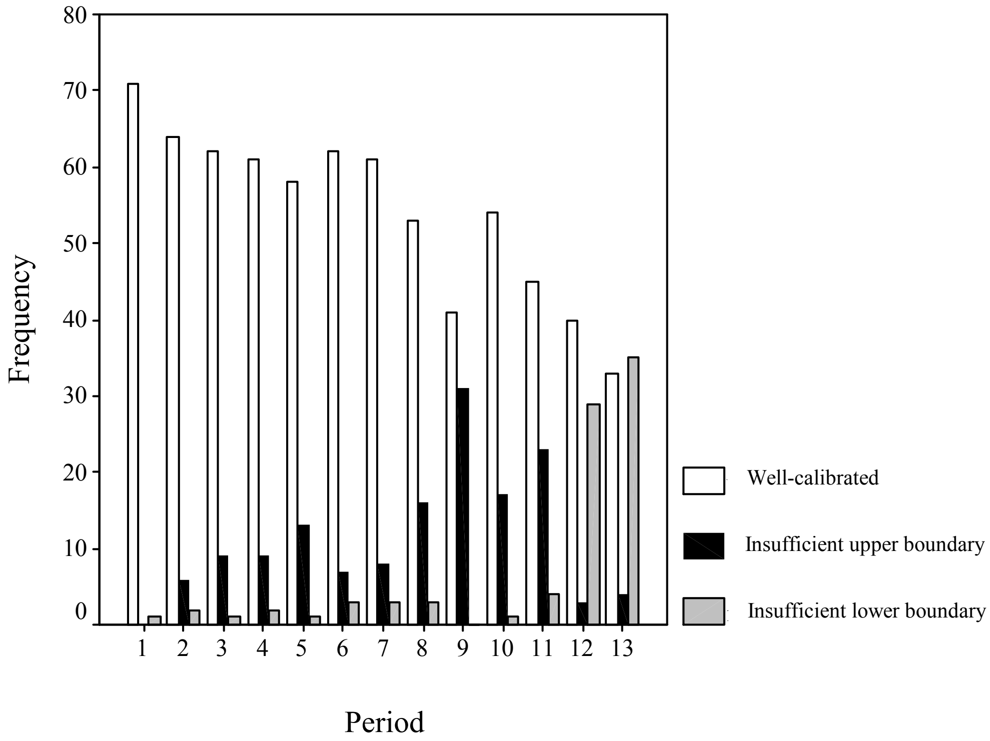


Figure 5 indicates that confidence intervals are of insufficient width across all trading periods, except the first trading period, in which only one violation of the required range is observed. Thus, our results with respect to the subjective confidence intervals suggest that individuals on our experimental asset market are overconfident, as their confidence intervals exclude the observed average trading prices far too often. Only in the very first trading period, participants can be classified as well-calibrated. However, especially in late trading periods when uncertainty about market duration comes into play, there is an increased frequency of confidence intervals that do not adequately cover the required range. The results of the non-parametric Friedman-test indicate that the number of outliers does not remain constant across trading periods ($\chi^2 = 234.05$, $p < .001$).

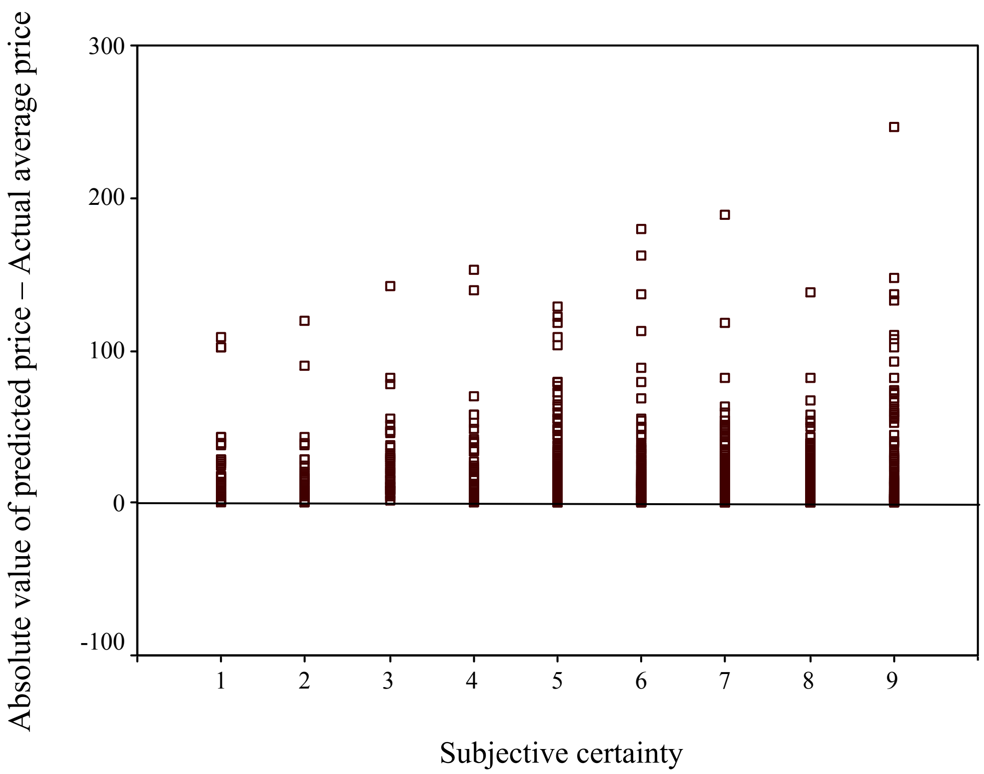
Under complete uncertainty, more precisely in the first trading period, confidence intervals are accurate. However, with increasing experience participants seem to rely too heavily on their subjective price predictions, causing their confidence intervals to narrow. Across trading periods, the number of outliers, that is actual average trading prices that exceed the upper boundary or fall short of the lower boundary, increases. This is especially pronounced in the last two trading periods, when participants do not adjust the lower boundaries of their confidence intervals adequately. Whereas only one out of 72 confidence intervals is not calibrated in the first trading period, 32 are not calibrated in period 12, and 39 are not calibrated in period 13. Thus, hypotheses 1 and 3 are both confirmed. Our results show that (i) participants generate confidence intervals that are not wide enough, indicating individual overconfidence in 12 out of 13 periods, and well-calibration only in the first trading period, and (ii) the degree of overconfidence is strongest in late market periods when participants are already experienced.

4.3 Comparison of objective accuracy to subjective certainty

We hypothesized that traders on an experimental asset market would be overconfident with respect to the accuracy of their price predictions, as their subjective certainty of having made accurate decisions exceeds the objective accuracy of their decisions (Hypothesis 2).

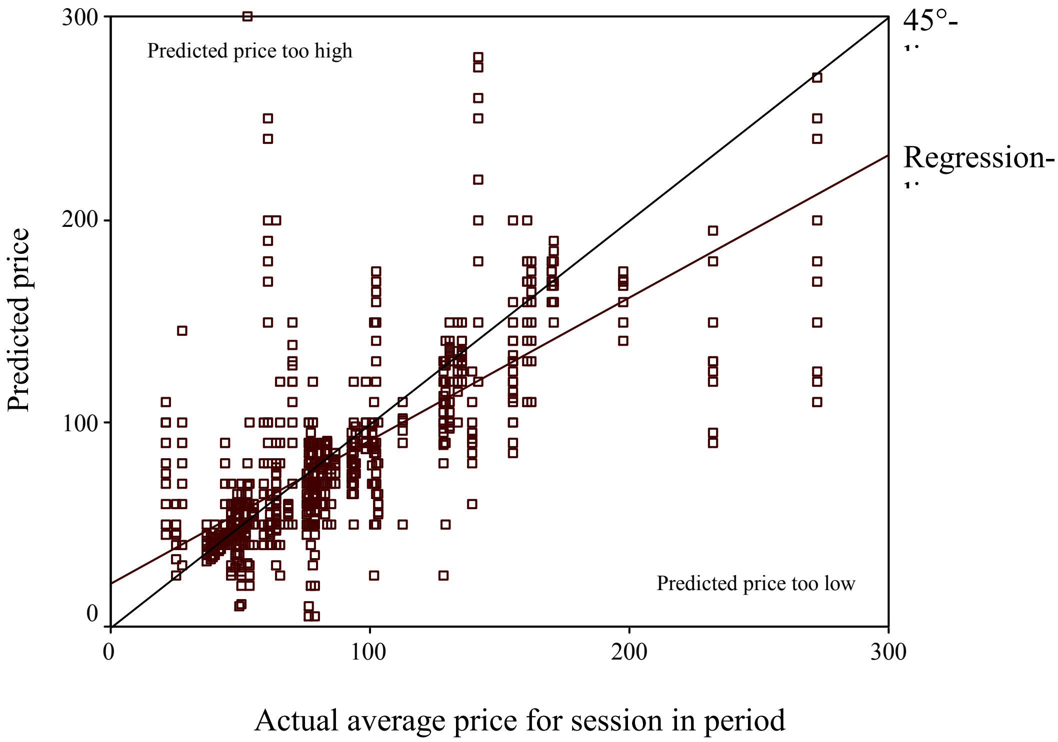
In each period before the market was opened, participants were asked to predict the next average trading price and to state how certain they were that their predictions would be accurate on a nine-step scale ranging from 1=not certain to 9=certain.

Figure 6: Scatterplot of predicted prices and actual average prices for all groups across periods



The scatterplot in Figure 6 shows the relation between individual price predictions and actual average trading prices for each session across periods. On the horizontal axis there is one data point for each of the six session's average price in each of the 13 periods, and on the vertical axis there is one data point for each of the 72 participants. Points above the 45°-line indicate that a person's predicted price was too high, whereas points below the line indicate that the predicted price was too low. The regression-line in Figure 6 indicates that the participants' price predictions are too low on average, since the slope of the regression-line is less than one (R^2 = .56; F(1; 934) = 1,168.39; p < .001).

Figure 7: Individual comparison of one's subjective certainty and his/her accuracy



If participants are well-calibrated with respect to their subjective certainty, then the absolute value of the predicted price minus the actual average trading price, as an indicator of objective accuracy, should be negatively correlated with subjective certainty, indicating that the higher one's certainty the lower the absolute deviation from his/her prediction to the actual average trading price. Figure 7 displays the relation between subjective certainty and the absolute value of the deviation from the prediction to the observed average trading price. The results do only weakly support this conjecture with respect to all periods (Average Spearman correlation ρ = -.11, p < .05). If one analyzes, however, the relation between subjective certainty and objective accuracy separately for each of the 13 periods, the results are only statistically significant at early stages of the experiment (see Table 3). More precisely in periods 2, 3, and 5. In these trading periods the results indicate that the higher the subjective certainty the lower the absolute deviation from the predicted price to the actual average price. However, in late trading periods, the relation between subjective certainty and objective accuracy is not statistically significant, indicating that subjective certainty is not related to objective accuracy.

Although we have empirically established for our data that the subjective certainty is only weakly correlated with the absolute value of the predicted price minus the actual average trading price, we have not yet investigated the joint-movement of subjective certainty and objective accuracy across periods. Thus, in a further step, we analyze the objective accuracy of the participants' predictions in the first trading period. More precisely, we investigate whether the participants' predicted prices minus the actual average trading prices are systematically different from zero. The results indicate that participants are well-calibrated in their price predictions in the first period, since the mean of the predicted prices minus the actual average trading prices falls within the confidence interval at a significance level of $\alpha = .05$. This finding corresponds to our results from the participants' subjective confidence intervals. But how does the subjective certainty of having made accurate decisions relate to the objective accuracy across periods?

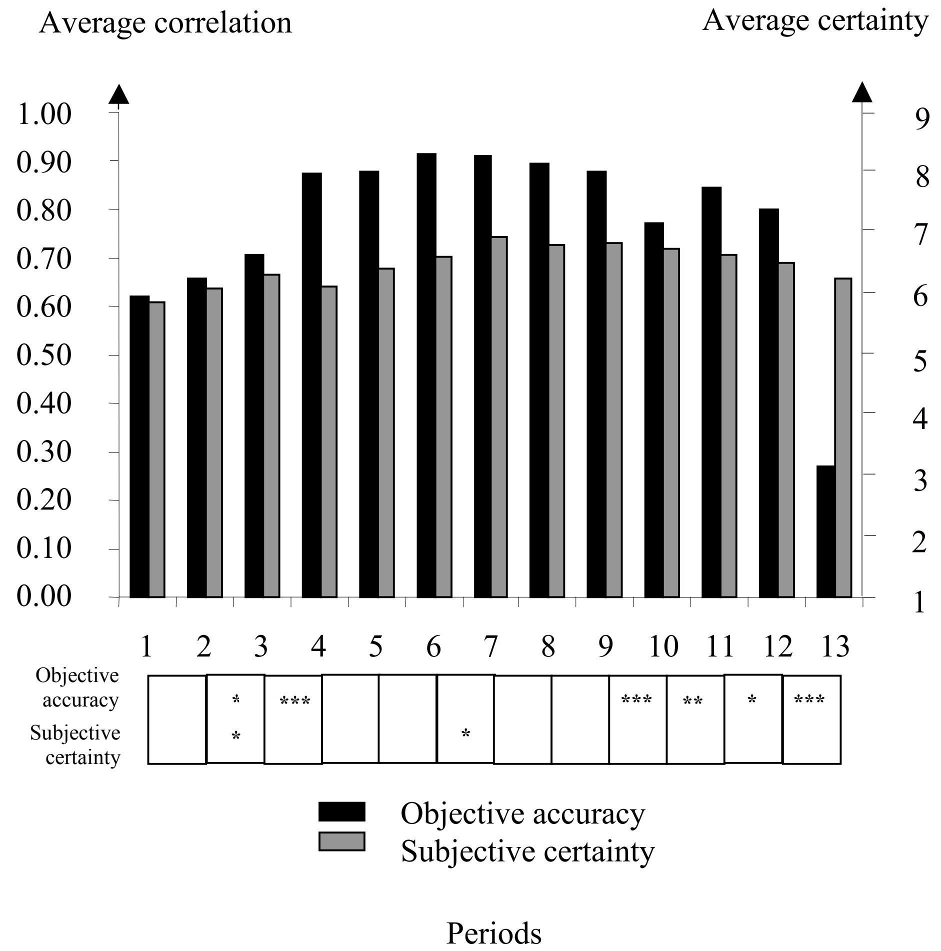
Table 3: The relation between the participants' subjective certainty and the absolute value of the deviation from the participants' predicted price to the actual average price

Periods	Spearman correlation	N	p
1	-.20	72	.10
2	-.27	72	.02*
3	-.28	72	.02*
4	-.19	72	.12
5	-.25	72	.03*
6	-.11	72	.35
7	-.11	72	.36
8	-.12	72	.32
9	-.14	72	.24
10	-.03	72	.83
11	.01	72	.96
12	-.03	72	.78
13	.01	72	.92

In order to be able to answer this question, we have to compare the participants' subjective certainty with the objective accuracy, as indicated by the correlation of price predictions with actual average trading prices, across periods. Since, participants are well-calibrated in their predictions in the first period, we also define their initial level of certainty as well-calibrated. From this starting point, we investigate whether there are any differences over periods with respect to the joint-movement of subjective certainty and objective accuracy. If accuracy increases significantly without an equivalent increase in certainty, participants can be tentatively classified as underconfident, whereas the reverse, a significant decline in accuracy that is not matched by an equivalent decline in certainty, can be referred to as overconfidence. Only when the objective accuracy moves in line with the subjective certainty, participants are well-calibrated in their predictions.

Figure 8 displays the relation between objective accuracy of the participants' price predictions and their subjective certainty of having made accurate predictions across trading periods. The results indicate that participants can be tentatively classified as well-calibrated in periods 2 and 3, since both the objective accuracy as well as the subjective certainty of having made accurate predictions increases significantly and simultaneously from period 2 to 3. However, whereas the objective accuracy further increases significantly from period 3 to 4, the subjective certainty of having made accurate predictions remains constant, indicating individual underconfidence. Only, from period 6 to 7 the subjective certainty slightly adjusts to the increase in objective accuracy by a (lagging) significant increase. Thus, participants can be tentatively classified as underconfident from periods 4 to 6. From period 7 onwards, the subjective certainty of having made accurate predictions does not change significantly from period to period, whereas the objective accuracy changes significantly four more times. Since, participants adjust their subjective certainty to the increase in accuracy from period 6 to 7, we tentatively classify them as well-calibrated in their predictions for the subsequent periods up to the decline in accuracy in period 10. In the last trading period, the sharp decline in objective accuracy is not predicted by the participants, since their subjective certainty of having made accurate predictions does not adjust correspondingly, indicating individual over-confidence.

Figure 8: Relation between objective accuracy and subjective certainty



Our results do not support hypothesis 2, indicating that participants are not *generally* over-confident. Instead, we report evidence that participants are well-calibrated in their predictions during some trading periods, whereas during other trading periods participants are over-confident as well as underconfident. One of our main research questions was to investigate correspondence of the two different measures of overconfidence used in this study, namely the subjective confidence intervals and the comparison of objective to subjective certainty. Table 4 indicates that these two methods lead to a different classification of behavior in our data-set. With respect to the subjective confidence intervals, overconfidence occurs in 12 out of 13 trading periods, whereas with respect to the comparison of objective accuracy to subjective certainty, overconfidence is only identifiable in three out of 13 trading periods. According to our classification based on the comparison of objective to subjective certainty, participants exhibit also underconfidence, and are also well-calibrated in their price predictions during some trading periods.

Table 4: Classification of well-calibration, over- and underconfidence according to the two study methods of subjective confidence intervals and the comparison of objective accuracy to subjective certainty

	Classification according to	
Periods	Subjective confidence intervals	Comparison of objective accuracy to subjective certainty
1	Well-calibration	Well-calibration[a]
2	Overconfidence	Well-calibration
3	Overconfidence	Well-calibration
4	Overconfidence	Underconfidence
5	Overconfidence	Underconfidence
6	Overconfidence	Underconfidence
7	Overconfidence	Well-calibration
8	Overconfidence	Well-calibration
9	Overconfidence	Well-calibration
10	Overconfidence	Overconfidence
11	Overconfidence	Underconfidence
12	Overconfidence	Overconfidence
13	Overconfidence	Overconfidence

[a] Participants were defined as being well-calibrated in the first trading period, in order to generate a starting point for our analysis.

4.4 Trading volume and individual earnings

We hypothesized that trading volume would be negatively correlated with individual earnings (Hypothesis 4).

The results do not confirm our hypothesis. Contrary to what we expected, trading volume is positively correlated with individual earnings ($r(72) = .39$, $p < .01$). However, since we formulated our hypothesis one-tailed, we cannot reject the null hypothesis, indicating that trading volume is not negatively correlated with individual earnings. Also, if we compute a median-split on only those contracts that are based on participants' own offers submitted to the market, participants with an above-average trading volume earn statistically significantly more than participants with a below-average trading volume ($M_A = 2{,}477.92$, $SD_A = 2{,}288.45$; $M_B = 1{,}547.08$, $SD_B = 1{,}224.31$; $F(1; 70) = 4.63$, $p < .05$).[6] In our experiment participants with a net-surplus of buying contracts (a higher buying than selling activity) earn statistically significantly more on the market than those participants with a net-surplus of selling contracts ($M_B = 2{,}779.50$, $SD_B = 2{,}439.68$; $M_S = 1{,}578.98$, $SD_S = 1{,}321.73$; $F(1; 70) = 7.37$, $p < .001$). In addition, we find that those participants who can be classified as overconfident according to their subjective confidence intervals, earn statistically significantly less than others ($r(72) = -.24$, $p < .05$).

[6] For comparison, a buy-and-hold strategy guaranteed market participants on average earnings of 1,762.50 Experimental Guilders.

5. Conclusions

Overall, our results indicate that traders on the experimental asset market are not *generally* prone to overconfidence. The existence of overconfidence is moderated by the methodology used.

In our experiment, we investigate correspondence between the two methods of subjective confidence intervals and the comparison of objective accuracy and subjective certainty. Whereas, participants are overconfident in 12 out of 13 trading periods according to the subjective confidence intervals, participants can only be classified as overconfident in three periods based on the comparison between objective accuracy and subjective certainty. With respect to the latter method, participants can also be classified as well-calibrated and as underconfident during some trading periods, whereas according to the subjective confidence intervals, participants are only well-calibrated in the first trading period.

In this paper, we also show that overconfidence, based on subjective confidence intervals, increases with experience and is negatively correlated with individual earnings, indicating that overconfident traders earn less than others on our experimental asset market. However, we do not observe that trading volume is negatively correlated with individual earnings. Our results further indicate that the precision of the participants' predictions is not related to their subjective certainty of having made accurate predictions in most of the trading periods. This finding is especially pronounced in late trading periods, when participants are experienced.

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