

Bubbles in hybrid markets

How expectations about algorithmic trading affect human trading

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

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1. Introduction

Experimental research on assets markets began in the mid 20th century and the experimental designs used in this field have 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, traders nowadays 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 on the market, but 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 do not get information

*We use R version 3.1.1 (2014-07-10) for the statistical analysis and figures in this paper.

on 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 between hybrid and human-only markets are substantial and 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 in their totality 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 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 result only from changes in human behaviour and without any active participation of algorithmic traders in hybrid markets.

One reason for a change in behaviour of human traders might be a change in expectations. Cheung, Hedegaard, and Palan (2014) explain bubbles in asset markets with the expectation that other market participants are less rational. Expecting more rationality in hybrid markets could discipline human traders and could be a cause for 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 engage less in trading because there are fewer opportunities to benefit from the irrationality of others? Or do human traders trade more on hybrid markets 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 exact properties of 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 stage we aggregate the intuition subjects have about algorithmic traders. We use this information as a stimulus to control expectations of participants in a second stage where 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 experiment's 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 an asset pays per round and the number of rounds. Hence, subjects could work out the fundamental value of an asset in SSW markets.

Assuming that subjects are rational and risk neutral one would expect no trade in these markets. Assets should be bought (and hence sold) only at the fundamental value and since supply and demand of assets is generated only by subjects, no transactions should take place. 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 assets starts below the fundamental value, but then quickly exceeds it (often even 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, 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 told that the other market participants were asked the same control questions, subjects in the other group are not told that all other participants got the same questions. Cheung, Hedegaard, and Palan (2014) find that markets in which subjects got 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 market. They follow an approach used by Holt and Laury (2002) (which we will also use) to measure risk aversion. Keller and Siegrist (2006) did a mail survey and found 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. It seems that the method to measure “overconfidence” matters. Moore and Healy (2008) and Hilton et al. (2011) describe different ways to measure overconfidence. 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. Hence, we chose to operationalize overconfidence specifically in the context of asset market (see section 3.5).

2.2. Human computer interaction

Since a hybrid market is characterized by human computer interaction some general (non economic) literature on human computer interaction will be covered 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) and Breaban and Noussair (2013) find that market bubbles increase in magnitude and amplitude when subjects are aroused or excited (induced by short videos before the SSW market). 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 when they know that they interact with computers than when knowing their counterpart is human. 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 game (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 explicitly state that it would be senseless to behave in a reciprocal or polite way towards computers. However, in behavioral terms they do so. 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

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 simulations of hybrid markets than in simulations of 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 algorithmic traders lead to a lower volatility of prices and that price discovery is quicker in hybrid markets.

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

While Grossklags and C. Schmidt (2006) compare two groups which obtain rather diverse information (one group is not informed at all while the other gets the full picture), we give participants in the two treatments exactly the same information, except for one small (but crucial) bit: Are algorithmic traders possible or are they not? All remaining information, in particular information about the concept of algorithmic traders in general, are kept constant. Grossklags and C. Schmidt (2006) 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.

Also different from Grossklags and C. Schmidt (2006) we cleanly and explicitly control the information given to participants. In our experiment subjects know about the different types of markets and about the information they would obtain in the different treatments. In contrast, Grossklags and C. Schmidt (2006) compare the behaviour of subjects who know that they are facing algorithmic traders with those who are ignorant about this feature of the experiment.

The wordle was shown to all (new) subjects in the subsequent stages of the experiment before they were informed about their treatment condition. Furthermore, subjects were told how the wordle was created and they were told that the algorithmic trader was programmed according to the wordle.

Providing information about the character of algorithmic traders in this way has two advantages: 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 and by writing the algorithm that generated the wordle we still may 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.

3.3. Treatments

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

treatment	type of market	information
A	only human traders	A
B	only human traders	B or C
C	hybrid	B or C

Table 1: Treatments

They 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 in 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.

3.4. Payoff

The markets and other tasks are designed such that the average earnings of subjects was 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.

3.5. Risk preference and overconfidence

To measure risk aversion of subjects we use the multiple price list method by Holt and Laury (2002).² In this tasks subjects choose between a lottery with high variance of payoffs (Option B) and lottery with less variance (Option A). As in Holt and Laury (2002) we use the relative frequency of B-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 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.

4. Descriptives

4.1. Subjects

Our dataset contains data from 72 subjects per treatment. These 72 subjects were nested within groups/markets of 6 subjects each, so there were 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 in general differs between genders, we chose to recrute 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.

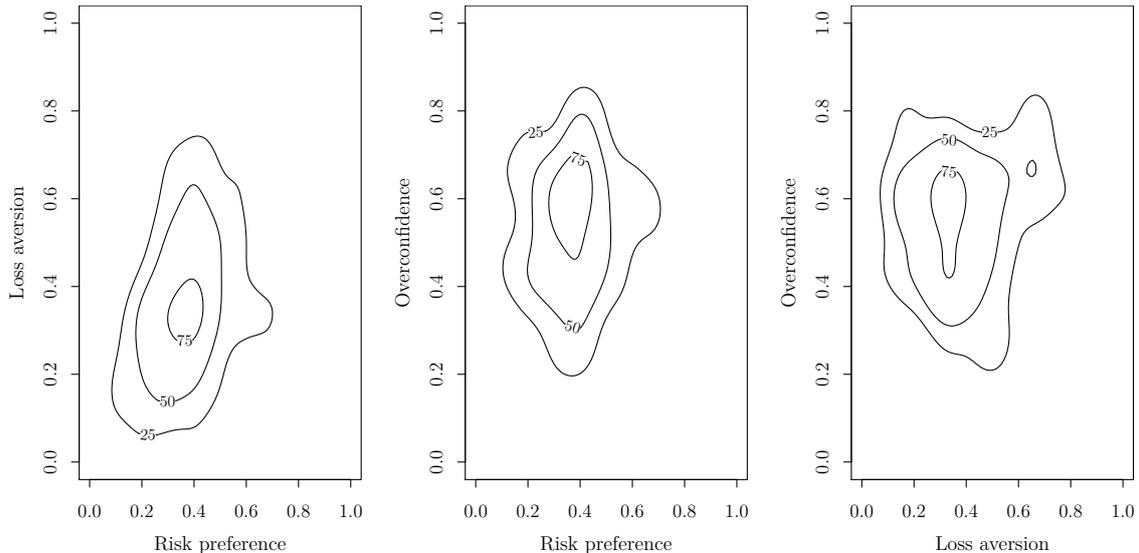
4.2. Questionnaire and additional measurements

After the two trading periods subjects were asked to fill in a questionnaire. When subjects have been trading in treatment B (see Table 1) they were asked: "Do you think that an algorithmic trader was active in the market?". Possible answers were “yes” and “no”. Although there was no algorithmic trader active in that treatment, 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 therefore conclude that our manipulation (eliciting uncertainty about participation of an algorithmic trader) worked.

Since attitude towards risk and overconfidence are two prominent explanations for bubbles in SSW markets (section 2.1), we measured these two traits of subjects before they 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

²The list can be found in Appendix A.4.

³The 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

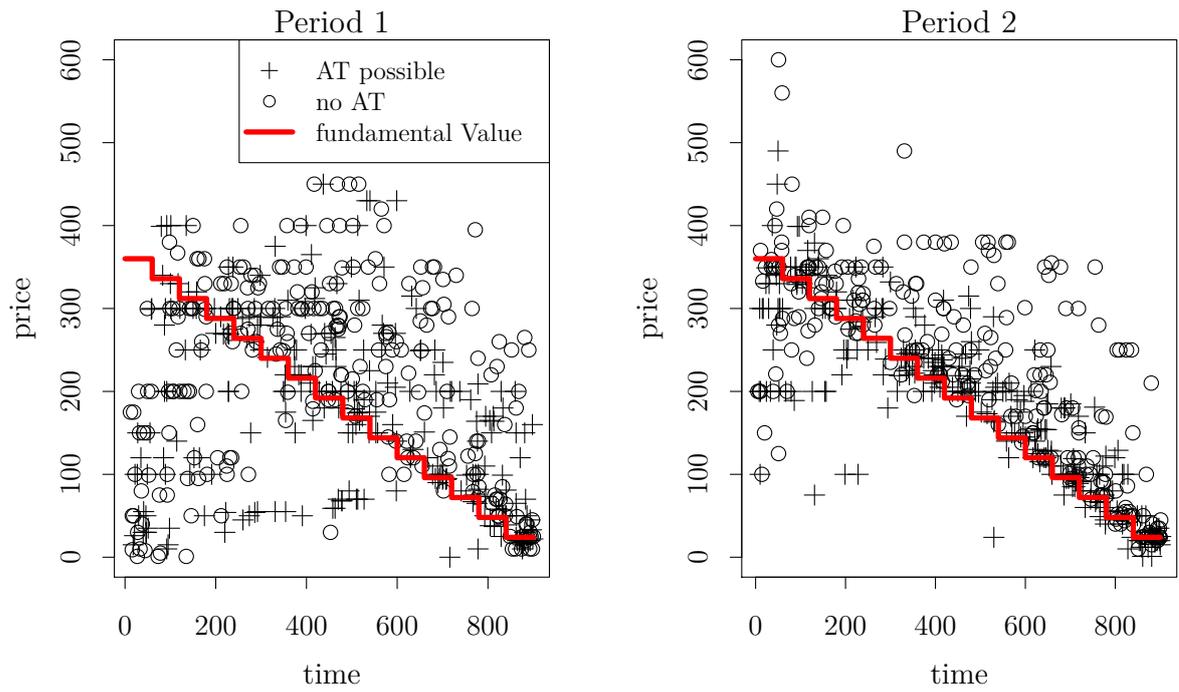
also find a moderate amount of overconfidence. 62.5% of all subjects expect to be better or equal to the average. This is in line with the standard effect (Hoorens, 1993). As we see in Figure 2, the three properties seem to be rather independent of each other. We will, hence, use them all as controls in our estimations below.

4.2.1. Trades

Figure 3 gives a first impression how individual prices develop over time. As expected, pricing of assets follows the bubble and crash pattern known from SSW. Figure 4 shows how aggregated trades develop over time. We denote the fundamental value with P_F and the actual trade i in group k with P_{ik} . The left panel in Figure 4 shows the development of $P_{ik} - P_F$ over the time of the experiment. The solid black lines show 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 \pm one standard deviation.⁴ It seems that the price is generally closer to the fundamental value in the treatment in which subjects could not rule out that algorithmic traders are trading in the market.

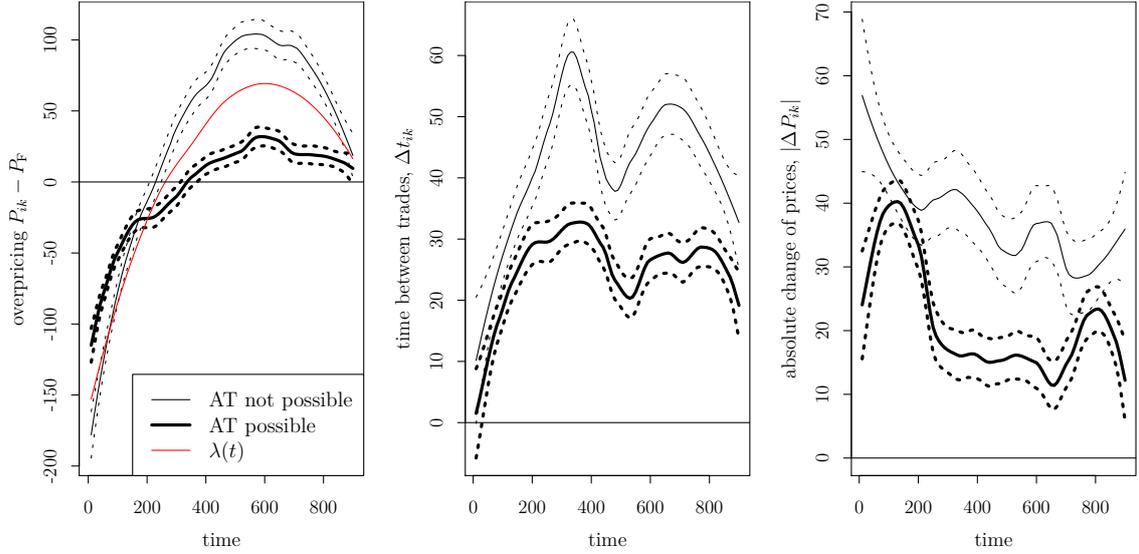
In Appendix A.7 we provide similar graphs but now for periodic behaviour within one round of a market. Our interpretation of these graphs is that, apart from the pattern already visible in Figure 4, there is no special difference in the periodic structure.

⁴The 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.



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

Figure 3: Prices over time



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

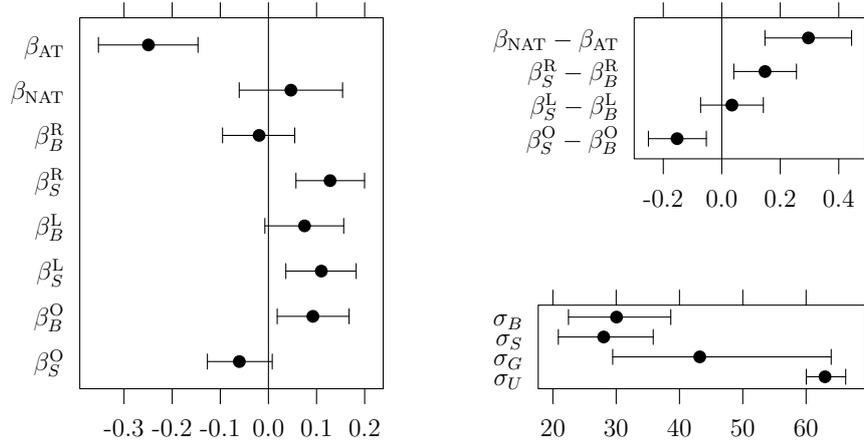
Figure 4: Trading behaviour over all rounds of one market

5. Results

Estimation strategy To take into account the nested structure of the data we use mixed effects models for analysis. We will look at 3 different dependent variables. The first is the mispricing of assets during trading $P_{ik} - P_F$. More specifically, we estimate whether the extent of the mispricing $\lambda(t)$ shown red in Figure 4 depends on the treatment. Next we look at the time in seconds between individual trades Δt_{ik} as an indicator for speed of trading. Finally we look at the absolute change of prices $|\Delta P_{ik}|$ as an indicator for volatility. 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, the seller and the group of traders of that round.

Here, d_{NAT} is a dummy which is one if participants are informed algorithmic traders will not participate on the market and zero otherwise. d_{AT} is a dummy which is one if participants are informed that algorithmic traders may participate on the market and zero otherwise. ϵ_G is a random effect for the matching group, ϵ_S is a random effect for the seller, ϵ_B is a random effect for the buyer. These random effects, the residual, and the coefficients β_0, β_1 are taken from a vague prior given by (2).

Bubbles We assume that the distribution of the difference of actual prices and the fundamental value, $P_{ik} - P_F$, 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



The graphs show 95%-credible intervals for the coefficients, for their differences, and for the standard deviations.

Figure 5: Estimation results for Equation (1), $P_{ik} - P_F$.

to participants, with the smoothing parameter α set to the default (Cleveland, Grosse, and Shyu, 1992).

$$P_{ik} - P_F \sim N(\mu_{ik}, \sigma_U)$$

$$\text{with } \mu_{ik} = \beta_0 + (1 + \beta_{\text{NAT}}d_{\text{NAT}} + \beta_{\text{AT}}d_{\text{AT}} + \beta_B^R R_{B_{ik}} + \beta_S^R R_{S_{ik}} + \beta_B^L L_{B_{ik}} + \beta_S^L L_{S_{ik}} + \beta_B^O O_{B_{ik}} + \beta_S^O O_{S_{ik}}) \cdot \lambda(t) + \epsilon_G + \epsilon_S + \epsilon_B \quad (1)$$

$$\text{with priors } \beta_0, \beta_1, \beta_2 \sim N(0, 100) \text{ and } \sigma_G, \sigma_S, \sigma_B, \sigma_U \sim \Gamma(1, 0.01) \quad (2)$$

We use JAGS to estimate the posterior distribution of coefficients for Equation (2). Initial values for JAGS are based on bootstraps of a mixed effects model (`lme4`). Results are averages of 4 independent chains. We discard 5000 samples for adaptation and burnin and use 10000 samples for each of the 4 chains. Results are given in Figure 5.

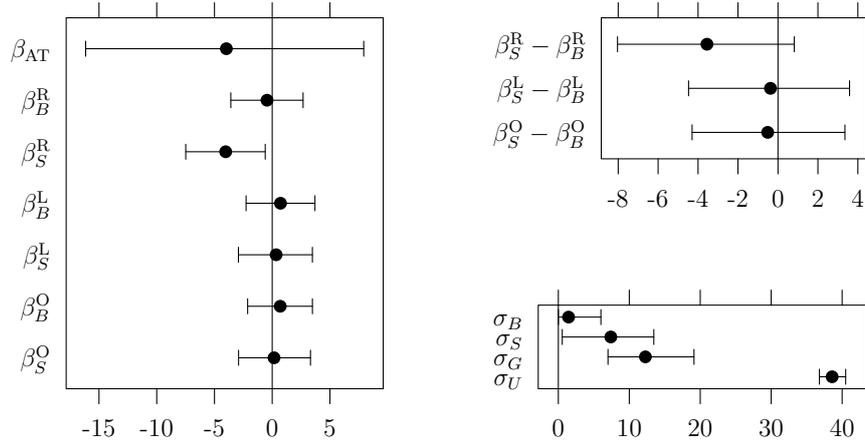
We find a clear difference between the two treatments. The 95% credible interval for the difference $\beta_{\text{NAT}} - \beta_{\text{AT}}$ is [0.15, 0.44]. Among our 40000 samples of the posterior we had $\beta_{\text{NAT}} > \beta_{\text{AT}}$ in 100% of all cases. We can, thus, be very sure that information about algorithmic traders reduce bubbles.

Time between trades

$$\Delta t_{ik} \sim N(\mu_{ik}, \sigma_U)$$

$$\text{with } \mu_{ik} = \beta_0 + \beta_{\text{AT}}d_{\text{AT}} + \beta_B^R R_{B_{ik}} + \beta_S^R R_{S_{ik}} + \beta_B^L L_{B_{ik}} + \beta_S^L L_{S_{ik}} + \beta_B^O O_{B_{ik}} + \beta_S^O O_{S_{ik}} + \epsilon_G + \epsilon_S + \epsilon_B \quad (3)$$

$$\text{with priors } \beta_0, \beta_1 \sim N(0, 100) \text{ and } \sigma_G, \sigma_S, \sigma_B, \sigma_U \sim \Gamma(1, 0.01) \quad (4)$$



The graphs show 95%-credible intervals for the coefficients, for their differences, and for the standard deviations.

Figure 6: Estimation results for Equation (3), Δt_{ik} .

The middle panel in Figure 4 shows already that participants trade more quickly in the no-algorithmic trader treatment. Figure 6 shows estimation results. The credible interval for β_{AT} is $[-16.16, 7.92]$. In our posterior estimate for β_{AT} we had $\beta_{AT} > 0$ in 25% and $\beta_{AT} \leq 0$ in 75% of all cases, i.e. we do not seem to see a clear effect of information about algorithmic traders on the frequency of trades.

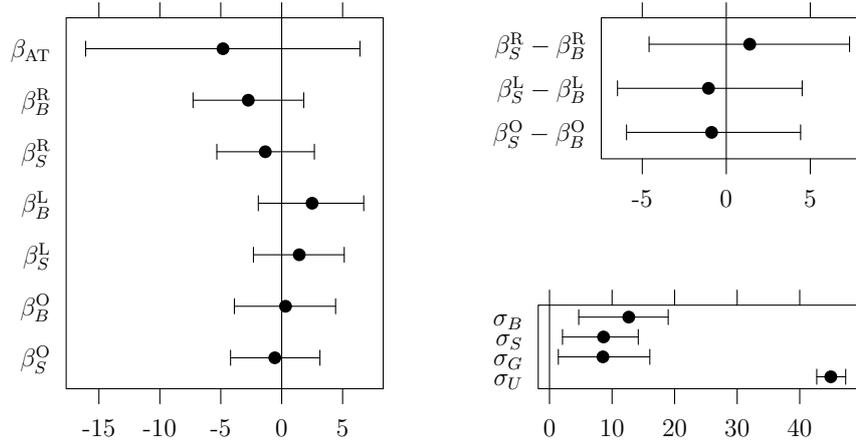
Changes of prices

$$|\Delta P_{ik}| \sim N(\mu_{ik}, \sigma_U)$$

$$\text{with } \mu_{ik} = \beta_0 + \beta_{AT}d_{AT} + \beta_B^R R_{B_{ik}} + \beta_S^R R_{S_{ik}} + \beta_B^L L_{B_{ik}} + \beta_S^L L_{S_{ik}} + \beta_B^O O_{B_{ik}} + \beta_S^O O_{S_{ik}} + \epsilon_G + \epsilon_S + \epsilon_B \quad (5)$$

$$\text{with priors } \beta_0, \beta_1 \sim N(0, 100) \text{ and } \sigma_G, \sigma_S, \sigma_B, \sigma_U \sim \Gamma(1, 0.01) \quad (6)$$

The right panel in Figure 4 shows that changes of prices from one trade to the next are smaller in the algorithmic trader treatment. Figure 7 shows estimation results. The credible interval for β_{AT} is $[-16.09, 6.42]$. In our posterior estimate for β_{AT} we had $\beta_{AT} > 0$ in 18.8% and $\beta_{AT} \leq 0$ in 81.2% of all cases, i.e. we do not seem to see a clear effect of information about algorithmic traders on the magnitude of changes of prices from one trade to the next.



The graphs show 95%-credible intervals for the coefficients, for their differences, and for the standard deviations.

Figure 7: Estimation results for Equation (5), ΔP_{ik} .

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

We found that bubbles are smaller and subjects are selling and buying assets closer to the fundamental value when they expected human traders and algorithmic traders to participate on the market compared to markets where they only expected human traders to participate. This is in line with Gsell (2008) who finds (through simulation) that price discovery is quicker in markets with algorithmic trader than without. While Gsell (2008) claims that the differences between the two markets are due to active participation of algorithmic traders we find qualitatively the same results without active participation of algorithmic traders on the market, but by simply manipulating the expectations of human traders. Different to Gsell (2008) we find that the volatility of prices does not seem to be affected substantially by algorithmic traders. The speed of trading between also did not differ between treatments.

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. One possible mechanism is that human traders are less excited when they expect algorithmic traders to participate and hence trade differently (see 2.2). An alternative mechanism may be that humans expect algorithmic traders to be more rational than human traders

and that this makes human traders trade differently (see 2.1).

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

What exactly is driving bubble formation in real world asset markets is still discussed among economists. Our results suggest that whatever humans contribute to bubble formation in human-only markets is less 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.

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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

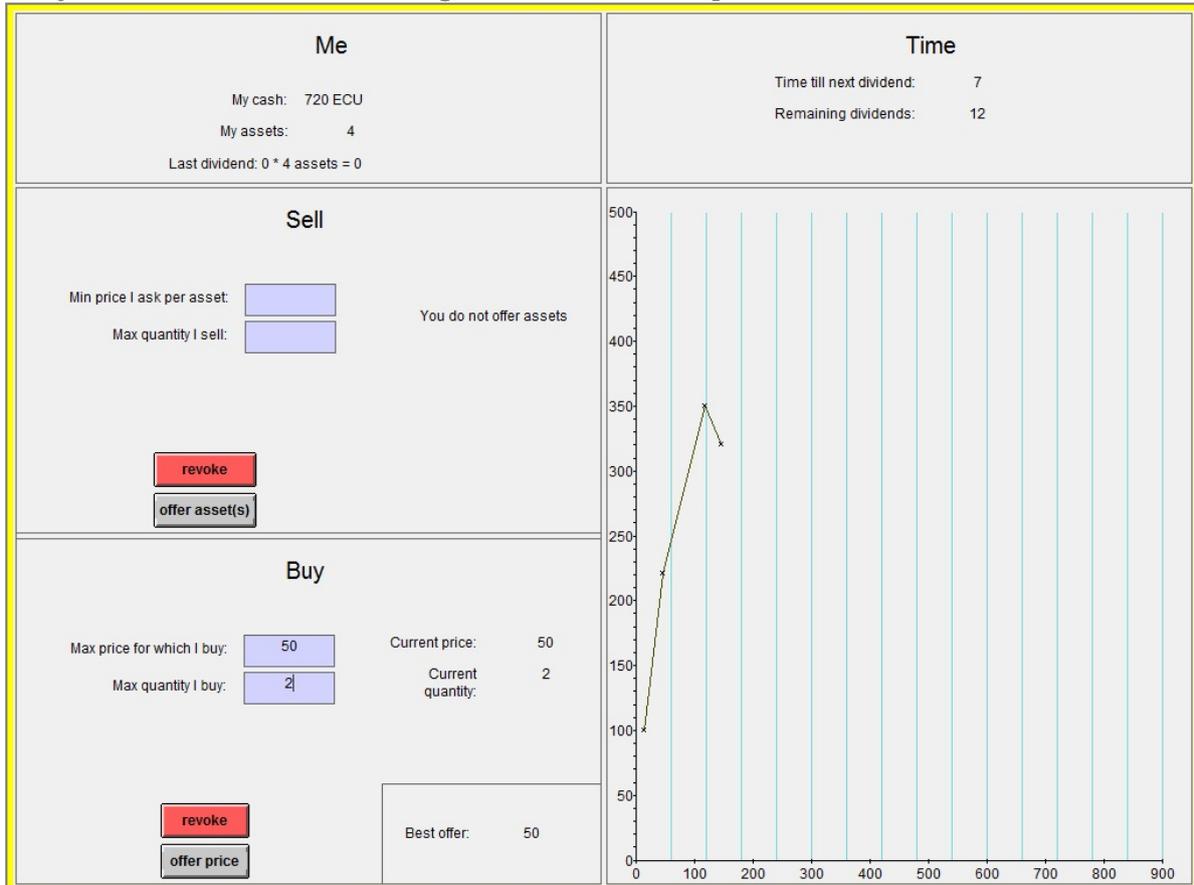
The following steps were taken to aggregate and standardize the response that subjects gave to the questions in A.1

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 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 word: drop words with $\text{freq} < 2$.
6. Input remaining words into <http://www.wordle.net/create>.

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 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.

