Bubbles in hybrid markets How expectations about algorithmic trading affect human trading*

Mike Farjam† Oliver Kirchkamp‡

November 23, 2015

Bubbles are omnipresent in lab experiments with asset markets. Most of these experiments were conducted in environments with only human traders. Today markets are substantially determined by algorithmic traders. Here we use a laboratory experiment to measure changes of human trading behaviour if these humans expect algorithmic traders. To disentangle the direct effect of algorithmic traders we use a design where we manipulate only the expectations of human traders. We find clearly smaller bubbles if human traders expect algorithmic traders to be present.

JEL: C92, G02

Keywords: Bubbles, Expectations, Experiment, Algorithmic Traders.

*We would like to thank the Max Planck Society for financial support through the International Max Planck Research School on Adapting Behavior in a Fundamentally Uncertain World. We would also like to thank the participants of the Experimental Finance conference 2015 in Nijmegen and the 2015 Annual Congress of the European Economic Association for their valuable feedback. We use R (2015) for the statistical analysis.

†University Jena, School of Economics, Carl-Zeiss-Str. 3, 07737 Jena, Mike.Farjam@uni-jena.de

‡University Jena, School of Economics, Carl-Zeiss-Str. 3, 07737 Jena, oliver@kirchkamp.de, ☎ +49 3641 943240, FAX +49 3641 943242.

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 below). 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. Instead of humans bargaining with and screaming at each other, today traders interact via computers. The use of computers on asset markets comes in many forms. It includes simple support of human traders in e.g. the scheduling of 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 behaviour between hybrid and human-only markets are substantial and whether these differences call for a revision of the classical experimental results from the 20th century.

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 trading activity of algorithmic traders and not to changes in human trading patterns. Algorithmic traders are seen as more able than humans to discover arbitrage possibilities than human traders. As a result we should see fewer bubbles 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 behaviour and without any active participation of algorithmic traders in hybrid markets.

Expectations crucially determine the behaviour of human traders. Cheung, Hedegaard, and Palan (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 below we will review the literature. We will see that the presence of algorithmic traders could change the behaviour 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 the second experiment we also manipulate expectations about the presence of algorithmic traders. In sections 4 and 5 we present our results. Section 6 concludes by looking at the experimental results in a broader context.

2. Literature

2.1. Experimental asset markets:

Smith, Suchanek, and Williams (1988) (SSW) study a laboratory situation where subjects trade assets which pay a random dividend per round 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 round and the number of rounds. 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 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. A full survey of this literature goes beyond the scope of this section (for a recent survey see Palan, 2013) but the following paragraphs should lead to our experimental design and predictions.

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, Hedegaard, and Palan (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, Hedegaard, and Palan (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, Straznicka, and Villeval (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 U. Schmidt (2011), Michailova (2010), Fellner and Krügel (2012), and Oechssler, C. Schmidt, and Schnedler (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 operationalize overconfidence specifically in the context of asset market (see section 3.4).

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, Inkpen, and Calvert (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, Odean, and Lin (2012) 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 behaviour 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, Suchanek, and Williams (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: Walsh et al. (2012) find that liquidity is higher in simulated hybrid markets than in simulated human-only markets. Hendershott, Jones, and Menkveld (2011) find in an empirical analysis of the NYSE since 2003 that liquidity increased in the market as the use of algorithmic traders increased. 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.

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

Akiyama, Hanaki, and Ishikawa (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 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, Hanaki, and Ishikawa 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 behaviour. In that respect Akiyama, Hanaki, and Ishikawa can not distinguish whether differences in trading between treatments are the result of different trading behaviour 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 C. 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 C. Schmidt 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 C. Schmidt find slightly (but not significantly) less trading when subjects are aware of the presence of algorithmic traders.

In contrast to Grossklags and C. Schmidt we give participants in the two treatments exactly the same information, except for one small (but crucial) bit: Are algorithmic traders potentially present or are they not? All remaining information, in particular information about the concept of algorithmic traders in general, is kept constant. Grossklags and C. Schmidt give information about algorithmic traders only in the hybrid market, not in the human-only market. As a result they cannot disentangle the effect of giving information about algorithmic traders in general from giving information about a specific market. From Cheung, Hedegaard, and Palan (2014) we know that general information may very well matter. In our experiment we can cleanly isolate the effect of the presence of algorithmic traders.

3. Methods

3.1. Market

The experiment was implemented with the help of z-Tree (Fischbacher, 2007). Participants were recruited with ORSEE (Greiner, 2004). Markets used in this experiment are very similar to those used by Smith, Suchanek, and Williams (1988). A screenshot is shown in Appendix A.6. As in SSW subjects trade in a continuous double auction during 15 rounds and receive a random dividend per round. The possible dividends are with equal probabilities 0, 8, 28, or 60 ECU. The average dividend per round is, thus, 24 ECU. The fundamental value of an asset in round 1 is $15 \times 24 = 360$ ECU, decreasing by 24 ECU at the end of each round. Each round lasts for 60 seconds, so that one market period in total takes 15 minutes. Each subject owns in round 1 an endowment of 4 assets which the subject can offer on the market for cash. Each subject also initially

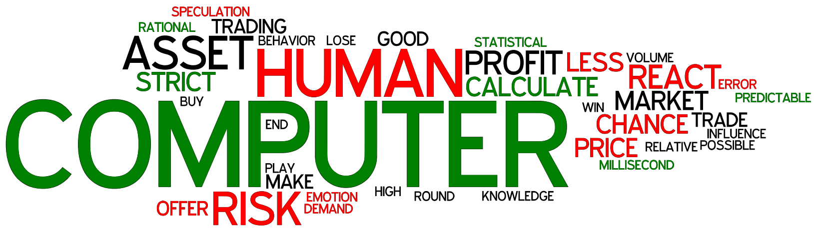


Figure 1: Wordle of most frequent words

owns 720 ECU in cash which can be used to buy assets. Kirchler, Huber, and Stockl (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.

Subjects got instructions in form of a video tutorial (11 minutes) and had a printed table with the fundamental value of an asset in each round at their disposal. Control questions were asked to make sure they understood the dynamics of the SSW market and the trading interface.

3.2. Algorithmic Traders

We ran two sessions of a first (preparatory) experiment. In that experiment six subjects per 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. 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. Figure 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).[1] The exact questions asked to subjects in the pilot sessions and the algorithm that produces the wordle can be found in Appendix A.2.

In a second (main) experiment the wordle was shown to all (new) subjects before they were informed about their treatment condition. Furthermore, subjects were told how the wordle was created. They were also told that the algorithmic trader was programmed according to the wordle.

[1] The original German wordle is shown in Appendix A.3.

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. 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 groups 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 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.

3.3. Treatments

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

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

Table 1: Treatments

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 groups 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 behaviour of the C group. C is only needed to make expectations of the B participants consistent.

The number of active traders was six in all conditions. To avoid that social preferences affect differences between A and B subjects know that in treatment C another passive human trader would receive the payoff of the algorithmic trader.

3.4. Risk preference and overconfidence

To measure risk aversion of subjects we use a multiple price list task as in Holt and Laury (2002).[2] 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 elicit loss aversion.[3]

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.

3.5. Payoff

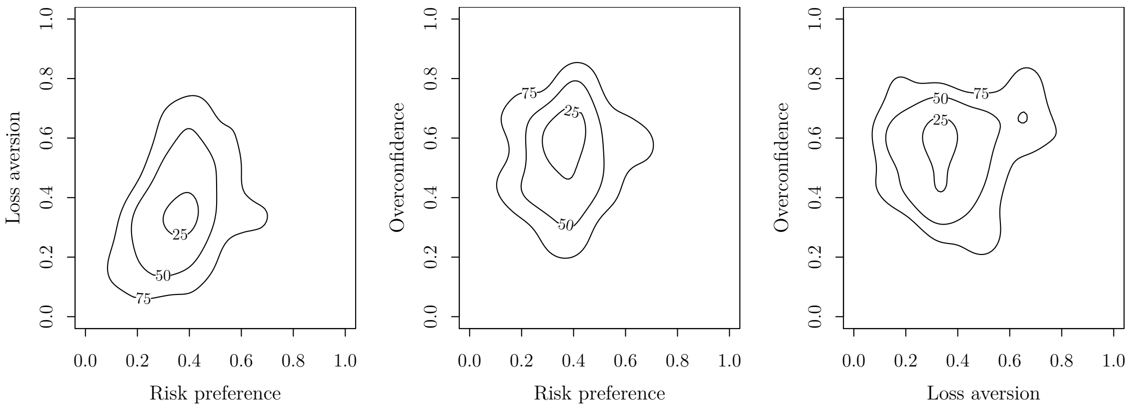
The markets and other tasks are designed such that the average earnings of subjects was about 11 euros. To avoid endowment effects only one of the tasks (risk preference, loss aversion or overconfidence measurements) or one of the trading periods was chosen randomly at the end of the session for payoff.

4. Descriptives

4.1. 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.

[2]The list can be found in Appendix A.4.
[3]The list can be found in Appendix A.5.



The graphs show contour lines of a kernel density estimate.

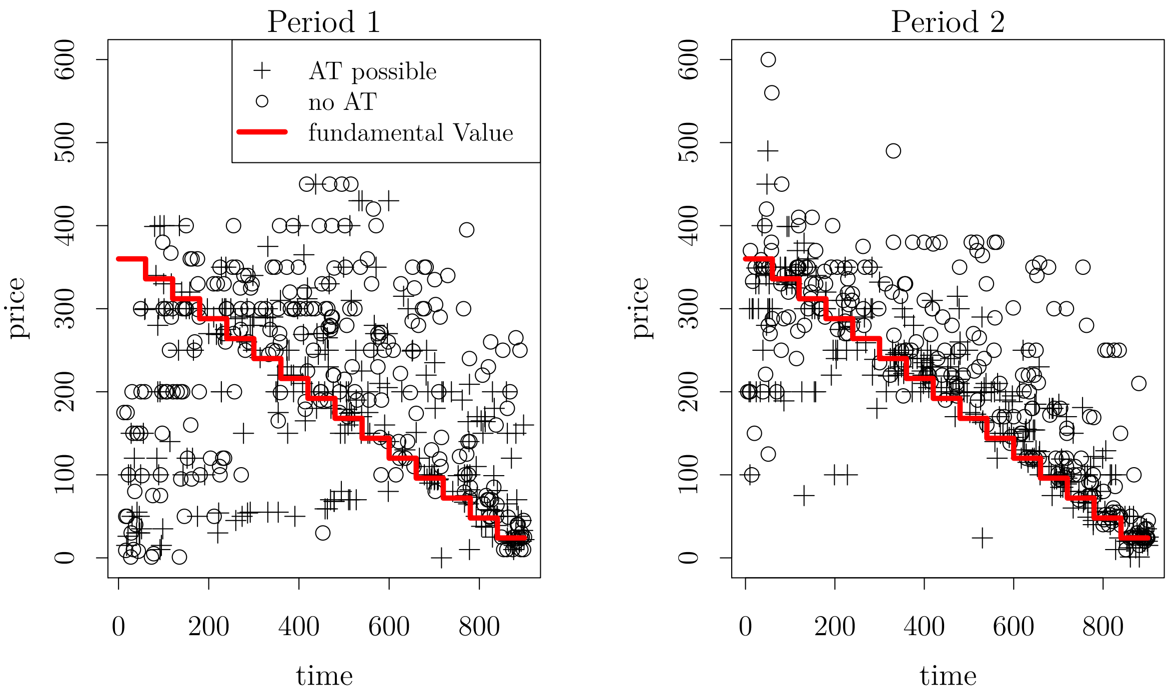
Figure 2: Joint distribution of preferences for risk, loss aversion and overconfidence

(2011) and Barber and Odean (2001) show that risk-preferences and trading behaviour differs between genders, we recruited only male subjects to reduce within group 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.

4.2. Questionnaire and additional measurements

After playing two successive market periods 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 periods of trading, there must have been a considerable amount of uncertainty among subjects at least in the first rounds of the first period. 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. Since loss-aversion is closely related to risk-aversion we chose to measure loss-aversion as well. The exact choices are presented in Appendices A.4 and A.5. Figure 2 shows the empirical joint distribution of these properties in our sample. The attitude towards risk in our sample seems to be in line with similar studies. We also find 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



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

Figure 3: Prices over time

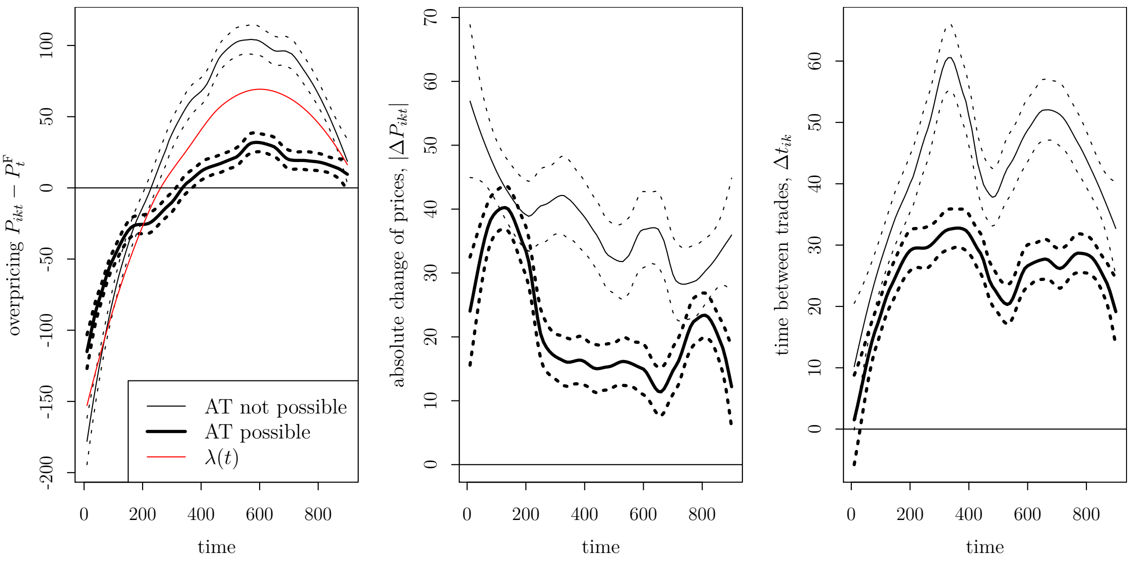
the standard effect (Hoorens, 1993). As we see in Figure 2, the three properties seem to be rather independent of each other. We will, hence, use them all as controls in our estimations below.

4.2.1. Trades

Figure 3 gives a first impression how individual prices develop over time. Each point represents one trade. As expected, pricing of assets follows the bubble and crash pattern known from SSW.

Figure 4 shows a more aggregated picture. Solid black lines in the Figure are loess smoothers (Cleveland, Grosse, and Shyu, 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 ± one standard deviation.[4] We denote the fundamental value at time t with P_t^{F} and the actual

[4]The standard setting for the smooting parameter is $\alpha = .75$. Since we have a large number of trades



Solid black lines show, separately for the two cases where algorithmic traders are possible and not possible, a loess smoother for overpricing, change of prices over time and time between trades. Dashed lines indicate ± one standard deviation. The red line showes a loess smoother for overpricing, independent of the information about algorithmic traders.

Figure 4: Trading behaviour over all rounds of one market

trade i in group k at time t with P_{ikt}. The left panel in Figure 4 shows the development of $P_{ikt} - P_t^F$ over the time of the experiment. Mispricing is clearly smaller in the treatment where algorithmic traders are possible. The other two panels in the Figure also show that in this treatment volatility is smaller and trading is quicker when algorithmic traders are possible.

In Appendix A.7 we provide similar graphs but now for periodic behaviour within one round of a market. Our interpretation of these graphs is that, apart from the pattern already visible in Figure 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 A.11.

5. Results

Estimation strategy We use a model with mixed effects to take into account the nested structure of the data. We will look at 3 different dependent variables: Mispricing of assets

we can provide more detail about the dynamics during the experiment. Hence, we use $\alpha = .2$ for the black lines.

during trading measured as $P_{ikt} - P_t^{\mathrm{F}}$, speed of trading measured as time in seconds between individual trades Δt_{ikt}, and volatility measured as the absolute change of prices between trades $|\Delta P_{ikt}|$. We also control for buyers B_{ik} and sellers S_{ik} separately for their risk aversion $R_{B_{ik}}$ and $R_{S_{ik}}$, their loss aversion $L_{B_{ik}}$ and $L_{S_{ik}}$, and their overconfidence $O_{B_{ik}}$ and $O_{S_{ik}}$. Furthermore we allow for random effects for the buyer B_{ik}, the seller S_{ik} and the group k of traders in that round.

Here, d_{NAT} is 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. ϵ_k^G, $\epsilon_{S_{ik}}^S$, and $\epsilon_{B_{ik}}^B$ are random effects for the matching group k, the seller S_{ik}, and the buyer B_{ik}, respectively. ϵ_{ikt}^U is the residual. The precision of the distribution for random effects and the residuals follow a vague prior given by (4). The prior distributions of coefficients $\beta_{\dots}$ follow a vague prior given by (3).

Bubbles We assume that the distribution of the difference of actual prices and the fundamental value, $P_{ikt} - P_t^{\mathrm{F}}$, is given by (1). $\lambda(t)$ is a loess spline of average overbidding over time (similar to the one given in Figure 4), independent of the information given to participants, with the smoothing parameter α set to the default (Cleveland, Grosse, and Shyu, 1992).

$$\begin{aligned} P_{ikt} - P_t^{\mathrm{F}} = \beta_0 + (1 + \beta_{\mathrm{NAT}} d_{\mathrm{NAT}} + \beta_{\mathrm{AT}} d_{\mathrm{AT}} + \beta_B^{\mathrm{R}} R_{B_{ik}} + \beta_S^{\mathrm{R}} R_{S_{ik}} + \beta_B^{\mathrm{L}} L_{B_{ik}} + \\ \beta_S^{\mathrm{L}} L_{S_{ik}} + \beta_B^{\mathrm{O}} O_{B_{ik}} + \beta_S^{\mathrm{O}} O_{S_{ik}}) \cdot \lambda(t) + \epsilon_k^G + \epsilon_{S_{ik}}^S + \epsilon_{B_{ik}}^B + \epsilon_{ikt}^U \qquad (1) \end{aligned}$$

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

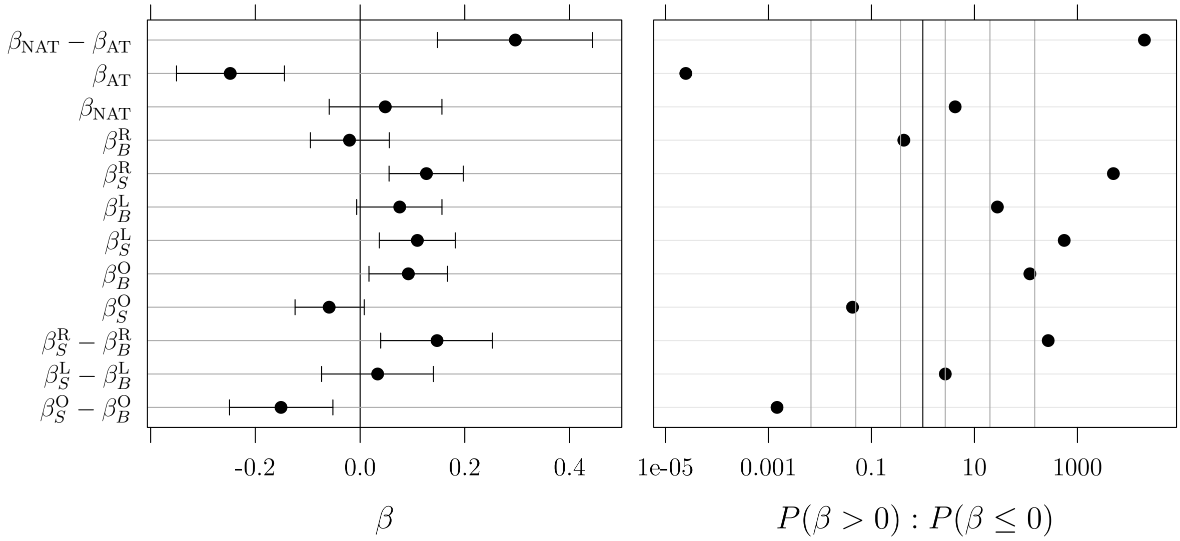
$$\text{vague priors } \beta_{\dots} \sim N(0, 10^2) \qquad (3)$$

$$\tau_{\dots} \sim \Gamma(m_{\dots}^2/s_{\dots}^2, m_{\dots}/s_{\dots}^2) \text{ with } m_{\dots} \sim \mathrm{Exp}(1), s_{\dots} \sim \mathrm{Exp}(1) \qquad (4)$$

We use JAGS to estimate the posterior distribution of coefficients for Equation (1). Results are based on 4 independent chains. We discard 5000 samples for adaptation and burnin and use 10000 samples for each of the 4 chains. Results are shown in Figure 5. Detailed results are given in Appendix A.8.

We find a clear difference between the two treatments. In particular, we find the posterior odds of $\beta_{\mathrm{NAT}} > \beta_{\mathrm{AT}}$ to be 20000:1. 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 strong (or even very strong) evidence that a



The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) odds for coefficients $\beta > 0$ (right).

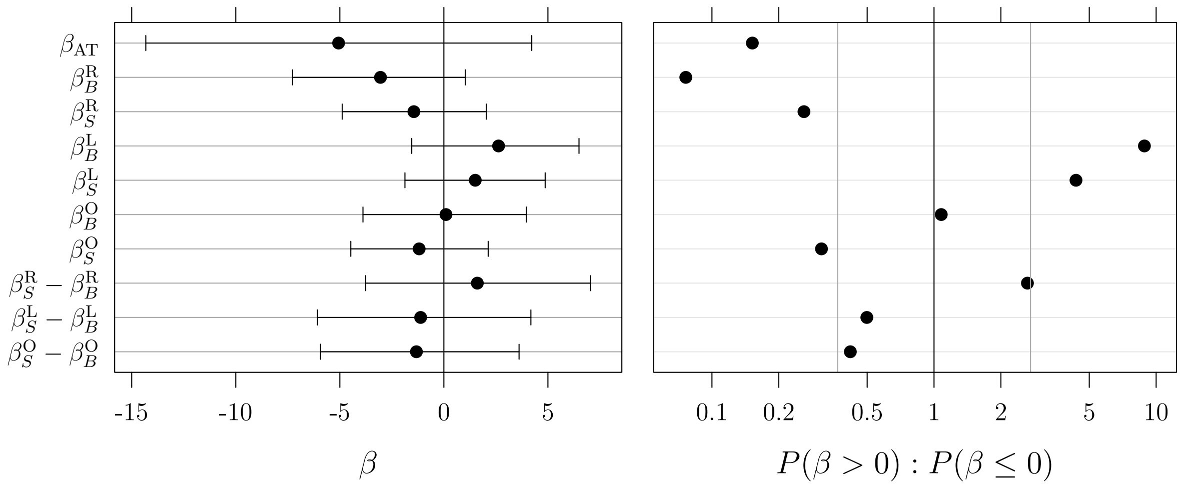
Figure 5: Estimation results for Equation (1), $P_{ikt} - P_t^{\text{F}}$.

seller's risk preference, seller's and buyer's loss aversion, buyer's overconfidence and seller's lack of overconfidence all contribute to bubbles.

Changes of prices We call $|\Delta P_{ikt}|$ the absolute amount of the change in prices from one trade to the next. We estimate the following equation:

$$|\Delta P_{ikt}| = \beta_0 + \beta_{\text{AT}} d_{\text{AT}} + \beta_B^{\text{R}} R_{B_{ik}} + \beta_S^{\text{R}} R_{S_{ik}} + \beta_B^{\text{L}} L_{B_{ik}} + \beta_S^{\text{L}} L_{S_{ik}} + \beta_B^{\text{O}} O_{B_{ik}} + \beta_S^{\text{O}} O_{S_{ik}} + \epsilon_k^G + \epsilon_{S_{ik}}^S + \epsilon_{B_{ik}}^B + \epsilon_{ikt}^U \tag{5}$$

Random effects and priors are as in Equations (2), (3) and (4). The middle panel in Figure 4 suggests that changes of prices from one trade to the next seem to be smaller in the algorithmic trader treatment. Figure 6 shows estimation results. Detailed results are given in Appendix A.9. We find the posterior odds for $\beta_{\text{AT}} > 0$ to be 1:6.58, 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.



The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) odds for coefficients $\beta > 0$ (right).

Figure 6: Estimation results for Equation (5), ΔP_{ikt}.

Time between trades We call Δt_{ikt} the time between trades and estimate the following equation:

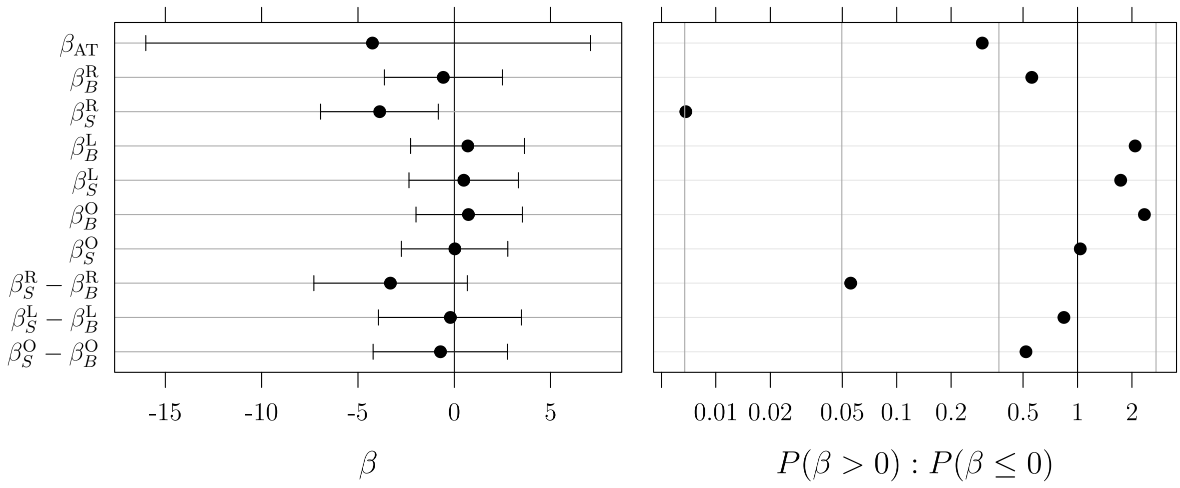
$$\begin{aligned}\Delta t_{ikt} = \beta_0 + \beta_{\mathrm{AT}} d_{\mathrm{AT}} + \beta_B^{\mathrm{R}} R_{B_{ik}} + \beta_S^{\mathrm{R}} R_{S_{ik}} + \beta_B^{\mathrm{L}} L_{B_{ik}} + \beta_S^{\mathrm{L}} L_{S_{ik}} + \\ \beta_B^{\mathrm{O}} O_{B_{ik}} + \beta_S^{\mathrm{O}} O_{S_{ik}} + \epsilon_k^G + \epsilon_{S_{ik}}^S + \epsilon_{B_{ik}}^B + \epsilon_{ikt}^U \end{aligned} \tag{6}$$

Random effects and priors are as in Equations (2, (3) and (4).

The right panel in Figure 4 shows that participants seem to trade more quickly in the no-algorithmic trader treatment. Figure 7 shows estimation results. Detailed results are given in Appendix A.10. We estimate the posterior odds of $\beta_{\mathrm{AT}} > 0$ to be 1:3.36, i.e. we have positive evidence that information about algorithmic traders increases the frequency of trades.

6. Discussion

In our experiment we study how the expected presence of algorithmic traders affects the trading activity of human traders on asset markets. We use a design where we can disentangle the direct effect algorithmic traders have in the market from the indirect



The graphs show 95%-credible intervals for the coefficients (left), and (on a log scale) odds for coefficients $\beta > 0$ (right).

Figure 7: Estimation results for Equation (6), Δt_{ikt}.

effect algorithmic traders have through the expectations of human market participants. We measure deviations from the fundamental value, speed of trading and volatility of prices.

We find that bubbles are smaller and subjects are selling and buying assets closer to the fundamental value when they expect human traders and algorithmic traders to participate in the market compared to markets where they only expect human traders to participate. This is in line with Gsell (2008) who finds (with the help of simulations) that price discovery is quicker in markets with algorithmic traders than without. While Gsell (2008) concludes that differences between the two markets are due to active participation of algorithmic traders we find qualitatively the same even without active participation of algorithmic traders on the market, but by simply manipulating the expectations of human traders. In line with Gsell (2008) we find that volatility of prices is reduced by algorithmic traders. The speed of trading also increases when algorithmic traders are present.

We also control for individual risk aversion, loss aversion and overconfidence but find no systematic effect there.

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, e.g., be less excited when they expect algorithmic traders to participate. The resulting difference in behaviour would then be independent of different expectations about the behaviour 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. As a result the humans would change their trading behaviour.

What exactly is the reason for bubbles in real world asset markets is still discussed among economists. Our results suggest that whatever humans contribute to the formation of bubbles in human-only markets is contributed less so in hybrid markets. This need not suggest that hybrid markets in general must 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 results we present have to be interpreted with the usual precautions when translating findings from the laboratory into real world policies. Our results suggest that in order to reduce bubbles in hybrid markets one should emphasize towards human traders that they are sharing the market with algorithmic traders. The mere awareness of algorithmic traders seems to reduce the human tendency to create bubbles. Also for the legislator it might be relevant to take into account the positive externality algorithmic traders have on the formation of prices in hybrid markets.

Our results can also be seen as a stimulant for those studying human behavior. In the modern world many situations which were previously characterized by human-human interaction change to situations with human-robot interaction. In order to keep laboratory results externally valid one has to reproduce this new characteristic in the lab or at least has to be aware of the fact that behaviour in a human-human context might be different from behaviour in a human-robot world.

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A. Appendix

A.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. Preprocessing for Wordle

The following steps were taken to aggregate and stadandardize the response that subjects gave to the questions in A.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 synonymes 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).

A.3. Wordle

In Figure 1 above we show 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 following version in the experiment:

A.4. Risk

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

Choice A	choice B
1800 ECU with $\frac{1}{10}$, 1440 ECU with $\frac{9}{10}$	3465 ECU with $\frac{1}{10}$, 90 ECU with $\frac{9}{10}$
1800 ECU with $\frac{2}{10}$, 1440 ECU with $\frac{8}{10}$	3465 ECU with $\frac{2}{10}$, 90 ECU with $\frac{8}{10}$
1800 ECU with $\frac{3}{10}$, 1440 ECU with $\frac{7}{10}$	3465 ECU with $\frac{3}{10}$, 90 ECU with $\frac{7}{10}$
1800 ECU with $\frac{4}{10}$, 1440 ECU with $\frac{6}{10}$	3465 ECU with $\frac{4}{10}$, 90 ECU with $\frac{6}{10}$
1800 ECU with $\frac{5}{10}$, 1440 ECU with $\frac{5}{10}$	3465 ECU with $\frac{5}{10}$, 90 ECU with $\frac{5}{10}$
1800 ECU with $\frac{6}{10}$, 1440 ECU with $\frac{4}{10}$	3465 ECU with $\frac{6}{10}$, 90 ECU with $\frac{4}{10}$
1800 ECU with $\frac{7}{10}$, 1440 ECU with $\frac{3}{10}$	3465 ECU with $\frac{7}{10}$, 90 ECU with $\frac{3}{10}$
1800 ECU with $\frac{8}{10}$, 1440 ECU with $\frac{2}{10}$	3465 ECU with $\frac{8}{10}$, 90 ECU with $\frac{2}{10}$
1800 ECU with $\frac{9}{10}$, 1440 ECU with $\frac{1}{10}$	3465 ECU with $\frac{9}{10}$, 90 ECU with $\frac{1}{10}$
1800 ECU with $\frac{10}{10}$, 1440 ECU with $\frac{0}{10}$	3465 ECU with $\frac{10}{10}$, 90 ECU with $\frac{0}{10}$

A.5. Loss aversion

As in for risk aversion we use the relative frequency of B-choices as a measure for loss aversion.

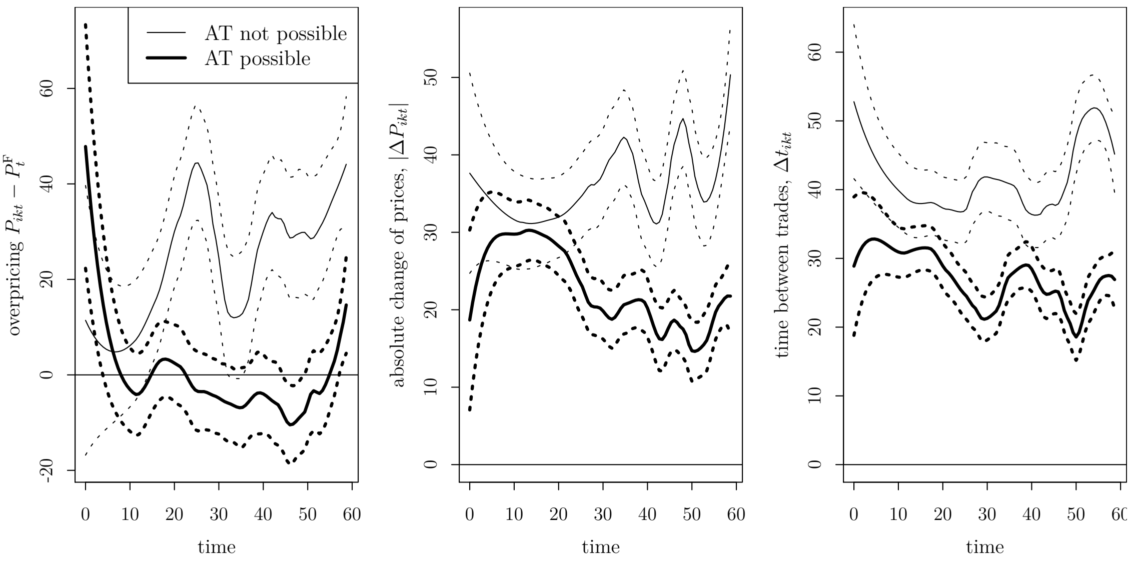
Choice A	choice B
with equal probability lose 570 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 855 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 1140 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 1425 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 1710 ECU and gain 1710 ECU	2000 ECU for sure
with equal probability lose 1995 ECU and gain 1710 ECU	2000 ECU for sure

A.6. Trading interface

Subjects would use the following interface for trading in the continuous double auction in the experiment:

A.7. Periodic behaviour within each round

In our experiment the fundamental value remains constant for 60 seconds and then drops by a fixed amount. This pattern repeats 15 times during the 900 seconds of the experiment. Here we check whether we can see a pattern in overpricing, time between trades and the absolute change of prices.



A.8. Estimation results for Equation (1) — bubbles

The following tables show the median of the estimated β, a 95%-credible interval, the odds that $\beta > 0$, the effective sample size (sseff) and the potential scale reduction factor (psrf).

	median	CI_{95}	odds($\beta > 0$)	sseff	psrf
$\beta_{NAT} - \beta_{AT}$	0.297	[0.148,0.444]	20000:1	20430	1.0000
β_{AT}	-0.248	[-0.351,-0.144]	1:40000	20674	1.0001
β_{NAT}	0.048	[-0.0591,0.156]	4.23:1	18276	1.0000
β_B^R	-0.020	[-0.0948,0.0558]	1:2.34	20155	1.0001
β_S^R	0.127	[0.0553,0.197]	5000:1	20440	1.0002
β_B^L	0.076	[-0.00636,0.156]	28:1	17104	1.0001
β_S^L	0.109	[0.0367,0.182]	555:1	17834	1.0002
β_B^O	0.092	[0.017,0.167]	119:1	21425	1.0001
β_S^O	-0.059	[-0.124,0.00783]	1:23.2	21032	1.0001
$\beta_S^R - \beta_B^R$	0.147	[0.0395,0.253]	271:1	19921	1.0001
$\beta_S^L - \beta_B^L$	0.034	[-0.0734,0.14]	2.73:1	17926	1.0001
$\beta_S^O - \beta_B^O$	-0.151	[-0.249,-0.0519]	1:677	19842	1.0002

	median	CI_{95}	sseff	psrf
σ_U	63.050	[60,66.3]	18206	1.0001
σ_G	42.083	[28.9,61.8]	6153	1.0004
σ_S	27.321	[20.1,35.6]	3370	1.0007
σ_B	29.661	[21.9,38.3]	3327	1.0003

A.9. Estimation results for Equation (5) — changes of prices

	median	CI_{95}	odds($\beta > 0$)	sseff	psrf
β_{AT}	-5.060	[-14.3,4.22]	1:6.58	4142	1.0025
β_B^R	-3.046	[-7.27,1.03]	1:13.1	9631	1.0056
β_S^R	-1.442	[-4.88,2.04]	1:3.85	19283	1.0007
β_B^L	2.628	[-1.54,6.49]	8.86:1	13020	1.0037
β_S^L	1.508	[-1.87,4.87]	4.36:1	14187	1.0024
β_B^O	0.100	[-3.89,3.96]	1.08:1	5529	1.0083
β_S^O	-1.188	[-4.47,2.13]	1:3.21	15841	1.0002
$\beta_S^R - \beta_B^R$	1.607	[-3.76,7.06]	2.63:1	14722	1.0022
$\beta_S^L - \beta_B^L$	-1.117	[-6.07,4.18]	1:2.01	10860	1.0053
$\beta_S^O - \beta_B^O$	-1.320	[-5.93,3.61]	1:2.38	9466	1.0056

	median	CI_{95}	sseff	psrf
σ_U	45.923	[43.5,48.4]	1947	1.0306
σ_G	5.405	[0.535,13.8]	347	1.0536
σ_S	1.358	[0.451,11.7]	88	1.0400
σ_B	10.437	[0.611,18.4]	305	1.2267

A.10. Estimation results for Equation (6) — time between trades

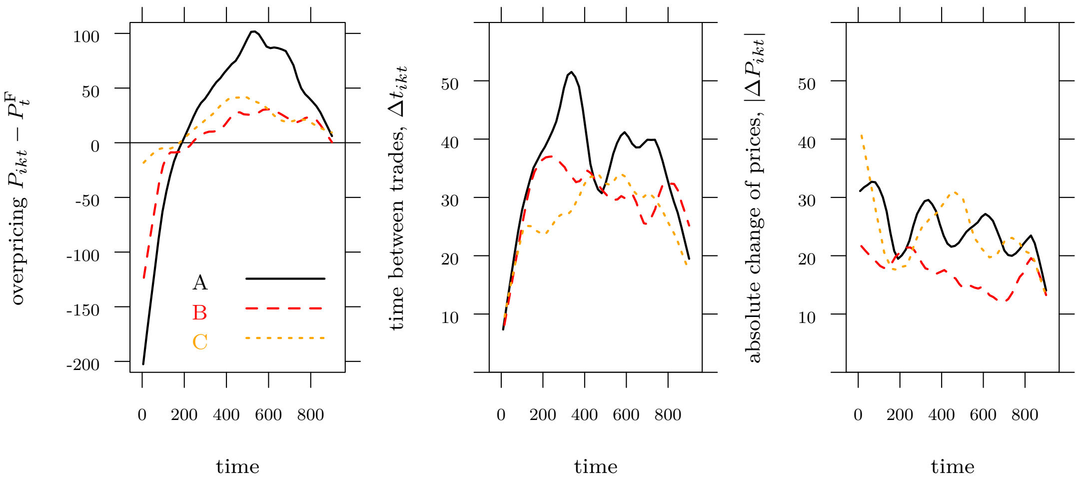
	median	CI_{95}	odds($\beta > 0$)	sseff	psrf
β_{AT}	-4.247	[-16,7.09]	1:3.36	1770	1.0034
β_B^{R}	-0.568	[-3.62,2.51]	1:1.79	17531	1.0001
β_S^{R}	-3.871	[-6.94,-0.832]	1:147	17314	1.0001
β_B^{L}	0.705	[-2.26,3.65]	2.08:1	18541	1.0000
β_S^{L}	0.496	[-2.35,3.33]	1.73:1	21318	1.0002
β_B^{O}	0.739	[-1.99,3.53]	2.34:1	24663	1.0003
β_S^{O}	0.032	[-2.75,2.78]	1.04:1	25442	1.0002
$\beta_S^{\mathrm{R}} - \beta_B^{\mathrm{R}}$	-3.314	[-7.29,0.674]	1:18	26617	1.0001
$\beta_S^{\mathrm{L}} - \beta_B^{\mathrm{L}}$	-0.199	[-3.93,3.49]	1:1.19	28005	1.0000
$\beta_S^{\mathrm{O}} - \beta_B^{\mathrm{O}}$	-0.714	[-4.22,2.77]	1:1.93	34705	1.0001

	median	CI_{95}	sseff	psrf
σ_U	39.005	[37.3,40.9]	14518	1.0011
σ_G	12.107	[7.64,18.5]	7316	1.0007
σ_S	1.070	[0.434,8.88]	114	1.0319
σ_B	1.011	[0.441,3.69]	190	1.0265

A.11. 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 treatment 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.


overpricing $P_{ikt} - P_t^{\mathrm{F}}$
time between trades, Δt_{ikt}
absolute change of prices, $|\Delta P_{ikt}|$
A
B
C
time
time
time