Bubbles in hybrid markets: How expectations about algorithmic trading affect human trading ☆

Mike Farjam [a], Oliver Kirchkamp [b],*

[a] Linnaeus University, Department of Social Studies, Universitetsplatsen 1, 35195 Växjö, Sweden
[b] University Jena, School of Economics, Carl-Zeiss-Str. 3, 07737 Jena, Germany

ARTICLE INFO

ABSTRACT

Bubbles are omnipresent in lab experiments with asset markets. Most of these experiments are conducted in environments with only human traders. Since today's markets are substantially determined by algorithmic trading, we use a laboratory experiment to measure how human trading depends on the expected presence of algorithmic traders. We find that bubbles are clearly smaller when human traders expect algorithmic traders to be present.

© 2017 Elsevier B.V. All rights reserved.

1. Introduction

Experimental research on assets markets began in the mid 20th century using a stable design which has hardly changed since (see Section 2). However, if we look at real world asset markets in the 21st century, we see great differences compared to asset markets in the 20th century. In the last century humans interacted with each other face to face. Today computers serve as an intermediary. The use of computers on asset markets comes in many forms. It includes simple support of human traders in scheduling sales of assets without influencing the asset price in the market. It also includes sophisticated algorithmic traders which can learn and autonomously decide which assets they sell or buy (Kirilenko and Lo, 2013).

While the markets of the 20th century were human-only markets, modern markets are hybrid markets where computers and humans trade and where neither party gets information whether they sold to or bought from humans or algorithmic traders. De Luca and Cliff (2011) estimate that algorithmic traders are involved in up to 70% of the total trading volume in major European and US equity exchanges. In this paper we ask whether differences in human trading behavior between hybrid and human-only markets are substantial and how insights gathered in human only markets need to be interpreted with care when applying them to hybrid markets.

We will discuss the literature on hybrid markets in more detail in Section 2.2. Most of this literature deals with optimization of algorithms in hybrid markets or compares hybrid markets per se with human markets. Differences between human-only markets and hybrid markets are attributed to the direct effect, i.e. to the trading activity of algorithmic traders, and not to the indirect effect, i.e. to the changes in human trading patterns that result from the perceived presence of algorithmic traders. Algorithmic traders are seen as more able than humans to discover arbitrage possibilities than human traders. As a result we should see less mispricing in hybrid than in human-only markets. In this paper we argue that differences between the two market types could already result only from changes in human behavior, anticipating the effects of an algorithmic trader and without any active participation of algorithmic traders in hybrid markets.

One phenomenon in the context of market dynamics which is of special interest for economists is the "bubble and crash" pattern. Its enormous potential to harm economies has been documented throughout history. According to King et al. (1993), bubbles form when goods are traded in high volumes at prices that are considerably at variance from intrinsic values and crash when prices suddenly drop to a more reasonable amount reflecting the good's intrinsic value. During the formation of bubbles expectations about the behavior of others crucially determine behavior of human traders. Cheung et al. (2014) relate bubbles in asset markets to the expectation that other market participants are less rational. Expecting more rationality in hybrid markets could discipline human traders and could cause a different performance in the two types of markets.

In Section 2 we will review the literature. We will see that the presence of algorithmic traders could change the behavior of human traders in different ways. Do human traders trade less because algorithmic traders leave fewer opportunities to exploit the irrationality of other traders? Or do human traders trade more because prices are perhaps more informative in hybrid markets?

In Section 3 we will present the design of our laboratory experiment. We explicitly do not focus on the properties of specific algorithmic traders used in the real world. Instead we exploit that most humans have an intuition when it comes to the differences between algorithmic traders and human traders. In a first experiment we aggregate the intuition subjects have about algorithmic traders. In a second experiment we use this information as a stimulus to control expectations of participants. In this experiment we also manipulate expectations about the presence of algorithmic traders. In Section 4 we present our results. Section 5 concludes by looking at the experimental results in a broader context.

2. Literature

2.1. Experimental asset markets

Smith et al. (1988) (SSW) study a laboratory situation where subjects trade assets which pay a random dividend per period in an anonymized continuous double action. Subjects start with an endowment of assets and some cash. Assets can be sold for cash and cash can be used to buy assets offered by other subjects. Subjects know the average dividend assets pay per period and the number of periods. Hence, subjects can work out the fundamental value of assets in SSW markets.

With common knowledge of rationality and risk neutrality one might expect no trade in these markets. Assets should be traded only at their fundamental value. Since the latter is known by all market participants there is no reason to trade. However, SSW find that asset prices in the experimental markets follow a "bubble and crash" pattern which is similar to speculative bubbles observed in real world markets. In their experiments the price per asset starts below the fundamental value, but then quickly rises, often above the sum of maximum possible dividends. Towards the end the price drops again quickly, approaching the fundamental value.

The baseline condition of our experiment (presented in Section 3) is a close replication of the SSW design. Since Smith et al. (1988) many modifications of the SSW design have been studied to understand why people trade in these markets and to generally test theory on market bubbles. (An exhaustive survey is provided by Palan, 2013). Alternative experimental designs with a higher external validity have been studied—e.g., with a constant fundamental value of assets (Kirchler et al., 2012). However, we chose to implement the original SSW design since it is by far the most popular design in this domain and has been shown to reliably lead to bubbles, the phenomenon we want to study.

Common knowledge of rationality: If traders have identical preferences, access to the same information, if they are perfectly rational and if they have common knowledge about all this then they should trade neither in hybrid nor in human-only markets. Akerlof (1970), Bhattacharya and Spiegel (1991) and Morris (1994) point out conditions under which differences in prior beliefs or information should not lead to a relaxation of the no-trade-theorem in SSW markets.

Common knowledge of rationality is a crucial assumption. Cheung et al. (2014) manipulate the expectations subjects have about the rationality of other market participants. They ask all their subjects a large number of control questions on how a SSW market works and which trading strategies are rational. Subjects in one group are reminded explicitly that the other market participants have to answer the same control questions, subjects in the other group do not get this reminder. Cheung et al. (2014) find that markets in which subjects get an explicit reminder produce smaller bubbles and that subjects trade less in these markets.

If subjects assume algorithmic traders to trade in a more rational way then we should expect smaller bubbles in hybrid markets.

Risk-aversion and overconfidence: Risk-aversion and overconfidence could very well have an impact on trading in asset markets. In our experiment we measure these traits per subjects before trading starts.

Robin et al. (2012) and Fellner and Maciejovsky (2007) find that risk-aversion leads to smaller bubbles and less trade in asset markets. They follow an approach used by Holt and Laury (2002) (which we will also use) to measure risk aversion. Keller and Siegrist (2006) use a mail survey and find that financial risk tolerance is a predictor for the willingness to engage in asset markets.

Odean (1999) assumes that overconfidence of traders is the reason that there is more trade than one would expect from rational traders. Michailova and Schmidt (2016), Michailova (2010), Fellner and Krügel (2012), and Oechssler et al. (2011) find that the size of bubbles and trading activity in SSW markets are, indeed, strongly correlated with overconfidence. Glaser and Weber (2007) and Biais et al. (2005) find no or only very weak correlations with overconfidence. One reason for the different results might be that the different studies operationalize overconfidence in different ways. Fellner and Krügel (2014) point out that well established measures of overconfidence from cognitive psychology—such as the miscalibration measure—differs considerably from the usage of the term in economics. Also Moore and Healy (2008) and Hilton et al. (2011) describe different ways to measure overconfidence. In this paper we measure overconfidence as expected performance in the experimental asset market (see Section 3.4).

Ambiguity aversion: In stock markets with algorithmic traders the exact properties of these algorithms are usually unknown to other traders. Studies based on the Ellsberg paradox (Ellsberg, 1961) demonstrate that humans dislike situations with many unknowns. Ambiguity aversion in markets has been studied in a number of experiments, e.g., Camerer (1987), Sarin and Weber (1993), Kocher and Trautmann (2013), Füllbrunn et al. (2014). In the case of hybrid markets subjects may feel more knowledgeable about human traders where they can generalize from themselves to other traders. They may view algorithmic traders as a source of uncertainty and may less engage in markets with algorithmic traders.

2.2. Human computer interaction

Since a hybrid market is characterized by human computer interaction we will discuss some non economic aspects of human computer interaction in the following paragraphs.

Arousal: Mandryk et al. (2006) and Weibel et al. (2008) study computer games and find that gamers are more aroused when they know that they are playing with or against humans than when they know their counterpart is a computer program. Andrade et al. (2016) induce emotions with the help of short videos before the SSW market. Breaban and Noussair (2013) measure emotions based on facial expressions. Both studies find that market bubbles increase in magnitude and amplitude when subjects are aroused or excited. If arousal is, as in computer games, also lower in hybrid asset markets, then we should find smaller bubbles in hybrid markets than in human only markets.

Evidence from neuroscience: Humans use different brain areas for the interaction with computers than for the interaction with humans. Krach et al. (2008) find that especially areas associated with social interaction and motor regulation are less active when subjects interact with computers. These findings are robust across different types of games like Rock-Paper-Scissors (Chaminade et al., 2012), prisoners' dilemma games (Krach et al., 2008; Rilling et al., 2004) and trust games (McCabe et al., 2001). These experiments also show that humans invest more effort when their counterpart is human.

Nass and Moon (2000) show that humans mindlessly apply to computers social responses in environments where they would usually interact with humans. Subjects do behave in a reciprocal or polite way towards computers although the same subjects explicitly state that this kind of behavior is senseless. The findings of Nass and Moon (2000) suggests that humans should trade in the same way in hybrid and human only markets.

2.3. Hybrid markets

As pointed out in Section 1, real-world asset markets have changed considerably since the experiments of Smith et al. (1988). In particular hybrid markets, i.e. markets with human and algorithmic traders, have become more prominent. The major part of studies on hybrid markets focuses on the computer side of hybrid markets. On the one hand, experiments like Das et al. (2001) and De Luca and Cliff (2011) show that in SSW markets where human and algorithmic traders are active some of their algorithms outperform human traders in terms of payoff. Other studies identify properties in which hybrid markets differ from human-only markets: Generally empirical research on real stock markets, theoretical models, and simulations suggest that the presence of algorithmic traders leads to more liquidity on markets (Hendershott et al., 2011; Walsh et al., 2012; Boehmer et al., 2014; Chaboud et al., 2014). With respect to volatility and price discovery there is mixed evidence for the effect of algorithmic traders on hybrid markets. On the one hand, Gsell (2008) shows with the help of simulations that the presence of algorithmic traders in hybrid markets reduces volatility of prices and speeds up price discovery. On the other hand, Jarrow and Protter (2012) show in a theoretical model that algorithmic traders may trade in a sub market in which only they can trade because of their super-human trading speed, which should lead to more volatility and slower price discovery. Chaboud et al. (2014) find that during the period of 2003–2007 algorithmic traders led to a quicker price discovery but did not affect volatility in foreign exchange markets. Summarized, research on the effect of algorithmic trading on markets is in parts still inconclusive.

We have found only two studies which are closer to our research question and which study the human side of hybrid markets.

Akiyama et al. (2013) investigate the impact of strategic uncertainty on bubbles. They study experimental asset markets with six traders. In their treatment 6H six human subjects are trading with each other, in 1H5C one subject trades with five

Table 1
Treatments.

Subjects are in treatment...	Type of market	Subjects get information that they are in...
A	Only human traders	A
B	Only human traders	B or C
C	Hybrid	B or C

computer traders. Subjects in 1H5C know that they trade with computers which sell and buy assets at their fundamental value. In 6H subjects know that they trade with humans. Hence, in the 6H treatment there is substantial strategic uncertainty while in 1H5C there is no strategic uncertainty at all. Akiyama et al. (2013) find that there are no bubbles in 1H5C. Their design allows to better understand the impact of strategic uncertainty on prices.

In our paper we want to find out whether expectations about the mere presence of algorithmic traders affect trading behavior. In that respect Akiyama et al. (2013) can not distinguish whether differences in trading between treatments are the result of different trading behavior of the algorithmic traders in the 1H5C treatment, or due to the knowledge that algorithmic traders are present in that treatment, or due to the information that all other traders trade only at fundamental value. Furthermore, their study looks at an extreme kind of hybrid market, where the human trader is a minority in a market populated by mostly computers. Since the subject gets full information on the computers' strategy the prices in the market can be predicted correctly. The kind of hybrid markets we are interested in are different since we want to allow for human–human interaction, while human–computer interaction is also possible.

Grossklags and Schmidt (2006) study experimental asset markets in which humans trade in hybrid markets. In one of their treatments subjects are ignorant of the presence of algorithmic traders while in the other the presence of algorithmic traders is common knowledge. In line with our findings below Grossklags and Schmidt (2006) find that market prices follow more closely the fundamental value when the presence of algorithmic traders is known. They also find that markets in which humans are aware of the (then hybrid) market type are more efficient. Grossklags and Schmidt (2006) find slightly (but not significantly) less trading when subjects are aware of the presence of algorithmic traders. One problem with the experiment of Grossklags and Schmidt (2006) is deception. Is it acceptable not to tell participants that other market participants are computers? Another, perhaps more important problem, is that Grossklags and Schmidt (2006)'s analysis is set in an environment with a specific computer algorithm. We have no reason to assume that their algorithm meets the expectations of their participants. We have also no reason to assume that their algorithm is close to algorithms which are used in practice.

Different from Grossklags and Schmidt (2006) we use a treatment where we can reveal to participants the possibility to interact with computers. More importantly, our results are not dependent on any specific algorithm. In our analysis we will compare two treatments. In both treatments no algorithmic traders are present, but in one of the treatments participants expect that algorithmic traders could be present. We also try to make sure that participants' expectations about algorithms are entirely driven by participants and not by us.

3. Methods

3.1. Treatments

Subjects were divided randomly and with equal probability into one of the treatments A, B, or C, as specified by Table 1.

Subjects were told that they would be informed whether they were in Treatment A or whether they were in Treatment B or C. They knew that they could not distinguish B or C. Interesting for us is the comparison of A and B. In both treatments we have only human traders but only subjects in the A treatment can rule out the possibility of algorithmic traders while subjects in the B treatment cannot. We are not interested in the behavior of the C market group. C is only needed to make expectations of the B participants consistent.

The number of active traders was six in all conditions. We want to avoid that social preferences affect differences between treatments. Therefore in Treatment C another passive human trader receives the payoff of the algorithmic trader.

3.2. Markets

In our experiment we want to study whether algorithmic traders can reduce bubbles. To be able to see this we have to start with a market that generates sufficiently large bubbles. The market used by Smith et al. (1988) has exactly this property. The interface is shown in Appendix AAppendix A.1.8. As in SSW subjects trade in a continuous double auction during 15 periods and receive a random dividend per period. The possible dividends are with equal probabilities 0, 8, 28, or 60 ECU. The average dividend per period is, thus, 24 ECU. The fundamental value of an asset in period 1 is $15 \times 24 = 360$ ECU, decreasing by 24 ECU at the end of each period. Each period lasts for 60 s, so that one market simulation in total takes 15 min.[1] Order

---

[1] In pilots to the experiment we found bubbles were almost identical with 60 s per trading period as in SSW (where the length was 240 s) and that most trading was happening at the beginning of a period. Although the shorter period length did seem to lead to the same kind of bubbles as observed in SSW, the trading volume is proportionally lower compared to SSW (SSW observe on average 4.4 trades per period, we find an average volume of 2.23).

Fig. 1. Wordle of most frequent words.

books were cleared after each period. Each subject owns in period 1 an endowment of 4 assets which the subject can offer on the market for cash. Each subject also initially owns 720 ECU in cash which can be used to buy assets. Kirchler et al. (2012) find that higher amounts of initial cash relative to the fundamental value of assets lead to larger bubbles on SSW markets. The ratio of cash to value we use is at the lower boundary of what seems to be necessary to induce bubbles. Each market consists of six anonymous traders.

The experiment was implemented in z-Tree (Fischbacher, 2007). We used ORSEE (Greiner, 2004) to recruit participants. Subjects got instructions in form of a video tutorial (11 min)[2] and had a printed table with the fundamental value of an asset in each period at their disposal. Control questions were asked to make sure they understood the dynamics of the SSW market and the trading interface.

3.3. Algorithmic traders

Below we will present results which are based on a comparison of the two treatments, A and B. In none of these two treatments algorithmic traders are present. However, in one of the treatments participants believe that algorithmic traders could be present. In a third treatment (C) algorithmic traders are present but this treatment is not used for our results. For our results it is, hence, irrelevant, which specific trading algorithm our algorithmic traders actually use in treatments C. It is, however, important what beliefs participants have.

Regarding beliefs, we have two aims: First, to reduce variance in our observations we would like to have a small variance in beliefs. This requires that we tell participants something about the algorithmic trader. What we tell them follows from our second aim: To obtain external validity, we would like to have beliefs which are similar to the beliefs of real decision makers. Algorithms behind algorithmic traders are usually a well guarded secret, not know to most market participants. We, therefore, start with the beliefs of our (mostly student) participants.

In a first (preparatory) experiment six subjects in each session were trading in a SSW market as described in the previous section. After trading subjects had to fill in a questionnaire in which they were asked to write down their expectations how an algorithmic trader would trade in a SSW market and what its impact on the market would be. We ran two sessions of this experiment. The most common words were then used to create a wordle (www.wordle.net). In this wordle the frequency of words is represented by font size.

Fig. 1 shows the resulting wordle (translated into English) in which words describing how algorithmic traders work that were used with a negation while are shown in red while positively used words are shown in green (black if mixed or unclear).[3] The exact questions asked to subjects in the pilot sessions and the algorithm that produces the wordle can be found in Appendix AAppendix A.2.2.

In a second (main) experiment the wordle was shown to all (new) subjects before they were informed about their treatment condition. Subjects were told how the wordle was created and that the algorithmic trader was programmed by an external programmer, not involved in the research underlying the experiment, who knew the wordle.

Providing information about the character of algorithmic traders in this way serves two purposes: First, we want to have rather homogeneous beliefs of subjects with respect to algorithmic traders. The wordle thus serves as a prime with regard to the algorithmic trader which all subjects have in common. This allows us (as experimenters) to restrict ex ante the number of alternative explanations for our findings which might otherwise be based on different beliefs subjects may or may not have. Second, we do not want to impose our own expectations with respect to algorithmic traders. Since subjects in the pilot sessions and the actual experiment are drawn from the same population, we can assume that both treatments had on average the same beliefs about algorithmic traders. Hence, the wordle should match on average the expectations of subjects.

Of course, subjects still can interpret the wordle in different ways. Hence, beliefs are still not perfectly homogeneous. Also, by writing the algorithm that generated the wordle we still might have introduced a demand effect into the experiment. However, for us this seemed the best possible compromise to make at the same time the beliefs of subjects more homogeneous without introducing a systematic demand effect.

One can also argue that the way we present information about the algorithmic trader is similar to how human traders get information about algorithmic traders in the real world. Information about the exact implementation and behavior of

---

[2] The video with English subtitles can be found on http://www.mikefarjam.de/video2.
[3] The original German wordle is shown in Appendix AAppendix A.1.5.

algorithmic traders in real world asset markets is usually kept secret by their owners. The only information available to human traders are more or less vague concepts of what algorithmic traders are capable of, leaving much room for interpretation.

3.4. Risk preference and overconfidence

As already outlined in Section 2, participants in the experiment differ in many respects, not only in their attitude towards risk, but also in their assessment of each other's rationality, their confidence, their ambiguity aversion, etc. It would be impossible to control for all possible traits. To keep the experiment simple we restrict ourselves here to simple measures for preferences regarding risk and overconfidence.

To measure risk aversion of subjects we use a multiple price list task as in Holt and Laury (2002).[4] In this task subjects choose between lotteries with a high variance of payoffs and lotteries with a low variance of payoffs. As in Holt and Laury (2002) we use the relative frequency of high variance choices as a measure for a preference for risk. We use a similar task to measure preferences for risk when losses are possible.[5]

Since there is no clear preference in the overconfidence literature for one task and since the overconfidence construct has many dimensions, we chose to measure overconfidence in the most direct way we could think of. We ask subjects "how well do you expect to perform in an experimental asset market?" We use the percentile at which they expect to perform compared to all other subjects as a measure of overconfidence.

Although we mainly intend to use these measures as controls, we also summarize in Appendix AAppendix A.3.6 in Table 12 their influence on earnings and asset holdings. It turns out that our measures do not explain earnings or asset holdings in the experimental asset market very well.

3.5. Payoff

The markets and other tasks are designed such that the average earnings of subjects was about 11 euros. To avoid endowment effects only one of the tasks (preference for risks, risk when losses are possible, overconfidence measurements) or one of the market simulations was chosen randomly at the end of the session to determine the payoff.

4. Results

The raw data and the methods are available at http://www.kirchkamp.de/research/bubbles.html.

4.1. Descriptives

4.1.1. Subjects

We use data from 216 subjects which are divided into three treatments of 72 subjects. Each market has a size of six subjects. Hence, we had 12 markets per treatment. All subjects were recruited via ORSEE (Greiner, 2004). Since studies like Dohmen et al. (2011) and Barber and Odean (2001) show that risk-preferences and trading behavior differs between genders, we recruited only male subjects to reduce variability. All sessions were run between July and November 2014 in the laboratory of the Friedrich Schiller University Jena. Most of our subjects were students.

4.1.2. Questionnaire and additional measurements

After playing two successive market simulations, subjects were asked to complete a questionnaire. Subjects in Treatment B (see Table 1) were asked: "Do you think that an algorithmic trader was active in the market?" Possible answers were "yes" and "no". Although no algorithmic trader was active in Treatment B, 13 out of 72 subjects guessed yes. If there is still so much uncertainty among subjects after two full market simulations, there must have been a considerable amount of uncertainty among subjects at least during the first periods of the first market. We conclude that our manipulation (creating uncertainty about participation of an algorithmic trader) worked.

In Section 2.1 we discussed attitudes towards risk and overconfidence as prominent explanations for bubbles in SSW markets. In our experiment we measured risk aversion and overconfidence before subjects started trading. To measure risk aversion we use a choice task involving gains only (see Appendix AAppendix A.1.1) and a choice task where losses are possible (see Appendix AAppendix A.1.2). Fig. 2 shows the joint distribution of these properties in our sample. Our measure for risk seems to be in line with similar studies. We also measure a moderate amount of overconfidence. 62.5% of all subjects expect to be better than or equal to the average. This is in line with the standard effect (Hoorens, 1993). As we see in Fig. 2, the three properties seem to be rather independent of each other. We will, hence, use them all as controls in our estimations below.
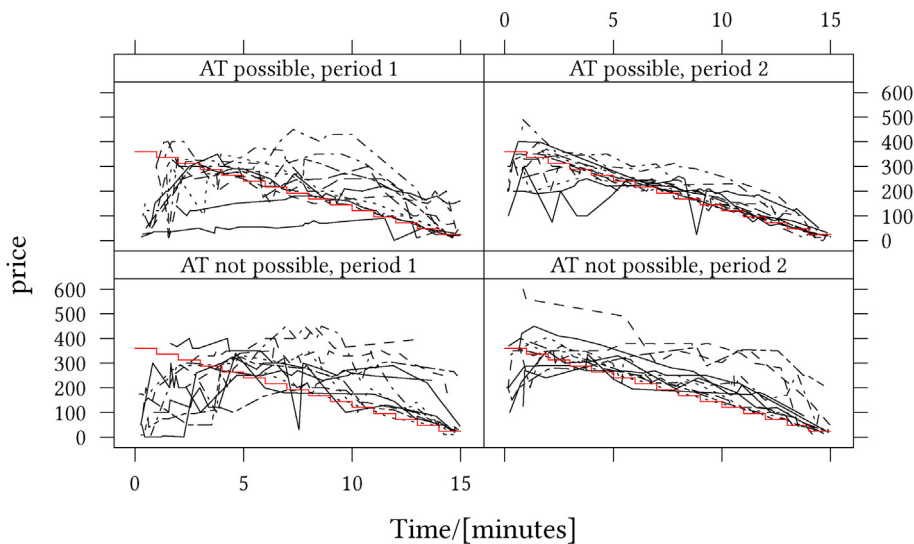
---

[4] The list can be found in Appendix AAppendix A.1.1.
[5] The list can be found in Appendix AAppendix A.1.2.
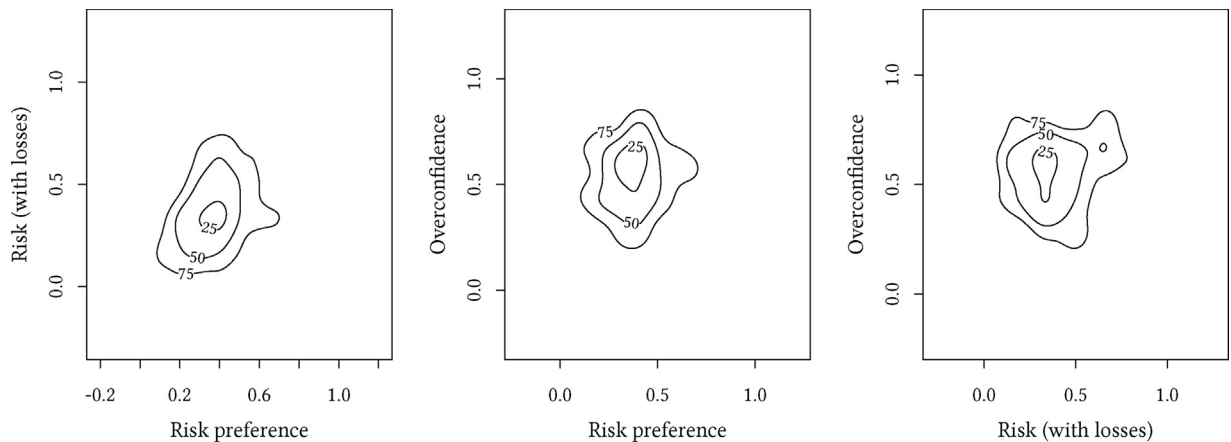
The graphs show contour lines of a kernel density estimate of the joint distribution.

Fig. 2. Joint distribution of preferences for risk, risk (with losses) and overconfidence. The graphs show contour lines of a kernel density estimate of the joint distribution.

Each line corresponds to one market in the experiment. The red line shows the fundamental value of the asset.

Fig. 3. Prices over time. Each line corresponds to one market in the experiment. The red (or, in the print version, gray) line shows the fundamental value of the asset. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

4.1.3. Trades

Fig. 3 gives a first impression how individual prices develop over time.

Each line corresponds to one market in the experiment. As expected, pricing of assets follows the bubble and crash pattern known from SSW.

Fig. 4 shows a more aggregated picture. Solid black lines in the figure are loess smoothers (Cleveland et al., 1992) for the two treatments: participants are either informed that algorithmic traders are not present in the market (A), or they are informed that algorithmic traders could be present (B). Dashed lines show $\pm$ one standard deviation.[6]

We denote the fundamental value in period ϕ with P_ϕ^F and the actual trade i in period ϕ in market group k with $P_{i\phi k}$. The average fundamental value during the experiment is $\bar{P}^F$. The leftmost panel in Fig. 4 shows the development of $(P_{i\phi k} - P_\phi^F)/\bar{P}^F$ over the time of the experiment. Mispricing is clearly smaller in the treatment where algorithmic traders are possible. The

---

[6] The standard setting for the smoothing parameter is $\alpha = .75$. Since we have a large number of trades we can provide more detail about the dynamics during the experiment. Hence, we use $\alpha = .2$ for the black lines. Trades are weighted with the volume of the trade.
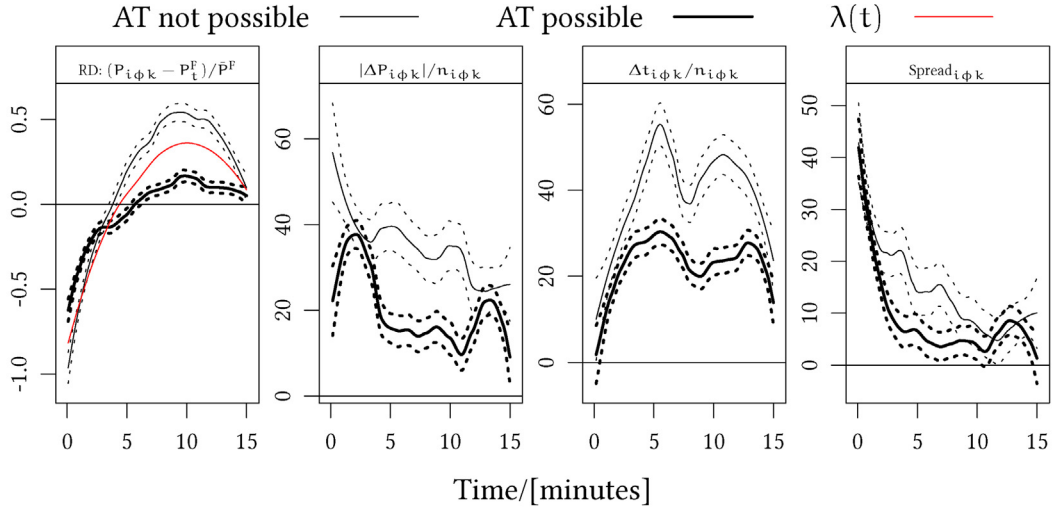
Solid black lines show, separately for the two cases where algorithmic traders are possible and not possible, a loess smoother for overpricing (weighted by volume of trade), change of prices per volume n over time and time between trades per volume n. Dashed lines indicate ± one standard deviation. The red line showes a loess smoother for overpricing, independent of the information about algorithmic traders.

Fig. 4. Trading behavior over all periods of one market. Solid black lines show, separately for the two cases where algorithmic traders are possible and not possible, a loess smoother for overpricing (weighted by volume of trade), change of prices per volume n over time and time between trades per volume n. Dashed lines indicate ± one standard deviation. The red (or, in the print version, gray) line shows a loess smoother for overpricing, independent of the information about algorithmic traders.

two panels in the middle of Fig. 4 confirm that in this treatment volatility is smaller and trading is quicker when algorithmic traders are possible. The rightmost panel in Fig. 4 shows the bid-ask spread for the two conditions.

In Fig. 11 of Appendix AAppendix A.3.1 we provide similar graphs but now for periodic behavior within one period of a market. Our interpretation of these graphs is that, apart from the pattern already visible in Fig. 4, there is no special difference in the periodic structure.

Since Treatment C is not relevant for our research question and only needed to make beliefs of subjects in Treatment B consistent, we discuss the results of Treatment C only briefly in Appendix AAppendix A.3.3.

4.2. Estimation

As in the previous section we use the index i to denote a single trade in period ϕ in market group k. The price of trade i in market group k during period ϕ would be denoted $P_{i\phi k}$. The seller involved in trade i during period ϕ in market group k would be denoted $S_{i\phi k}$ and the buyer would be denoted $B_{i\phi k}$. Properties of these sellers and buyers, e.g., their preference regarding risk R, would be denoted $R_{S_{i\phi k}}$ for the seller participating in this trade and $R_{B_{i\phi k}}$ for the buyer.

Estimation strategy

We are mainly interested in bubbles which we measure as deviation of prices from the fundamental value relative to the average fundamental value $RD = (P_{i\phi k} - P_\phi^F)/\bar{P}^F$ (as proposed by Stöckl et al., 2010). To demonstrate robustness we also show in Appendix AAppendix A.3.2, Table 3, results for deviations of prices from the fundamental value relative to the fundamental value in this period $(P_{i\phi k} - P_\phi^F)/P_\phi^F$. Unless stated otherwise we weigh observations with the number of shares traded. To show robustness, Appendix AAppendix A.3.2 presents in Table 4 results from the unweighted estimation. Here we use a Bayesian framework in our estimations to gain flexibility. To show robustness we present qualitatively the same results within a parametric and frequentist framework in Appendix AAppendix A.3.4. We also include a non-parametric frequentist assessment in Appendix AAppendix A.3.5.

We include three more measures: Speed of trading, volatility, and bid-ask spread. Speed of trading is measured as time in seconds between two trades for each share, $\Delta t_{i\phi k}/n_{i\phi k}$ (where $n_{i\phi k}$ is the number of shares for a given trade i in period ϕ in market group k). Volatility is measured as the absolute change of prices between trades relative to the number of traded shares, $|\Delta P_{i\phi k}|/n_{i\phi k}$. The bid-ask spread is measured as the difference between the price offered by the buyer and the price demanded by the seller.

We use d_{NAT} as a dummy which is one if participants are informed that algorithmic traders will not participate in the market and zero otherwise. d_{AT} is a dummy which is one if participants are informed that algorithmic traders may participate in the market and zero otherwise.
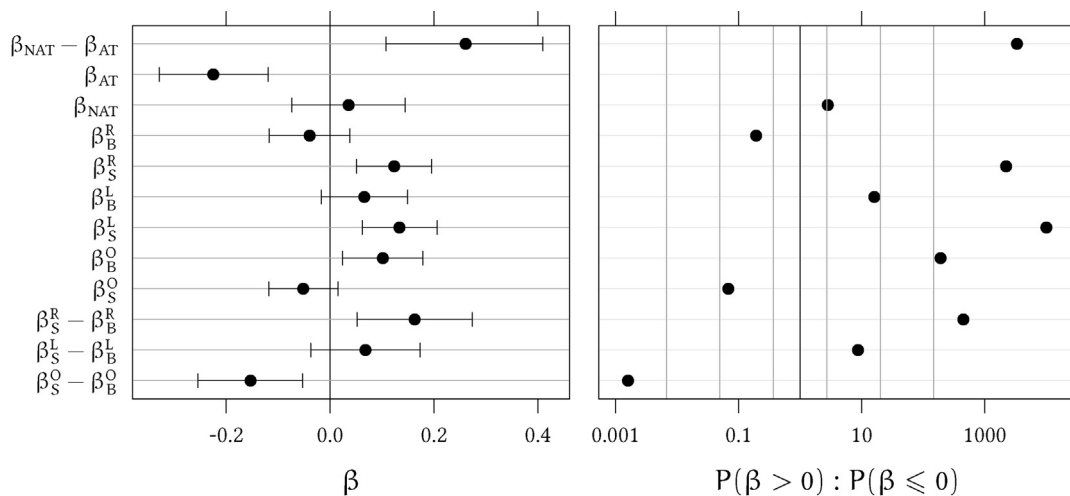
The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) posterior odds for coefficients $\beta > 0$ (right).

Fig. 5. Estimation results for Eq. (1), $(P_{i\phi k} - P_\phi^F)/\bar{P}^F$. The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) posterior odds for coefficients $\beta > 0$ (right).

For all estimations we control for the characteristics of buyer $B_{i\phi k}$ and seller $S_{i\phi k}$ involved in this trade. We take into account their preferences regarding risk ($R_{B_{i\phi k}}$ and $R_{S_{i\phi k}}$), risk when losses are possible ($L_{B_{i\phi k}}$ and $L_{S_{i\phi k}}$), and their overconfidence ($O_{B_{i\phi k}}$ and $O_{S_{i\phi k}}$).[7]

To take into account the panel structure of the data we use a model with mixed effects. We include separate random effects $\epsilon^B_{B_{i\phi k}}$, $\epsilon^S_{S_{i\phi k}}$, ϵ^G_k to account for the idiosyncrasy of the buyer $B_{i\phi k}$, the seller $S_{i\phi k}$ and the market group k of traders in that market. $\epsilon^U_{i\phi k}$ is the residual.

The prior distribution of coefficients $\beta_{...}$ follows a vague prior given by (3). The precision of the distribution for random effects $\epsilon^B_{B_{i\phi k}}$, $\epsilon^S_{S_{i\phi k}}$, and ϵ^G_k and the residuals $\epsilon^U_{i\phi k}$ follows a vague prior given by (4).

Bubbles

We assume that the relative deviation of actual prices of trade i during period ϕ in market group k from the fundamental value, $(P_{i\phi k} - P_\phi^F)/\bar{P}^F$, is given by (1). $\lambda(t)$ is a loess spline of average overpricing over time (similar to the one given in Fig. 4), independent of the information given to participants, with the smoothing parameter α set to the default (Cleveland et al., 1992).

$$\frac{P_{i\phi k} - P_\phi^F}{\bar{P}^F} = \beta_0 + (1 + \beta_{NAT}d_{NAT} + \beta_{AT}d_{AT} + \beta_B^R R_{B_{i\phi k}} + \beta_S^R R_{S_{i\phi k}} + \beta_B^L L_{B_{i\phi k}} \tag{1}$$
$$+ \beta_S^L L_{S_{i\phi k}} + \beta_B^O O_{B_{i\phi k}} + \beta_S^O O_{S_{i\phi k}}) \cdot \lambda(t) + \epsilon_k^G + \epsilon_{S_{i\phi k}}^S + \epsilon_{B_{i\phi k}}^B + \epsilon_{i\phi k}^U$$

$$\text{random effects } \epsilon^j \sim N(0, 1/\tau_j) \quad \text{with } j \in G, S, B; \qquad \epsilon^U \sim N(0, n/\tau_U) \tag{2}$$

$$\text{vague priors } \beta_{...} \sim N(0, 10^2) \tag{3}$$

$$\tau_{...} \sim \Gamma(m_{...}^2/s_{...}^2, m_{...}/s_{...}^2) \quad \text{with } m_{...} \sim \text{Exp}(1), s_{...} \sim \text{Exp}(1) \tag{4}$$

We use JAGS to estimate the posterior distribution of coefficients for Eq. (1). Results are based on 4 independent chains. We discard 5000 samples for adaptation and burnin and use 10,000 samples for each of the 4 chains. Results are shown in Fig. 5. Detailed results are given in Table 2 in Appendix AAppendix A.3.2.

We find a clear difference between the two treatments. In particular, we find the posterior odds of $\beta_{NAT} > \beta_{AT}$ to be 3330:1. We have, thus, very strong evidence (in the sense of Kass and Raftery, 1995) that the mere expectation of the presence of algorithmic traders reduces bubbles.

Turning to our controls we also have very strong evidence that a seller's preferences regarding risk as well as the buyer's overconfidence all contribute to bubbles.

---

[7] These control variables are always demeaned in the following.
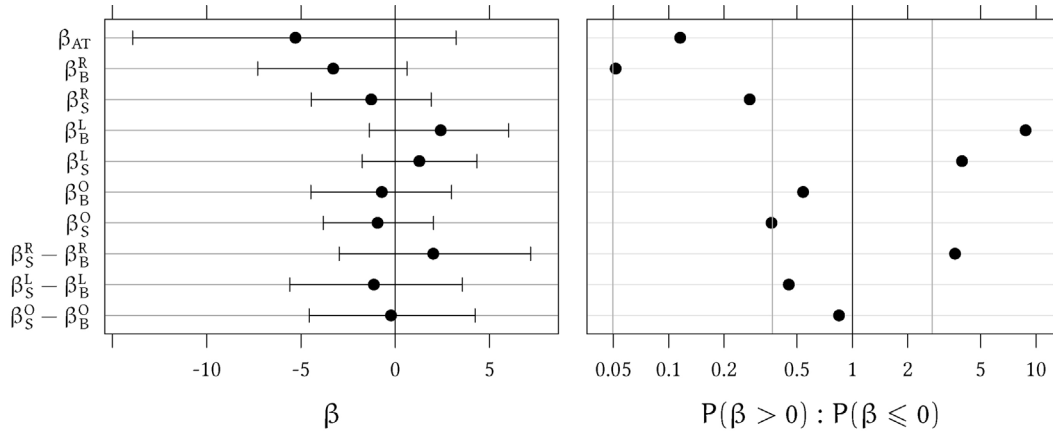
The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) posterior odds for coefficients $\beta > 0$ (right).

Fig. 6. Estimation results for Eq. (5), $\Delta P_{i\phi k}/n_{i\phi k}$. The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) posterior odds for coefficients $\beta > 0$ (right).

Alternative specifications of this model are presented in Appendix AAppendix A.3.2, Tables 3 and 4 as well as in Appendix AAppendix A.3.4, Table 8. In line with our finding above also the two alternative Bayesian specifications yield very strong evidence that algorithmic traders reduce bubbles (posterior odds for $\beta_{NAT} > \beta_{AT}$ are 4440:1 if we use a relative measure for bubbles and 20000:1 if we use unweighted observations). Also the frequentist estimation in Appendix AAppendix A.3.4 finds a highly significant effect of algorithmic traders.

Changes of prices: We call $|\Delta P_{i\phi k}|$ the absolute amount of the change in prices for trade i during period ϕ in market group k compared to the previous trade. We call $n_{i\phi k}$ the number of shares traded with i during period ϕ in market group k. We estimate the following equation:

$$
\begin{aligned}
\frac{1}{n_{i\phi k}}|\Delta P_{i\phi k}| \quad &= \beta_0 + \beta_{AT}d_{AT} + \beta_B^R R_{B_{i\phi k}} + \beta_S^R R_{S_{i\phi k}} + \beta_B^L L_{B_{i\phi k}} + \beta_S^L L_{S_{i\phi k}} \\
&\quad + \beta_B^O O_{B_{i\phi k}} + \beta_S^O O_{S_{i\phi k}} + \epsilon_k^G + \epsilon_{S_{i\phi k}}^S + \epsilon_{B_{i\phi k}}^B + \epsilon_{i\phi k}^U
\end{aligned}
\tag{5}
$$

Random effects and priors are as in Eqs. (2)–(4).

The second panel in Fig. 4 suggests that changes of prices from one trade to the next seem to be smaller in the algorithmic trader treatment. Fig. 6 shows estimation results. Detailed results are given in Table 5 in Appendix AAppendix A.3.2. We find the posterior odds for $\beta_{AT} > 0$ to be 1:8.65, i.e. we have positive evidence (in the sense of Kass and Raftery, 1995) that information about the potential presence of algorithmic traders reduces the amount of changes of prices.

Time between trades: We call $\Delta t_{i\phi k}$ the time between trade i during period ϕ in market group k and the previous trade. We call $n_{i\phi k}$ the number of shares traded. We estimate the following equation:

$$
\begin{aligned}
\frac{1}{n_{i\phi k}}\Delta t_{i\phi k} \quad &= \beta_0 + \beta_{AT}d_{AT} + \beta_B^R R_{B_{i\phi k}} + \beta_S^R R_{S_{i\phi k}} + \beta_B^L L_{B_{i\phi k}} + \beta_S^L L_{S_{i\phi k}} \\
&\quad + \beta_B^O O_{B_{i\phi k}} + \beta_S^O O_{S_{i\phi k}} + \epsilon_k^G + \epsilon_{S_{i\phi k}}^S + \epsilon_{B_{i\phi k}}^B + \epsilon_{i\phi k}^U
\end{aligned}
\tag{6}
$$

Random effects and priors are as in Eqs. (2)–(4).

The third panel in Fig. 4 shows that participants seem to trade more quickly in the no-algorithmic trader treatment. Fig. 7 shows estimation results. Detailed results are given in Table 6 in Appendix AAppendix A.3.2. We estimate the posterior odds of $\beta_{AT} > 0$ to be 1:6.71, i.e. we have positive evidence that information about algorithmic traders increases the frequency of trades.

Bid-ask spread: We call Spread$_{i\phi k}$ the difference between bid and ask for each trade. We estimate the following equation:

$$
\begin{aligned}
\text{Spread}_{i\phi k} \quad &= \beta_0 + \beta_{AT}d_{AT} + \beta_B^R R_{B_{i\phi k}} + \beta_S^R R_{S_{i\phi k}} + \beta_B^L L_{B_{i\phi k}} + \beta_S^L L_{S_{i\phi k}} \\
&\quad + \beta_B^O O_{B_{i\phi k}} + \beta_S^O O_{S_{i\phi k}} + \epsilon_k^G + \epsilon_{S_{i\phi k}}^S + \epsilon_{B_{i\phi k}}^B + \epsilon_{i\phi k}^U
\end{aligned}
\tag{7}
$$

Random effects and priors are as in Eqs. (2)–(4).

The right panel in Fig. 4 shows that the bid-ask spread looks slightly larger in the no-algorithmic trader treatment. Fig. 8 shows estimation results. Detailed results are given in Table 7 in Appendix AAppendix A.3.2. We estimate the posterior odds
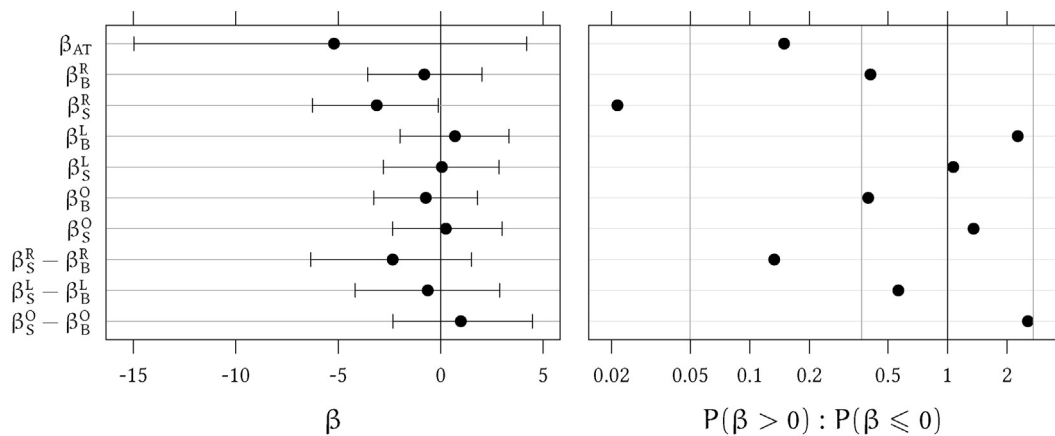
The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) posterior odds for coefficients $\beta > 0$ (right).

Fig. 7. Estimation results for Eq. (6), $\Delta t_{i\phi k}/n_{i\phi k}$. The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) posterior odds for coefficients $\beta > 0$ (right).
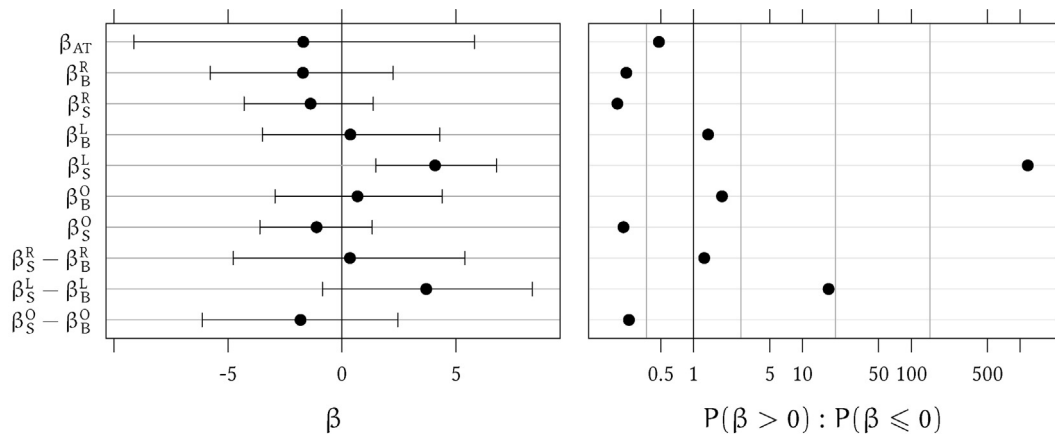
The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) posterior odds for coefficients $\beta > 0$ (right).

Fig. 8. Estimation results for Eq. (7), $Spread_{i\phi k}$. The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) posterior odds for coefficients $\beta > 0$ (right).

of $\beta_{AT} > 0$ to be 1:2.08, i.e. we have no substantial evidence that information about algorithmic traders affects the bid-ask spread.

5. Discussion

In our experiment we study how the expected presence of algorithmic traders affects the trading activity of human traders on asset markets. We separate the direct effect algorithmic traders might have in the market from the indirect effect algorithmic traders have through the expectations of human market participants. We measure deviations from the fundamental value, speed of trading, volatility of prices and bid-ask spread. The most important finding is that bubbles are smaller and prices are closer to the fundamental value when subjects expect human traders and algorithmic traders to participate in the market compared to markets where they expect only human traders.

Our results are in line with Gsell (2008), Boehmer et al. (2014), Chaboud et al. (2014) who find that price discovery is quicker in markets with algorithmic traders than without. While these authors find differences between the two market types due to the active participation of algorithmic traders, we find qualitatively the same even without active participating algorithmic traders. The mere change of expectations of the human traders is sufficient. In line with Gsell (2008) and contrary

to Jarrow and Protter (2012) and Boehmer et al. (2014) we find that volatility of prices is reduced by algorithmic traders. The speed of trading of human traders also increases when algorithmic traders are expected to participate on the market.

We also control for individual preferences regarding risky choices and overconfidence. We find that for most specifications sellers' risk preference and buyers' overconfidence contribute to bubbles.

We can only speculate about the underlying mechanisms that make humans trade closer to the fundamental value when they expect algorithmic traders on the market. As discussed earlier in Section 2.2, human traders might behave differently towards computers only because these are computers. Humans might perhaps be less excited when they expect algorithmic traders to participate. The resulting difference in behavior would then be independent of different expectations about the behavior of these computers. Alternatively, and as discussed in Section 2.1, human traders might assume that algorithmic traders do behave in a different, perhaps more rational way. Introducing algorithmic traders would then be similar to introducing more rational traders. As a result, humans would change their trading behavior. This mechanism would be in line with Sutter et al. (2012) who find that asymmetric information abates bubbles. Interestingly we find that the ambiguity with respect to the exact implementation of the algorithmic traders did not seem to discourage human traders to trade on hybrid markets. On the contrary we see that trading speed of human traders is higher when algorithmic traders might be active on the market. It seems thus unlikely that our results are driven by ambiguity aversion (see Section 2.1).

What exactly drives bubbles in real world asset markets is still an issue of discussion among economists. Our results suggest that humans contribute to bubbles in hybrid markets not in same way as they do in human-only markets. In our experiment humans produced smaller bubbles when they expect to trade with algorithmic traders. However, this need not suggest that hybrid markets in general produce less bubbles. Algorithmic traders themselves may be catalysts for bubbles in asset markets in their interaction with other algorithmic traders or human traders.

For policy makers the laboratory results we present have to be interpreted with the usual words of caution. Still, our results suggest a positive effect if human traders are reminded of the presence of algorithmic traders in the market.

Our results can also be seen as more general warning. In the modern world many situations which were previously characterized by human-human interaction are now at least partially characterized by human–machine interaction. As discussed in Farjam (2015) humans may have a general tendency to interact differently with non-human than human agents for all kind of psychological and evolutionary reasons. Experimental designs including only human agents may have been ecologically relevant in the past. However, given the economic consequences that it may have one should take into account the effects that an anticipatory response of humans towards interacting with a machine might have.

Appendix A. Details of the experiment

A.1 Details of the experiment

At the beginning of the experiment participants would find a printed table with the fundamental values of the asset in each period at their desk. They would read the following information on their screen (translated into English):

> Thank you for participating in the Experiment. The experiment will last for about 65 min. Part 1 takes about 15 min, part 2 takes about 50 min. You will solve several tasks during the experiment. One of these tasks will be paid out at the end. The computer decides at the end of the experiment randomly, for which task you will be paid. During the entire experiment we use the currency ECU. 200 ECU are equivalent to 1€. At the end of the experiment your ECU payoff will be translated into EUR and paid to you. We will now start with part 1. Part 1 contains 3 shorter tasks in which you will answer questions or make choices.

A.1.1 Risky choices

In part 1, participants would start with the following task (translated into English):

> In this part of the experiment you have to make 10 choices. If the computer chooses this part for payoff, one of the lotteries will be selected randomly by the computer.

Choice A	Choice B
In 1 of 10 cases you receive 1800 ECU. In 9 of 10 cases you receive 1440 ECU.	In 1 of 10 cases you receive 3465 ECU. In 9 of 10 cases you receive 90 ECU.
In 2 of 10 cases you receive 1800 ECU. In 8 of 10 cases you receive 1440 ECU.	In 2 of 10 cases you receive 3465 ECU. In 8 of 10 cases you receive 90 ECU.
In 3 of 10 cases you receive 1800 ECU. In 7 of 10 cases you receive 1440 ECU.	In 3 of 10 cases you receive 3465 ECU. In 7 of 10 cases you receive 90 ECU.
In 4 of 10 cases you receive 1800 ECU. In 6 of 10 cases you receive 1440 ECU.	In 4 of 10 cases you receive 3465 ECU. In 6 of 10 cases you receive 90 ECU.
In 5 of 10 cases you receive 1800 ECU. In 5 of 10 cases you receive 1440 ECU.	In 5 of 10 cases you receive 3465 ECU. In 5 of 10 cases you receive 90 ECU.
In 6 of 10 cases you receive 1800 ECU. In 4 of 10 cases you receive 1440 ECU.	In 6 of 10 cases you receive 3465 ECU. In 4 of 10 cases you receive 90 ECU.
In 7 of 10 cases you receive 1800 ECU. In 3 of 10 cases you receive 1440 ECU.	In 7 of 10 cases you receive 3465 ECU. In 3 of 10 cases you receive 90 ECU.
In 8 of 10 cases you receive 1800 ECU. In 2 of 10 cases you receive 1440 ECU.	In 8 of 10 cases you receive 3465 ECU. In 2 of 10 cases you receive 90 ECU.
In 9 of 10 cases you receive 1800 ECU. In 1 of 10 cases you receive 1440 ECU.	In 9 of 10 cases you receive 3465 ECU. In 1 of 10 cases you receive 90 ECU.
In 10 of 10 cases you receive 1800 ECU. In 0 of 10 cases you receive 1440 ECU.	In 10 of 10 cases you receive 3465 ECU. In 0 of 10 cases you receive 90 ECU.

As in Holt and Laury (2002) we use the relative frequency of B-choices as a measure for preference for risk.

A.1.2 Risky choices involving losses

For the second task, participants would read the following information on their screen (translated into English):

In this part of the experiment you have to make 6 choices. If the computer chooses this part for payoff you get 2000 ECU on your account. Furthermore, one of the following lotteries will be selected randomly. If a lottery is selected which you have rejected, then you just receive these 2000 ECU. If you have accepted this lottery, then the outcome of the lottery will be added to or subtracted from your account.

Lottery	Your choice
In 5 of 10 cases you lose 570 ECU. In 5 of 10 cases you gain 1710 ECU	reject/accept
In 5 of 10 cases you lose 855 ECU. In 5 of 10 cases you gain 1710 ECU	reject/accept
In 5 of 10 cases you lose 1140 ECU. In 5 of 10 cases you gain 1710 ECU	reject/accept
In 5 of 10 cases you lose 1425 ECU. In 5 of 10 cases you gain 1710 ECU	reject/accept
In 5 of 10 cases you lose 1710 ECU. In 5 of 10 cases you gain 1710 ECU	reject/accept
In 5 of 10 cases you lose 1995 ECU. In 5 of 10 cases you gain 1710 ECU	reject/accept

Similar to Section A.1.1 we use the relative frequency of accepted lotteries to assess the preference for risk when losses are possible.

A.1.3 Overconfidence

To assess overconfidence participants were asked the following question (translated into English):

In a few minutes you will participate in an electronic stock market together with other participants. There are dividends which are paid regularly for each share. You can buy and sell shares and you accumulate a payoff which can be paid out to you at the end of the experiment. (You learn more details about the stock market in a few minutes). We ask you in the following question to assess how large your payoff at the end of the stock market is compared with the payoff of other participants. In other words: How well (compared with other participants) do you expect to perform in the stock market?
worst. . . . . .best

A.1.4 Treatment information

Participants obtained information about their treatment as follows:

In a few minutes you will participate with other participants in a stock market. It is possible that one of the six human players in the market will be replaced with a computer program. This computer trader has during the experiment the same options as a human. The computer starts with the same endowment in cash and in shares. If a human trader is replaced by a computer in the experiment, then the replaced human receives at the end of the experiment the amount that the computer has earned.
In this experiment there are three groups. Group 1 and group 2 will trade in a market without computerized traders. Group 3 trades in a market with a computerized trader. You will be allocated randomly to one of these groups. If you are in group 1 you are told that you are in group 1. If you are in group 2 or 3 you are only told that you are in group 2 or 3, but not in which of these two groups. Hence, if you are not in group 1 there is a 50% chance that you trade in a market with a computerized trader. This allocation to groups holds for both market simulations in the session.
In a previous experiment with the same stock market we asked participants, how they expect a computer trader to trade in a market. Below you find a graphical summary of the answers of participants.

A.1.5 Wordle

In Appendix AAppendix A.2 we explain how we generated the wordle. Fig. 1 shows an English version of the wordle that we used to explain algorithmic traders in the experiment. Since the experiment was conducted with German speaking students, we used the version shown in Fig. 9.

On the next screen participants obtained the following information:

This completes part 1 of the experiment. In a few moments a video starts. This video explains the 2nd part of the experiment. You can adjust the volume with the wheel of your mouse. Please pay attention since the second part of

Fig. 9. German version of the Worlde.

the experiment can be selected for payoff. At the end of the experiment you will learn which task is relevant for your payoff. Please put on your earphones and have the table, that we distributed earlier, ready.

A.1.6 Video instructions

The video with English subtitles can be found at http://www.mikefarjam.de/video2.

A.1.7 Control questions for the trading interface

After watching a video which explained the interface, participants answered the following control questions (translated into English):

- Assume you are just before the end of round 4 of the market experiment. In round 1 each share paid a dividend of 0 ECU. In round each share paid a dividend of 60 ECU. In round 3 each share paid a dividend of 8 ECU. Which dividend will the computer possibly select for round 4? (Possible dividends are 0, 8, 28 and 60 ECU).
  – 0 ECU
  – 8 ECU
  – 28 ECU
  – 60 ECU
  – All dividends are equally likely
    In case of a wrong answer participants obtained the following feedback: In each round there are 4 possible dividends per share (0, 8, 28, 60). Each of these dividends is equally probable in each round. The dividend that was paid in the previous round is not relevant, since the computer selects randomly which dividend is paid in this round.
- To answer the next question you need the printed table. Assume you are in round 14 and you own 2 shares. Assume that you will neither sell nor buy, how large is the average value of the SUM of the dividends you obtain until the end of the experiment?
  – 48 ECU
  – 24 ECU
  – 96 ECU
    In case of a wrong answer participants obtained the following feedback: Your answer is not correct. In each round there are four possible dividends per share (0, 8, 28 and 80 ECU). Each dividend is equally probable in each round. The average value of these 4 dividends is 24 ECU. This is the dividend you can expect on average per round. Since in round 14 you have 2 outstanding dividends (round 14 and 15), you will obtain on average 2×24 ECU. Since in the example you have 2 shares you obtain $2 \times 2 \times 24 = 96$ ECU.
- Assume that you see on your screen that a participant would sell shares at a minimum price of 100 ECU. You want to accept this offer and you enter an offer to buy. Which of the following offers to buy would not be successful?
  – 99 ECU
  – 100 ECU
  – 101 ECU
    In case of a wrong answer participants obtained the following feedback: You answer is not correct. Another participant has made an offer to sell at a minimum of 100 ECU. If you bid only 99 ECU this would be smaller than the asked price of at least 100 ECU.
- Consider the same scenario as in the previous question: On your screen you see that a participant would sell at a minimum price of at least 100 ECU. You want to accept this offer and enter an offer to buy of 101 ECU. At which price will the share be sold to you?
  – 99 ECU
  – 100 ECU
  – 101 ECU
    In case of a wrong answer participants obtained the following feedback: Your answer is not correct. Somebody has made an offer to sell at at least 100 ECU. You have made an offer to buy at 101. Share will always be sold at the seller's price.
- Assume you want to buy shares. You enter an offer to buy of 100 ECU. After a minute you decide that you want to buy at only 90 ECU. You enter a corresponding new offer to buy. What happens with your old offer of 100 ECU (all this happens within one round):
  – The old offer is no longer valid.
  – The old offer is still valid.
    In case of a wrong answer participants obtained the following feedback: Your answer is not correct. If you enter a new offer your old offer will be deleted.

A.1.8 Trading interface

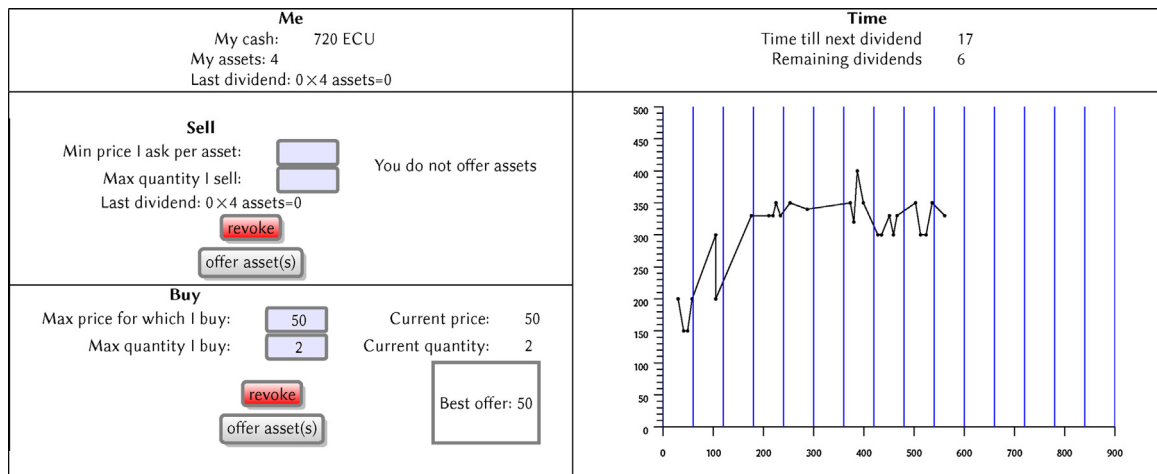In the experiment participants would use an interface similar to the one shown in Fig. 10.

Fig. 10. Trading interface.

A.2 Creating the wordle

A.2.1 Questions

In a pilot study subjects ($N = 12$) were asked four questions just after they traded in a SSW market. Subjects were asked to answer every question with at most two sentences. No other restrictions were made with respect to length or content of the answers.

Those were the questions translated to English (in brackets the original German questions):

1. How would you expect that a computerized trader would trade in an asset market as the one you just traded in? (Wie würden Sie erwarten, dass ein Computerprogramm in einem Aktienmarkt (wie dem eben) handeln würde?)
2. In what way would the behavior of a computerized trader be different from the behavior of a human trader? (Inwiefern würde sich das Verhalten des Computerprogramms am Aktienmarkt (wie dem eben) von dem eines Menschen unterscheiden?)
3. How would the participation of a computerized trader change the dynamics on the market? (Inwiefern würde das Handeln eines Computerprogramms den Markt beeinflussen?)
4. How would the activity of the computerized trader change your trading behavior as a human? (Inwiefern würde das Handeln eines Computerprogramms am Markt das Handeln für Sie als Mensch verändern?)

A.2.2 Preprocessing for Wordle

The following steps were taken to aggregate and stadandardize the response that subjects gave to the questions in Appendix AA.2.1

1. Correct spelling, delete articles, prepositions, conjunctions, negations, pronouns, grammatical particles, modal and auxiliary verbs.
2. Delete non-sense (e.g. "?" or "I don't know") and response that was not related to algorithmic trading (e.g. "Humans like gambling").
3. All nouns were changed to nominative singular, all verbs to infinitive, adverb and adjectives into their basic form.
4. Find synonyms and use the same word for both (e.g. "strikt" (strict) and "streng" (rigorous)). Use same word for derivats and words that are semantically very close ("statistisch" (statistical) and "Statistik" (statistic)).
5. Of the remaining words: drop words with freq <2.
6. Input remaining words into http://www.wordle.net/create.
7. Delete common German words (default option for wordle).
8. Check if remaining words were used in the raw response to describe how computers should or should not behave. Paint words that were used with a negation while describing how algorithmic traders work red, positively used words green (leave black if mixed or unclear).
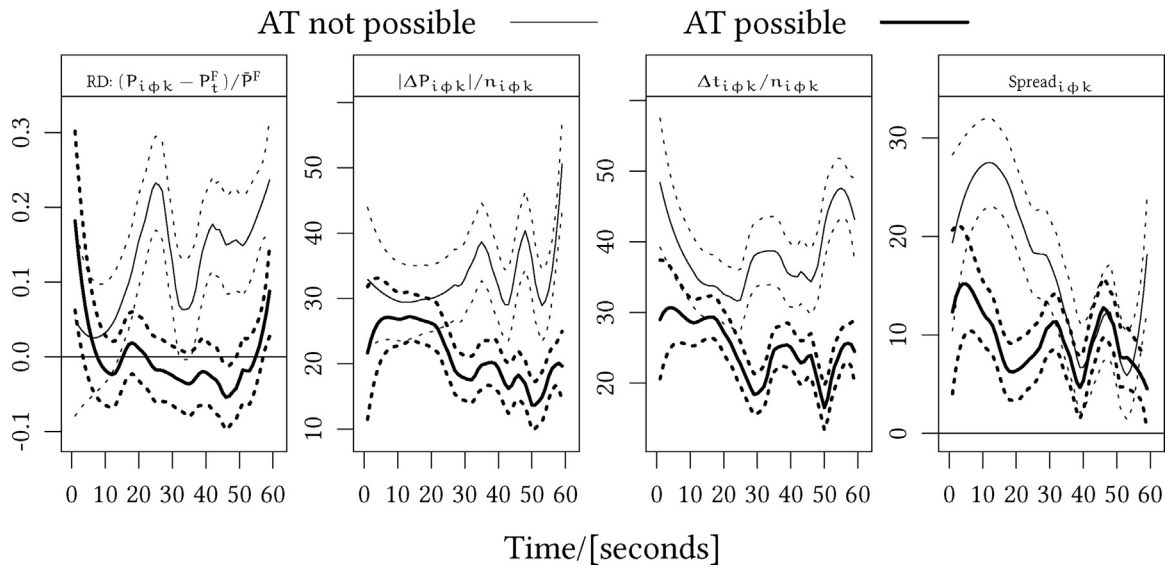
Fig. 11. Periodic behavior within each period.

Table 2
Estimation results for Eq. (1)—bubbles.

	Median	CI$_{95}$	odds($\beta > 0$)	sseff	psrf
$\beta_{\text{NAT}} - \beta_{\text{AT}}$	0.261	[0.108,0.41]	3330:1	20141	1.0001
β_{AT}	−0.225	[−0.329,−0.119]	0:1	20551	1.0002
β_{NAT}	0.036	[−0.0737,0.145]	2.82:1	19492	1.0001
β_B^R	−0.039	[−0.118,0.0382]	1:5.18	19098	1.0000
β_S^R	0.124	[0.0509,0.196]	2220:1	21453	1.0002
β_B^L	0.066	[−0.0169,0.149]	16:1	16884	1.0001
β_S^L	0.134	[0.062,0.206]	10000:1	17393	1.0000
β_B^O	0.102	[0.0241,0.179]	191:1	21839	1.0005
β_S^O	−0.052	[−0.118,0.015]	1:14.7	21704	1.0000
$\beta_S^R - \beta_B^R$	0.163	[0.0518,0.274]	448:1	18985	1.0001
$\beta_S^L - \beta_B^L$	0.068	[−0.0372,0.173]	8.72:1	17760	1.0001
$\beta_S^O - \beta_B^O$	−0.153	[−0.254,−0.0528]	1:624	20337	1.0002

	median	CI$_{95}$		sseff	psrf
σ_U	0.356	[0.339,0.374]		15511	1.0001
σ_G	0.254	[0.168,0.398]		4313	1.0003
σ_S	0.139	[0.103,0.181]		3546	1.0014
σ_B	0.173	[0.133,0.218]		4185	1.0005

A.3 More results

A.3.1 Periodic behavior within each period

In our experiment the fundamental value remains constant for 60 s and then drops by a fixed amount. This pattern repeats 15 times during the 15 min of the experiment. To check whether we can see a pattern in overpricing, time between trades and the absolute change of prices Fig. 11 show the aggregated statistics within each period.

A.3.2 Estimation results for Eqs. (1), (5), (6), (8), and (7)

Tables 2–7 show the median of the estimated fixed effects β and random effects σ, a 95%-credible interval, the posterior odds that $\beta > 0$, the effective sample size (sseff) and the potential scale reduction factor (psrf) for Eq. (1), Eq. (1) without weights for trade volume, and Eqs. (8), (5), (6), (7), respectively. Different from Eq. (1) (see Table 2) we use in Eq. (8) (see Table 3) a measure of overpricing relative to the fundamental value in the trading period:

$$\frac{|P_{i\phi k} - P_\phi^F|}{\bar{P}^F} = \beta_0 + (1 + \beta_{\text{NAT}} d_{\text{NAT}} + \beta_{\text{AT}} d_{\text{AT}} + \beta_B^R R_{B_{i\phi k}} + \beta_S^R R_{S_{i\phi k}} + \beta_B^L L_{B_{i\phi k}}$$
$$+ \beta_S^L L_{S_{i\phi k}} + \beta_B^O O_{B_{i\phi k}} + \beta_S^O O_{S_{i\phi k}}) \cdot \lambda'(t) + \epsilon_k^G + \epsilon_{S_{i\phi k}}^S + \epsilon_{B_{i\phi k}}^B + \epsilon_{i\phi k}^U \tag{8}$$

Estimation results are shown in Table 3.

Table 3
Estimation results for Eq. (8)—relative deviation.

	Median	CI$_{95}$	odds($\beta > 0$)	sseff	psrf
$\beta_{NAT} - \beta_{AT}$	0.690	[0.33,1.05]	4440:1	21040	1.0002
β_{AT}	−0.383	[−0.636,−0.133]	1:1080	20232	1.0001
β_{NAT}	0.308	[0.0503,0.568]	97.3:1	21477	1.0001
β_B^R	0.054	[−0.134,0.24]	2.49:1	19537	1.0002
β_S^R	0.175	[0.00595,0.347]	44.4:1	23991	1.0000
β_B^L	0.182	[−0.0151,0.385]	27:1	17357	1.0001
β_S^L	0.019	[−0.152,0.191]	1.43:1	19769	1.0000
β_B^O	−0.023	[−0.209,0.162]	1:1.48	21641	1.0000
β_S^O	−0.022	[−0.179,0.135]	1:1.52	23421	1.0001
$\beta_S^R - \beta_B^R$	0.122	[−0.142,0.391]	4.5:1	20266	1.0002
$\beta_S^L - \beta_B^L$	−0.163	[−0.418,0.0894]	1:8.82	19581	1.0001
$\beta_S^O - \beta_B^O$	0.002	[−0.239,0.243]	1.03:1	21437	1.0000

	median	CI$_{95}$		sseff	psrf
σ_U	0.864	[0.824,0.908]		14765	1.0003
σ_G	0.390	[0.226,0.585]		2950	1.0008
σ_S	0.258	[0.164,0.357]		1879	1.0025
σ_B	0.418	[0.338,0.509]		4203	1.0005

Table 4
Estimation results for Eq. (1)—no weights.

	Median	CI$_{95}$	odds($\beta > 0$)	sseff	psrf
$\beta_{NAT} - \beta_{AT}$	0.291	[0.142,0.44]	20000:1	19170	1.0004
β_{AT}	−0.252	[−0.356,−0.15]	0:1	20581	1.0001
β_{NAT}	0.038	[−0.0693,0.147]	3.17:1	18326	1.0004
β_B^R	−0.020	[−0.0944,0.0558]	1:2.27	19703	1.0001
β_S^R	0.129	[0.056,0.2]	10000:1	20919	1.0001
β_B^L	0.078	[−0.00458,0.16]	29.7:1	17472	1.0001
β_S^L	0.112	[0.039,0.184]	869:1	17653	1.0001
β_B^O	0.095	[0.0197,0.17]	134:1	21870	1.0001
β_S^O	−0.062	[−0.129,0.00536]	1:27.6	21940	1.0000
$\beta_S^R - \beta_B^R$	0.148	[0.0409,0.255]	287:1	19559	1.0001
$\beta_S^L - \beta_B^L$	0.034	[−0.0735,0.142]	2.73:1	17681	1.0002
$\beta_S^O - \beta_B^O$	−0.157	[−0.256,−0.0575]	1:888	21023	1.0001

	median	CI$_{95}$		sseff	psrf
σ_U	0.328	[0.313,0.345]		19566	1.0001
σ_G	0.268	[0.179,0.418]		3623	1.0019
σ_S	0.154	[0.117,0.196]		3970	1.0011
σ_B	0.165	[0.126,0.209]		3835	1.0004

Table 5
Estimation results for Eq. (5)—changes of prices.

	Median	CI$_{95}$	odds($\beta > 0$)	sseff	psrf
β_{AT}	−5.293	[−13.9,3.22]	1:8.65	3792	1.0009
β_B^R	−3.291	[−7.29,0.615]	1:19.4	7575	1.0031
β_S^R	−1.275	[−4.46,1.9]	1:3.62	21551	1.0003
β_B^L	2.407	[−1.37,6]	8.78:1	12438	1.0005
β_S^L	1.274	[−1.75,4.33]	3.96:1	19766	1.0003
β_B^O	−0.714	[−4.47,2.98]	1:1.85	5059	1.0023
β_S^O	−0.941	[−3.82,2.02]	1:2.75	15174	1.0004
$\beta_S^R - \beta_B^R$	2.012	[−2.98,7.17]	3.62:1	13928	1.0013
$\beta_S^L - \beta_B^L$	−1.136	[−5.59,3.56]	1:2.22	13754	1.0006
$\beta_S^O - \beta_B^O$	−0.227	[−4.56,4.23]	1:1.18	15179	1.0010

	median	CI$_{95}$		sseff	psrf
σ_U	45.395	[43.1,47.8]		2706	1.0066
σ_G	5.083	[0.533,12.9]		308	1.0290
σ_S	1.134	[0.431,7.84]		121	1.0091
σ_B	10.620	[0.737,17.3]		242	1.0680

Table 6
Estimation results for Eq. (6)—time between trades.

	Median	CI$_{95}$	odds ($\beta > 0$)	sseff	psrf
β_{AT}	−5.204	[−15,4.19]	1:6.71	2067	1.0041
β_B^R	−0.798	[−3.56,2.02]	1:2.45	16663	1.0001
β_S^R	−3.117	[−6.26,−0.122]	1:46.7	12623	1.0014
β_B^L	0.701	[−1.98,3.34]	2.27:1	19771	1.0001
β_S^L	0.058	[−2.79,2.86]	1.07:1	13207	1.0020
β_B^O	−0.722	[−3.26,1.8]	1:2.52	24020	1.0000
β_S^O	0.254	[−2.34,2.99]	1.35:1	14723	1.0036
$\beta_S^R - \beta_B^R$	−2.339	[−6.33,1.5]	1:7.52	17490	1.0012
$\beta_S^L - \beta_B^L$	−0.629	[−4.17,2.88]	1:1.77	20825	1.0010
$\beta_S^O - \beta_B^O$	0.985	[−2.34,4.47]	2.55:1	15346	1.0026

	median	CI$_{95}$	sseff	psrf
σ_U	37.985	[36.1,39.9]	1552	1.0129
σ_G	9.583	[1.02,15.4]	499	1.0134
σ_S	4.034	[0.527,13.1]	87	1.0876
σ_B	1.019	[0.416,3.66]	221	1.0286

Table 7
Estimation results for Eq. (7)—bid-ask spread.

	Median	CI$_{95}$	odds($\beta > 0$)	sseff	psrf
β_{AT}	−1.693	[−9.13,5.82]	1:2.08	3204	1.0006
β_B^R	−1.709	[−5.78,2.24]	1:4.15	6494	1.0001
β_S^R	−1.375	[−4.29,1.37]	1:5.02	13022	1.0016
β_B^L	0.372	[−3.49,4.3]	1.36:1	6845	1.0000
β_S^L	4.089	[1.49,6.78]	1180:1	15720	1.0011
β_B^O	0.686	[−2.93,4.4]	1.82:1	8200	1.0003
β_S^O	−1.110	[−3.6,1.33]	1:4.41	20900	1.0003
$\beta_S^R - \beta_B^R$	0.355	[−4.77,5.4]	1.25:1	7633	1.0007
$\beta_S^L - \beta_B^L$	3.703	[−0.85,8.36]	17.4:1	8404	1.0005
$\beta_S^O - \beta_B^O$	−1.816	[−6.13,2.45]	1:3.93	10384	1.0000

	median	CI$_{95}$	sseff	psrf
σ_U	37.271	[35.5,39.1]	7541	1.0027
σ_G	1.148	[0.462,6.46]	668	1.0034
σ_S	1.711	[0.467,10.5]	117	1.0456
σ_B	15.361	[11.6,19.2]	3974	1.0085

The main result does not change if we use a measure relative to the fundamental value in the actual period as compared to the average fundamental value. As in the estimation of Eq. (1) we have very strong evidence (in the sense of Kass and Raftery, 1995) that the mere expectation of the presence of algorithmic traders reduces bubbles.

A.3.3 Treatment C

Although Treatment C was not part of our research question the results of this treatment may be interesting for others. Below we give a short summary of the algorithmic trader used in treatment C and a short comparison with the other treatments. A full analysis of this treatment would go beyond the scope of this paper.

In Treatment C of our experiment one human trader was replaced by an algorithmic trader. The trader programmed for this treatment is offering all assets at its disposal at a price identical to the fundamental value of an asset in the respective period. At the same time the algorithmic trader is willing to buy assets at a price smaller than the fundamental value. The figure below shows how overpricing, the time between trades and the price volatility developed in Treatments A, B, and C. Note that Treatment C differs from Treatment A in two ways: subjects expect an algorithmic trader to participate in the market *and* an algorithmic trader participates on the market. A ceteris-paribus comparison between treatments A and C thus is not possible. A comparison between Treatments B and C shows the impact that the trading activity of the algorithmic trader had on the market. Fig. 12 shows overpricing, times between individual trades (per volume n) and changes of prices (per volume n) for all three treatments.

A.3.4 Parametric and frequentist statistics

In our discussion of Eq. (1) in Section 4.2 we describe the average bubble with the help of a smooth curve. With the help of the Bayesian approach that we use in the paper we can interpret our data in a straightforward way.

In this section we follow a more restrictive approach, using a parametric and frequentist framework. In Fig. 4 we have seen that overpricing $(P_{i\phi k} - P_\phi^F)/\bar{P}^F$ follows a concave pattern. As in most other experiments of this type prices start below the fundamental value, then increase until the bubble bursts. Instead of using any smooth curve to approximate this pattern we could here describe the bubble with the help of a quadratic function of the time (normalized to be between 0 and 1),
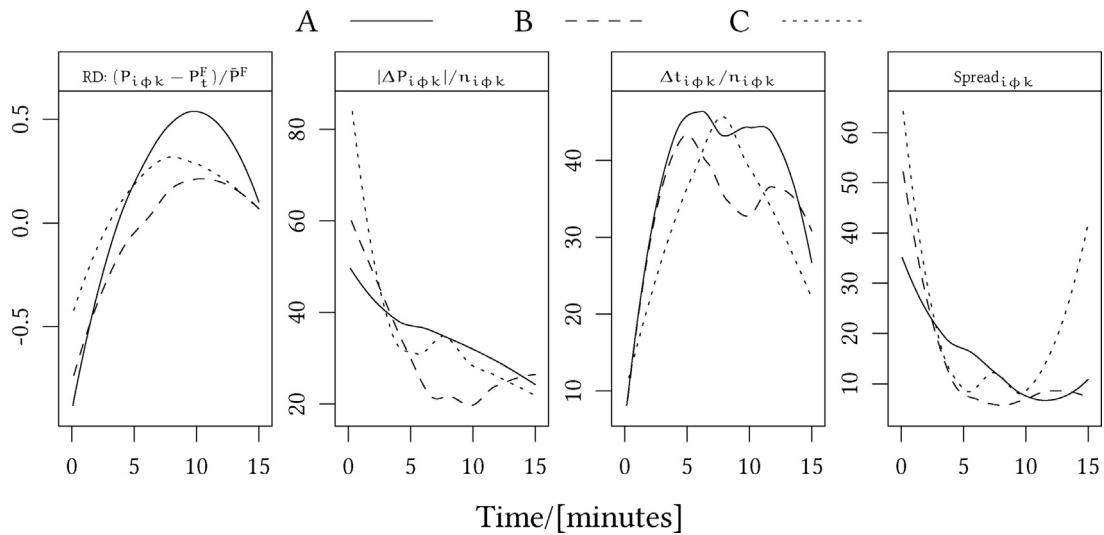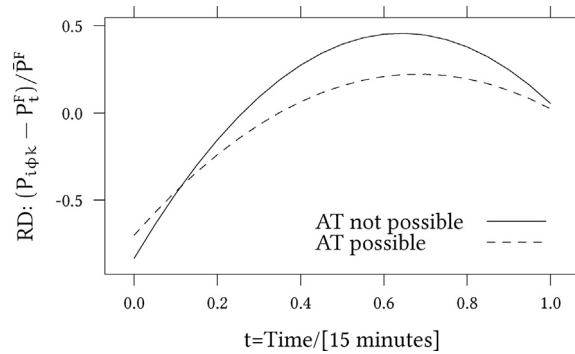
Fig. 12. Comparison of all three treatments.

Fig. 13. Parametric approximation of the bubble according to Eq. (9).

t = Time/[15 min], where the shape of the quadratic function is allowed to depend on the treatment. A more concave shape (a more negative coefficient of t^2) would indicate a more pronounced bubble. Analogous to Eq. (1) we estimate the following:

$$
\begin{aligned}
\frac{P_{i\phi k} - P_\phi^{\mathrm{F}}}{\bar{P}^{\mathrm{F}}} &= \beta_0 + \beta_{\mathrm{AT}} d_{\mathrm{AT}} + \beta_t t + \beta_{t^2} t^2 + \beta_{\mathrm{AT} \times t} d_{\mathrm{AT}} \cdot t + \beta_{\mathrm{AT} \times t^2} d_{\mathrm{AT}} \cdot t^2 \\
&\quad + \beta_B^{\mathrm{R}} R_{B_{i\phi k}} + \beta_S^{\mathrm{R}} R_{S_{i\phi k}} + \beta_B^{\mathrm{L}} L_{B_{i\phi k}} + \beta_S^{\mathrm{L}} L_{S_{i\phi k}} + \beta_B^{\mathrm{O}} O_{B_{i\phi k}} + \beta_S^{\mathrm{O}} O_{S_{i\phi k}} \\
&\quad + \epsilon_k^G + \epsilon_{S_{i\phi k}}^S + \epsilon_{B_{i\phi k}}^B + \epsilon_{i\phi k}^U
\end{aligned}
\tag{9}
$$

Random effects remain as specified in Eq. (2). We use `lme4-1.1-12` to estimate Eq. (9). Fig. 13 shows the approximation of the bubbles in line with Eq. (9). Table 8 shows estimation results. Standard errors are based on a normal bootstrap with 200 replications. Most importantly, the coefficient for AT $\times t^2$, i.e. the interaction of our treatment with t^2, is highly significant: Our treatment clearly has an effect on the shape of the bubble.

In the baseline treatment, where algorithmic traders are not possible, the coefficient of t^2 is negative ($\beta_{t^2} = -3.14$), i.e. the function is rather concave. This quadratic term becomes significantly smaller in absolute terms (by $\beta_{\mathrm{AT} \times t^2} = 1.16$) in the treatment where algorithmic traders are possible, i.e. concavity clearly decreases. It is this concavity which essentially describes the deviation of the price from the fundamental value.

Similarly, we can use frequentist methods to estimate Eqs. (5) and (6). Results are provided in Tables 9 and 10.

The results are (as expected) very similar to those given in Tables 5 and 6.

A.3.5 Non-parametric frequentist statistics

A different approach from the frequentist world would be, similar to Cheung et al. (2014), an exact Fisher-Pitman permutation test to compare the NAT treatment against AT. Table 11 shows the result of the exact Fisher-Pitman test.

Table 8
Frequentist estimation results for Eq. (9).

	β	σ	t	$P > \lvert t \rvert$
β_0	−0.82	0.094	−8.72	0.00000
β_{AT}	0.133	0.125	1.06	0.28911
β_{t^2}	−3.14	0.235	−13.33	0.00000
β_t	4.02	0.262	15.36	0.00000
β_B^R	0.0182	0.0264	0.69	0.48954
β_S^R	0.00687	0.0219	0.31	0.75334
β_B^L	0.00418	0.0253	0.16	0.86908
β_S^L	−0.033	0.0206	−1.60	0.10918
β_B^O	−0.0272	0.0229	−1.19	0.23564
β_S^O	0.00509	0.0173	0.29	0.76855
$\beta_{AT \times t^2}$	1.16	0.335	3.45	0.00056
$\beta_{AT \times t}$	−1.32	0.368	−3.59	0.00033

Table 9
Frequentist estimation results for Eq. (5).

	β	σ	t	$P > \lvert t \rvert$
β_0	36.2	4.26	8.49	0.00000
β_{AT}	−3.39	5.75	−0.59	0.55532
β_B^R	−3.3	2.17	−1.52	0.12833
β_S^R	−1.08	1.75	−0.62	0.53813
β_B^L	2.71	2.22	1.22	0.22195
β_S^L	1.66	1.63	1.01	0.31036
β_B^O	0.366	2.02	0.18	0.85584
β_S^O	0.0382	1.85	0.02	0.98356

Table 10
Frequentist estimation results for Eq. (6).

	β	σ	t	$P > \lvert t \rvert$
β_0	42.2	3.97	10.61	0.00000
β_{AT}	−4.22	5.57	−0.76	0.44825
β_B^R	−0.656	1.36	−0.48	0.62883
β_S^R	−3.06	1.47	−2.09	0.03695
β_B^L	1.17	1.33	0.88	0.37645
β_S^L	0.154	1.36	0.11	0.90955
β_B^O	−0.0757	1.21	−0.06	0.95002
β_S^O	0.0831	1.5	0.06	0.95577

Table 11
Non-parametric frequentist comparison of the two treatments.

	K	Z	$P_{>Z}$
$\dfrac{1}{\sum_\phi I_{\phi k}} \sum_{i,\phi} \lvert P_{i\phi k} - P_\phi^F \rvert / \bar{P}^F$	24	1.5748	0.0588
$\dfrac{1}{\sum_{i,\phi} n_{i\phi k}} \sum_{i,\phi} n_{i\phi k} \lvert P_{i\phi k} - P_\phi^F \rvert / \bar{P}^F$	24	1.5598	0.0607
$\dfrac{1}{\sum_\phi I_{\phi k}} \sum_{i,\phi} (P_{i\phi k} - P_\phi^F) / \bar{P}^F$	24	1.0617	0.1535
$\dfrac{1}{\sum_{i,\phi} n_{i\phi k}} \sum_{i,\phi} n_{i\phi k} (P_{i\phi k} - P_\phi^F) / \bar{P}^F$	24	0.9630	0.1785
$\dfrac{1}{\sum_\phi I_{\phi k}} \sum_{i,\phi} \Delta P_{i,\phi}$	24	0.9555	0.1753
$\dfrac{1}{\sum_\phi I_{\phi k}} \sum_{i,\phi} \Delta t_{i,\phi}$	24	0.8686	0.2075

The table shows the result of an exact Fisher-Pitman test against the alternative hypothesis that the aggregate statistic is larger in the NAT treatment than in AT.

While in the estimation of Eqs. (1), (5), (6) and (9), we use random effects for the seller, the buyer and for the market group to model the panel structure of the data explicitly, in Table 11 we just use averages for each of the K independent observations.

We call $n_{i\phi k}$ the volume of trade i in period ϕ in market group k. We call $I_{\phi k}$ the number of trades in market group k in period ϕ. K is the number of market groups. Z is the test statistic and $P_{>Z}$ is the probability to obtain a larger test statistic under the Null.

Table 12

Influence of risk attitude and overconfidence on earnings and asset holdings.

	Earnings	Assets
Risk measure	1.29:1	1:1.75
Risk w. losses	1:1.3	1:15
Overconfidence	2.55:1	1:2.13

The Table shows the posterior odds of a positive effect (measured as β_1 in Eq. (10)) of our measure of risk attitude and overconfidence on either (total) earnings or assets (held on average).

Different from the results presented above, we do not model the panel structure of the data. Frequentist test results are, instead, based only on averages for each matching group.

A.3.6 Risk and overconfidence measures, earnings and asset holdings

Table 12 relates individual measures of risk aversion and overconfidence to (total) earnings and (average) asset holdings. To assess the relationship we estimate Eq. (10). Measures of risk aversion and overconfidence of individual i from market group k are denoted X_{ik}. Total earnings or average asset holdings are denoted Y_{ik}. To account for the panel structure we include a random effect ϵ_k^G for the market group.

$$Y_{ik} = \beta_0 + \beta_1 X_{ik} + \epsilon_k^G + \epsilon_{ik}^U \qquad (10)$$

Random effects and priors are as in Eqs. (2)–(4). Most of the effects in Table 12 are unremarkable. We find posterior odds of 1:15 for the effect of "Risk w. losses" on "Assets", i.e. we have positive evidence for a negative effect of "Risk w. losses" on "Assets".

References

Akerlof, G.A., 1970. The market for lemons: quality uncertainty and the market mechanism. Q. J. Econ. 84 (3), 488–500.

Akiyama, E., Hanaki, N., Ishikawa, R., 2013. It Is Not Just Confusion! Strategic Uncertainty in an Experimental Asset Market. Discussion Paper 2013-40. Aix-Marseille School of Economics.

Andrade, E.B., Odean, T., Lin, S., 2016. Bubbling with excitement: an experiment *. Rev. Finance 20 (2), 447.

Barber, B.M., Odean, T., 2001. Boys will be boys: gender, overconfidence, and common stock investment. Q. J. Econ. 116 (1), 261–292.

Bhattacharya, U., Spiegel, M., 1991. Insiders, outsiders, and market breakdowns. Rev. Financ. Stud. 4 (2), 255–282.

Biais, B., Hilton, D., Mazurier, K., Pouget, S., 2005. Judgemental overconfidence, self-monitoring, and trading performance in an experimental financial market. Rev. Econ. Stud. 72 (2), 287–312.

Boehmer, E., Fong, K.Y., Wu, J.J., 2014. International evidence on algorithmic trading. AFA 2013 San Diego Meetings Paper.

Breaban, A., Noussair, C., 2013. Emotional State and Market Behavior. Center for Economic Research 2013-031. Tilburg University.

Camerer, C., 1987. Do biases in probability judgment matter in markets? Experimental evidence. Am. Econ. Rev. 77 (5), 981–997.

Chaboud, A.P., Chiquoine, B., Hjalmarsson, E., Vega, C., 2014. Rise of the machines: algorithmic trading in the foreign exchange market. J. Finance 69 (5), 2045–2084.

Chaminade, T., Rosset, D., Da Fonseca, D., Nazarian, B., Lutcher, E., Cheng, G., Deruelle, C., 2012. How do we think machines think? An fMRI study of alleged competition with an artificial intelligence. Front. Hum. Neurosci. 6 (103).

Cheung, S.L., Hedegaard, M., Palan, S., 2014. To see is to believe: common expectations in experimental asset markets. Eur. Econ. Rev. 66, 84–96.

Cleveland, W.S., Grosse, E., Shyu, W.M., 1992. Local regression models. In: Chambers, J., Hastie, T. (Eds.), Statistical Models in S. Wadsworth & Brooks/Cole (Chapter 8).

Das, R., Hanson, J.E., Kephart, J.O., Tesauro, G., 2001. Agent–human interactions in the continuous double auction. In: Nebel, B. (Ed.), Proceedings of the International Joint Conference on Artificial Intelligence, vol. 17. Lawrence Erlbaum Associates Ltd, pp. 1169–1178.

De Luca, M., Cliff, D., 2011. Human-agent auction interactions: adaptive-aggressive agents dominate. In: Walsh, T. (Ed.), Proceedings of the International Joint Conference on Artificial Intelligence, vol. 22. AAAI Press, pp. 178–185.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: measurement, determinants, and behavioral consequences. J. Eur. Econ. Assoc. 9 (3), 522–550.

Ellsberg, D., 1961. Risk, ambiguity, and the savage axioms. Q. J. Econ. 75 (4), 643–669.

Farjam, M., 2015. On Whom Would I Want to Depend; Humans or Nature? Jena Economic Research Papers 2015-19. Friedrich-Schiller University.

Fellner, G., Krügel, S., 2012. Judgmental overconfidence: three measures, one bias? J. Econ. Psychol. 33 (1), 142–154.

Fellner, G., Krügel, S., 2014. Judgmental overconfidence and trading activity. J. Econ. Behav. Organ. 107 (B), 827–842.

Fellner, G., Maciejovsky, B., 2007. Risk attitude and market behavior: evidence from experimental asset markets. J. Econ. Psychol. 28 (3), 338–350.

Fischbacher, U., 2007. z-Tree: Zurich toolbox for ready-made economic experiments. Exp. Econ. 10 (2), 171–178.

Füllbrunn, S., Rau, H.A., Weitzel, U., 2014. Does ambiguity aversion survive in experimental asset markets? J. Econ. Behav. Organ. 107 (PB), 810–826.

Glaser, M., Weber, M., 2007. Overconfidence and trading volume. Geneva Risk Insur. Rev. 32 (1), 1–36.

Greiner, B., 2004. An online recruitment system for economic experiments. Göttingen. Ges. für Wiss. Datenverarbeitung In: Kremer, K., Macho, V. (Eds.), Forschung und wissenschaftliches Rechnen GWDG Bericht, vol. 63, pp. 79–93.

Grossklags, J., Schmidt, C., 2006. Software agents and market (in) efficiency: a human trader experiment. IEEE Trans. Syst. Man Cybern. Part C: Appl. Rev. 36 (1), 56–67.

Gsell, M., 2008. Assessing the Impact of Algorithmic Trading on Markets: A Simulation Approach. Center for Financial Studies 2008-49, Universität Frankfurt a. M.

Hendershott, T., Jones, C.M., Menkveld, A.J., 2011. Does algorithmic trading improve liquidity? J. Finance 66 (1), 1–33.

Hilton, D., Regner, I., Cabantous, L., Charalambides, L., Vautier, S., 2011. Do positive illusions predict overconfidence in judgment? A test using interval production and probability evaluation measures of miscalibration. J. Behav. Decis. Making 24 (2), 117–139.

Holt, C.A., Laury, S.K., 2002. Risk aversion and incentive effects. Am. Econ. Rev. 92 (5), 1644–1655.

Hoorens, V., 1993. Self-enhancement and superiority biases in social comparison. Eur. Rev. Soc. Psychol. 4 (1), 113–139.

Jarrow, R.A., Protter, P., 2012. A dysfunctional role of high frequency trading in electronic markets. Int. J. Theor. Appl. Finance 15 (3), 1–15.

Kass, R.E., Raftery, A.E., 1995. Bayes factors. J. Am. Stat. Assoc. 90 (430), 773–795.

Keller, C., Siegrist, M., 2006. Investing in stocks: the influence of financial risk attitude and values-related money and stock market attitudes. J. Econ. Psychol. 27 (2), 285–303.

King, R.R., Smith, V.L., Williams, A.W., Van Boening, M., 1993. The robustness of bubbles and crashes in experimental stock markets. In: Day, R.H., Chen, P. (Eds.), Nonlinear Dynamics and Evolutionary Economics. Oxford University Press, Oxford, pp. 183–200 (Chapter 13).

Kirchler, M., Huber, J., Stockl, T., 2012. Thar she bursts: reducing confusion reduces bubbles. Am. Econ. Rev. 102 (2), 865–883.

Kirilenko, A.A., Lo, A.W., 2013. Moore's Law versus Murphy's Law: algorithmic trading and its discontents. J. Econ. Perspect. 27 (2), 51–72.

Kocher, M.G., Trautmann, S.T., 2013. Selection into auctions for risky and ambiguous prospects. Econ. Inq. 51 (1), 882–895.

Krach, S., Hegel, F., Wrede, B., Sagerer, G., Binkofski, F., Kircher, T., 2008. Can machines think? Interaction and perspective taking with robots investigated via fMRI. PLoS ONE 3 (7), e2597.

Mandryk, R.L., Inkpen, K.M., Calvert, T.W., 2006. Using psychophysiological techniques to measure user experience with entertainment technologies. Behav. Inf. Technol. 25 (2), 141–158.

McCabe, K., Houser, D., Ryan, L., Smith, V., Trouard, T., 2001. A functional imaging study of cooperation in two-person reciprocal exchange. Proc. Natl. Acad. Sci. 98 (20), 11832–11835.

Michailova, J., 2010. Overconfidence, Risk Aversion and (Economic) Behavior of Individual Traders in Experimental Asset Markets. MPRA Paper 26390. University Library of Munich, Germany.

Michailova, J., Schmidt, U., 2016. Overconfidence and bubbles in experimental asset markets. J. Behav. Finance 17 (3), 280–292.

Moore, D.A., Healy, P.J., 2008. The trouble with overconfidence. Psychol. Rev. 115 (2), 502–517.

Morris, S., 1994. Trade with heterogeneous prior beliefs and asymmetric information. Econometrica 62 (6), 1327–1347.

Nass, C., Moon, Y., 2000. Machines and mindlessness: social responses to computers. J. Soc. Issues 56 (1), 81–103.

Odean, T., 1999. Do investors trade too much? Am. Econ. Rev. 89, 1279–1298.

Oechssler, J., Schmidt, C., Schnedler, W., 2011. On the ingredients for bubble formation: informed traders and communication. J. Econ. Dyn. Control 35 (11), 1831–1851.

Palan, S., 2013. A review of bubbles and crashes in experimental asset markets. J. Econ. Surv. 27 (3), 570–588.

R Development Core Team, 2017. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria, ISBN 3-900051-07-0.

Rilling, J.K., Sanfey, A.G., Aronson, J.A., Nystrom, L.E., Cohen, J.D., 2004. The neural correlates of theory of mind within interpersonal interactions. Neuroimage 22 (4), 1694–1703.

Robin, S., Straznicka, K., Villeval, M.-C., 2012. Bubbles and Incentives: An Experiment on Asset Markets. Discussion Paper 2012-35. GATE.

Sarin, R.K., Weber, M., 1993. Effects of ambiguity in market experiments. Manag. Sci. 39 (5), 602–615.

Smith, V.L., Suchanek, G.L., Williams, A.W., 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. Econometrica 56 (5), 1119–1151.

Stöckl, T., Huber, J., Kirchler, M., 2010. Bubble measures in experimental asset markets. Exp. Econ. 13 (3), 284–298.

Sutter, M., Huber, J., Kirchler, M., 2012. Bubbles and information: an experiment. Manag. Sci. 58 (2), 384–393.

Walsh, T., Xiong, B., Chung, C., Mukerji, P., 2012. The impact of algorithmic trading in a simulated asset market. Proceedings 18th International Conference on Computing in Economics and Finance (CEF 2012).

Weibel, D., Wissmath, B., Habegger, S., Steiner, Y., Groner, R., 2008. Playing online games against computer- vs. human-controlled opponents: effects on presence, flow, and enjoyment. Comput. Hum. Behav. 24 (5), 2274–2291.