Experience Does not Eliminate Bubbles: Experimental Evidence*

Anita Kopányi-Peuker† Matthias Weber‡

August 17, 2020

Abstract

We study the role of experience in the formation of asset price bubbles. Therefore, we conduct a call market experiment in which participants trade assets with each other and a learning-to-forecast experiment in which participants only forecast future prices (while trade based on these forecasts is computerized). Each experiment comprises three treatments varying the information that participants receive about the fundamental value. Each market is repeated three times. Throughout, we observe sizable bubbles that do not disappear with experience. Our findings in the call market experiment stand in contrast to the literature. Our findings in the learning-to-forecast experiment are novel.

JEL classification: G40, G41, C92, D90.

*Thanks for comments and suggestions go to Lauren Cohen (the editor), two anonymous reviewers, Martin Brown, Olimpia Carradori, Cars Hommes, Jürgen Huber, Immanuel Lampe, Tibor Neugebauer, Mikael Paaso, Joep Sonnemans, Grigory Vilkov, participants of the European Economic Science Association Meetings in Dijon, the 34th Annual Congress of the European Economic Association in Manchester, the 2nd Baltic Economic Conference in Riga, the Prague Conference on Behavioral Sciences, the Research in Behavioral Finance Conference in Amsterdam, the Experimental Finance Conference in Heidelberg, the BEAM-ABEE Workshop in Amsterdam, and seminar participants at the University of Amsterdam and the Bank of Lithuania. Parts of the research were conducted while Weber was at the Bank of Lithuania. Financial support from the H2020 grant of the IBSEN project ("Bridging the gap: from Individual Behavior to the Socio-Technical Man", grant number: 662725), from University of St. Gallen GFF Project Funding, and from the Bank of Lithuania are gratefully acknowledged.

†CPB Netherlands Bureau for Economic Policy Analysis & Amsterdam School of Economics, University of Amsterdam. Email: a.g.kopanyi-peuker@uva.nl.

‡School of Finance, University of St. Gallen. Postal address: Swiss Institute of Banking and Finance (University of St. Gallen), Unterer Graben 21, 9000 St. Gallen, Switzerland. Email: matthias.weber@unisg.ch.

Experimental investigations of asset markets have improved our knowledge on the workings and the efficiency of financial markets substantially. One finding that reappears regularly is that prices rise substantially above fundamental values when participants first take part in an experimental asset market, but that such large price deviations are no longer observed after the same market is repeated multiple times. In short: bubbles disappear with experience.

Whether or not bubbles disappear with experience is relevant in a variety of ways outside the laboratory. If bubbles are indeed a phenomenon of inexperienced investors only, authorities responsible for financial stability should not be too concerned about price movements in markets with mainly professional investors, such as the stock market (as these investors would price the assets generally well). Markets with many inexperienced investors, for example markets of so-called cryptocurrencies, may then be fundamentally different and still prone to bubbles. Similarly, if mainly inexperienced traders are prone to mispricing, one may wonder about the effects of policies encouraging non-professional investors to hold more stocks, for example as retirement savings, on price accuracy. Such policies may lead to an inflow of inexperienced traders into the market and thus to more bubble formation. The topic is similarly relevant for consumer protection. If experienced traders are not prone to severe mispricing, financial regulation could be relatively mild regarding those investors, while more protection may be appropriate if severe mispricing does not disappear with experience.

Unfortunately, however, studying the effects of experience on bubble formation with observational data is extremely difficult. It may already prove difficult to obtain data on markets with the necessary individual-level trader characteristics. Even when this information is available, there are a variety of problems. True fundamental values can, for example, not be observed outside the laboratory, and a variety of confounding factors may drive the results as there is no random assignment to treatments. Making sound statements about causality on this topic based on observational data is thus very difficult. The high level of control that the laboratory offers is the main reason that a rich literature on experimental asset markets developed.

In most experimental asset markets, participants trade financial assets with others making use of a continuous double auction or a call market mechanism.[1] The finding that bubbles disappear when identical markets are repeated is very robust in these settings, in which participants trade for a finite number of periods, with usually about 10-20 periods per market (e.g., Smith et al., 1988; King et al., 1993; Van Boening et al., 1993; Dufwenberg et al., 2005; Haruvy et al., 2007; Hussam et al., 2008; the findings can even persist in considerably more difficult variations, e.g., Weber et al., 2018; Füllbrunn et al., 2019). Nevertheless, it is not clear how robust this finding is to changing the whole market environment and how much it hinges on the provision of full information about the fundamental value that is in general given to participants in these settings.

Markets in which participants directly trade assets with one another in the laboratory are not the only type of experimental asset markets. So-called learning-to-forecast experiments have become increasingly important. In such experiments, participants only forecast future prices. The trading, which determines market prices, is carried out by computerized mean-variance maximizers that base their supply and demand decisions on the participants' price forecasts.[2] The advantage of the learning-to-forecast setting is that the forecasting decision is separated from the optimizing decision, so that it is clear that the results on pricing originate from the forecasting behavior. These learning-to-forecast markets

[1]For very early studies, see Smith et al. (1988) and Plott and Sunder (1988). For more recent studies, see Haruvy and Noussair (2006), Bossaerts et al. (2007), Haruvy et al. (2007), Bossaerts et al. (2010), Palan (2010), Cheung and Palan (2012), Kirchler et al. (2012), Sutter et al. (2012), Huber and Kirchler (2012), Cheung et al. (2014), Füllbrunn et al. (2014), Noussair et al. (2016), Holt et al. (2017), Hoshihata et al. (2017), and Bosch-Rosa et al. (2018). Bossaerts (2009), Noussair and Tucker (2013), Palan (2013), and Nuzzo and Morone (2017) review the literature.

[2]For recent contributions using the learning-to-forecast paradigm to analyze financial asset markets, see Hommes et al. (2005), Hommes et al. (2008), Sonnemans and Tuinstra (2010), Hüsler et al. (2013), Bao et al. (2017), Colasante et al. (2017), Colasante et al. (2018), Hennequin (2019), Bao et al. (2020), and Hommes et al. (2020). Learning-to-forecast experiments have also been used in other environments, including goods markets (e.g., Sonnemans et al., 2004, Hommes et al., 2007, Bao et al., 2013) and macroeconomics (e.g., Pfajfar and Žakelj, 2014, Arifovic and Petersen, 2017, Cornand and M'baye, 2018, Hommes et al., 2019). See Hommes (2011) or Assenza et al. (2014) for reviews.

usually have a longer horizon of about 50 periods. Similar to the experiments with trade in the laboratory, sizable price bubbles are regularly observed in such markets. However, it is unclear whether these bubbles disappear with experience as there is no prior literature containing repeated learning-to-forecast asset markets. The study that comes closest to repeating identical markets is that by Hennequin (2019), where participants take part in one round with computerized players (with pre-determined forecasts) before playing one round with humans. In that experiment, bubbles in the round with only human traders are observed when the computer players in the first round submit forecasts very far from the fundamental value, while no bubbles arise in the round with human traders when the computer players submit forecasts close to the fundamental value in the first round.

One of the main goals of this paper is to investigate whether bubbles also disappear with experience in the learning-to-forecast setting, and, if not, understand which difference between the two market paradigms drives this result. Our prediction before designing the experiment was that bubbles do not disappear with experience in the standard learning-to-forecast setting. This prediction is based on the fact that in previous learning-to-forecast markets (which are not repeated markets but markets with many periods) new bubbles often form if a first bubble forms and deflates early in the market. Such consecutive bubbles seem to speed up rather than slow down and prices do not converge to the fundamental value.

If bubbles indeed turn out not to disappear with experience in the learning-to-forecast setting, the question arises what drives this difference between the two market paradigms. Our idea was that the difference lies in the way that information about the fundamental value is provided to participants. In the markets with trade, participants are told directly what the fundamental value in the terminal period (the buyout price) is. In learning-to-forecast markets, participants usually have enough information to calculate this value, but they are not provided with the fundamental value directly.

To investigate the effects of information provision on bubble formation in repeated markets, we design two experiments. One is a learning-to-forecast experiment and one is an experiment with trade in the laboratory, making use of a call market mechanism (we refer to these as the learning-to-forecast experiment and the call market experiment). The designs try to make the experiments as similar as possible, with the possibility of varying the information that participants receive about the fundamental value. Our designs allow us to give no direct information about the fundamental value to participants, some information, or full information. Not giving full information directly to participants seems valuable from the point of view that the direct communication of the fundamental value is something that does in general not exist in markets outside the laboratory (people have to infer the fundamental value from asset characteristics and past history).

In both experiments and all treatments, bubbles do not disappear with experience. This means the finding that bubbles disappear with experience in markets with actual trade in the laboratory is not as robust as previously thought. However, we believe that our findings are nevertheless reassuring for the experimental method: there is no important difference between the two market paradigms in such an important characteristic as whether bubbles keep arising when the experiments are designed to resemble each other.

We also analyze how the general pricing pattern changes over time and how the shapes of bubbles differ between the experiments. We find that pricing only becomes slightly more accurate in the last round of the experiment in the two treatments with information in the call market experiment, while pricing does not improve in the no-information treatment and in all treatments of the learning-to-forecast experiment. Bubbles have different shapes in the two experiments. While bubbles are often relatively flat in the call market experiment, there are clear boom-and-bust cycles in the learning-to-forecast experiment. In both experiments, bubbles appear earlier in later repetitions of the markets.

We provide two variations of a model that can explain the predictions and the data observed in the experiment. The model is based on level-k reasoning (for recent contributions on level-k reasoning, see, e.g., Mauersberger and Nagel, 2018; Hanaki et al., 2019;

Khaw et al., 2019). Level-0 reasoners base their forecasts on trend-extrapolation and some of the agents learn over the course of the experiment. The ex-ante predictions for the experiment arise in the model if level-0 agents slowly incorporate their knowledge about the fundamental value into their forecasts. Behavior similar to that actually observed in the experiment arises if instead agents slowly learn to base their forecasts on higher levels of reasoning.

Our findings in the call market experiment stand in contrast to the literature. In the concluding remarks to the previous version of this paper, we hypothesized that this may be due to the high cash-to-asset ratio in our experiment (it is a well-known finding that a high cash-to-asset ratio facilitates bubble formation in non-repeated markets, as for example discussed in the review article by Palan, 2013). In response to the comments by the reviewers of this journal, we now test this hypothesis with an additional treatment mimicking our call market treatment with full information, in which we use a lower cash-to-asset ratio. We receive much more accurate pricing in that treatment. Note that we consider the high cash-to-asset ratio the more relevant case; considering for instance equity markets, total means are many times greater than total equity market capitalization (bond market capitalization alone is already much larger; e.g., Roxburgh et al., 2011).

1 Experimental Designs

With our design, we attempt to make the two market paradigms as comparable as possible while leaving the underlying principles of these types of experiments untouched.[3] Experiments with trade in the laboratory are usually relatively short compared to the learning-to-forecast ones (around 10-20 periods per round as compared to about 50). We opt for an

[3] Therefore, some of the design choices are compromises between the two market paradigms, such as choosing an intermediate number of periods. If in doubt, we have a slight bias in favor of the standard in learning-to-forecast experiments, as our contribution is the first experiment with repetition within this paradigm.

intermediate number, so that we have, on the one hand, a sufficient number of periods to be able to observe bubbles in both experiments (earlier learning-to-forecast experiments often show bubbles appearing only after about 20 periods), while, on the other hand, rounds are short enough so that we can run three of them in an experimental session. As we desire one treatment in which subjects are not explicitly informed about the fundamental value in the terminal period of the experiment, while they still need to have enough information to infer the fundamental value, we use a constant fundamental value and an indefinite number of periods per round. A constant fundamental value is standard in the learning-to-forecast asset pricing literature and also not uncommon in the literature with trade in the laboratory. An indefinite number of periods is useful in the call market experiment (sometimes abbreviated as CME, henceforth) to have a clear benchmark of what the buyout price is when it is not explicitly communicated to subjects (the buyout price is the fundamental value of the infinitely lived asset; with a fixed finite horizon, the fundamental value would be less straightforward, as a value of zero in the last period might appear natural). We also believe that indefinite end times are a more natural setting when investigating bubbles in asset markets: when talking about bubbles, one has often equity markets in mind, which do not have a predetermined final period (as opposed to bond markets, for example, where the bonds mature at a predetermined time).

In both experiments, subjects are randomized to groups of six. The group composition remains fixed throughout the experiment. In both experiments, each multi-period market is repeated three times (there are thus three rounds). Subjects do not know the number of periods per round. However, they do know that the number of periods lies between 25 and 40.[4] The rounds are otherwise identical. In both experiments, only one round is paid out. The round for payment is randomly selected by the computer at the individual

[4]The number of periods with a market price is 28 in the first round, 32 in the second round, and 26 in the third round. This means that the number of periods in which subjects trade in the call market experiment is also 28, 32, and 26, while the number of periods for which subjects forecast prices in the learning-to-forecast experiment is 29, 33, and 27. This is so, because in that experiment the market price in period t depends on the expectations of the price in period $t+1$.

level. In both experiments, subjects receive one euro for 900 points. Interest rates and dividend processes are identical in the two experiments. Consequently, the fundamental values are identical. As experiments with trade in the laboratory are more common, we start by describing the call market experiment.

1.1 The call market experiment

In the call market experiment, subjects can trade assets with each other. Each subject starts with an initial endowment of three assets and 5500 points in their cash account. Each subject interacts with five others throughout the experiment. In each period, subjects can buy or sell assets in the market by submitting marginal bids and asks simultaneously. The computer then calculates the aggregate demand and supply schedules, and the market price is determined by market clearing, where the demand and supply functions intersect. When the lowest ask price is higher than the highest bid price, or when there is no bid or ask, there is no trade in the given period. Furthermore, in case of excess supply or demand at the realized market price, which bids or asks are successful is decided at random among the bids or asks submitted exactly at the market price. In case of a possible price interval for the equilibrium price, the realized price is the midpoint of the interval. Subjects are allowed to submit as many bids and asks as they want with the following restrictions:

1. Both bid and ask prices can be at most 1500.[5]
2. Subjects cannot try to sell more assets than they hold. Similarly, they cannot try to buy more assets than the available number on the market (18 minus their own holdings).
3. Subjects cannot enter bids that they would not be able to pay for with the points in their cash account.

[5] An upper limit is standard in learning-to-forecast experiments. We thus also use an upper limit in the call market experiment to keep both experiments comparable.

4. Ask prices have to be higher than bid prices. That is, subjects cannot buy assets from themselves.

If any of these conditions is violated, the software displays an error message. Subjects can then adjust their bids and offers.

After the trade in a period is realized, dividend and interest earnings are paid ("overnight"). Both dividend and interest earnings are paid to a separate savings account, which yields interest but cannot be used for buying assets. Therefore, the cash-to-asset ratio is constant over time. The realized dividend from an asset in each period is either ten or zero (uniform for everybody), each with equal probability. The interest rate is 4%, both for money in the cash and in the savings account. This means that the fundamental value is constant at 125 (this is the value that equalizes expected earnings from the dividends and interest payments for this value; for details, see Section 1.3).

When a round ends (abruptly), each asset is bought back from subjects for a "fair price", which is the fundamental value of 125. Depending on the treatment (discussed in Section 1.3), subjects receive differential information about this buyout price. Subjects' round earnings are the sum of the money in the cash and savings accounts and the money they receive for the assets that they hold once the round is terminated.

Subjects have the possibility to submit an empty schedule when they do not want to trade. Once all subjects submit their bids and offers, the market price is determined, and trade takes place. Each period, a history table is displayed on the screen containing information about past market prices (which are also shown on a graph), cash holdings, savings, asset holdings, and trades. However, subjects do not have any information on others' trades or cash balances. A screenshot of a subject's decision situation can be found in Online Appendix A.

We impose a time limit on subjects' decisions. Subjects have two minutes in the first 10 periods of the first round and one minute in all other periods to make a decision. If subjects do not make a decision in time, the computer automatically proceeds to the next period. No decision by a subject is equivalent to this subject submitting an empty schedule of bids and asks (that is, this subject does not trade in the given period).

The ratio of cash to assets priced at the fundamental value in our call market experiment is $5500/375 = 14.\bar{6}$, which is very high in comparison to similar experiments. We choose such a high cash-to-asset ratio for the following reasons: (i) there are no cash constraints in the learning-to-forecast experiment (sometimes abbreviated as LtFE, henceforth), so that we do not want cash constraints to play an important role in the call market experiment; (ii) considering actual equity markets, the ratio of available wealth to the value of equities is very high (this can, for instance, be seen from the fact that total bond market capitalization alone is a multiple of total equity market capitalization; e.g., Roxburgh et al., 2011); (iii) we want to examine whether bubbles disappear with experience, therefore we need to have bubbles to start with (that higher cash-to-asset ratios lead to higher asset prices with inexperienced subjects has, for example, been shown by Caginalp et al., 1998).

The fundamental value is the equilibrium price assuming risk-neutral subjects. Note that it is also a very good approximation of the equilibrium price assuming risk-averse subjects, as long as this risk aversion takes the classical form commonly assumed in economics (expected utility theory with asset integration and non-excessive levels of risk aversion). This can be illustrated with the following example. Assume a decision maker with a CARA utility function (similar examples can be constructed with a CRRA utility function), who is indifferent between participating and not participating in a gamble with a 50-50 chance of winning 20 or losing 5 euros (we consider this a high level of risk aversion). Assuming a fixed end time of the asset after two more dividend payments, the value of the asset for this risk-averse person would still be at about 124.4 points (with an exchange rate of 900 points = 1 euro). The reason for risk aversion having such a small impact on equilibrium prices is that utility is almost linear for very small stakes with reasonable calibrations of risk-aversion parameters. This is discussed in detail in Rabin (2000). There are thus good reasons to use the fundamental value as benchmark (as done in a large part of the experimental asset market literature). Risk aversion would lead to slightly lower equilibrium prices, so that mispricing in bubbles would be slightly more severe when put in relation to an equilibrium price calculated with risk aversion.[6]

1.2 The learning-to-forecast experiment

The structure of the learning-to-forecast experiment is similar to the experiment conducted in Hommes et al. (2008). Subjects take the role of advisers to a company. Their only task is to predict the future price of a risky asset. Computerized companies then trade based on the advisers' forecasts (computerized trading in period t is based on the forecasts of prices in period $t+1$ and determines market prices in period t).

1.2.1 Market structure

The companies allocate their money between the risky financial asset and a risk-free investment based on mean-variance optimization. The asset pays a dividend of y_t in period t (the distribution of y_t is the same across time periods), and the risk-free investment yields a gross rate $R = 1 + r$. The companies choose how many assets to hold by maximizing their utility

$$\max_{z_{i,t}} \left\{ E_{i,t} W_{i,t+1} - \frac{a}{2} V_{i,t}(W_{i,t+1}) \right\}, \tag{1}$$

[6]Similarly, the equilibrium price with risk-averse subjects depends on subjects' beliefs about the number of trading periods. A later end of the market includes more dividend payments, which are risky, so that an equilibrium with risk-averse participants that expect a late termination of the market would be lower than the equilibrium calculated with the same market participants expecting an early termination. Here as well, the quantitative effects of different beliefs would be very small (as rounds can last no longer than 40 periods). Reasonable belief structures would also lead to a slightly lower equilibrium price, as the markets terminate relatively early.

where $W_{i,t+1} = RW_{i,t} + z_{i,t}(p_{t+1} + y_{t+1} - Rp_t)$ denotes the wealth of firm i in period $t+1$, p_t is the price of the risky asset in period t, and a is a parameter of risk-aversion. $E_{i,t}$ and $V_{i,t}$ are a company's individual expectations about their future wealth and the variance of their future wealth. The latter is assumed to be homogeneous across agents and constant over time, $V_{i,t} = \sigma^2$. Taking the first-order condition and solving for $z_{i,t}$ yields the net demand schedule for the risky asset in period t by firm i:

$$z^*_{i,t} = \frac{E_{i,t}(\rho_{t+1})}{aV_{i,t}(\rho_{t+1})} = \frac{p^e_{i,t+1} + y^e_{i,t+1} - Rp_t}{a\sigma^2}, \tag{2}$$

where $\rho_{t+1} = p_{t+1} + y_{t+1} - Rp_t$ is the excess return and $p^e_{i,t+1}$ is the price expectation of company i for period $t+1$. We assume that expectations about the dividend payment are correct, that is $y^e_{i,t+1} = \bar{y}$ is constant. The price is then set by market clearing. For simplicity, we assume that the outside supply of the risky asset is zero (companies only trade with each other). This leads to the market clearing equation:

$$\sum_{i=1}^{N} z^*_{i,t} = 0 \quad \Rightarrow \quad \sum_{i=1}^{N} \frac{p^e_{i,t+1} + y_{t+1} - Rp_t}{a\sigma^2} = 0. \tag{3}$$

This, in turn, leads us to the market clearing price

$$p_t = \frac{1}{R}(\bar{p}^e_{t+1} + \bar{y}), \tag{4}$$

where $\bar{p}^e_{t+1}$ is the average of the companies' expectations of the price in period $t+1$ (that is, the average of the advisers' price forecasts for period $t+1$). Taking into account that the fundamental price is $p^f = \bar{y}/r$, we arrive at the pricing equation

$$p_t = p^f + \frac{1}{R}(\overline{p}^e_{t+1} - p^f). \tag{5}$$

In the experiment, we use the same values for the interest rate and the dividend process as in the call market experiment, namely $r = 0.04$ and $y_t \in \{0, 10\}$ with 50% probability each. This results in $\bar{y} = 5$ and the fundamental value $p^f = 125$.[7]

1.2.2 Experimental implementation

Subjects are randomized to groups of six. Their task consists of submitting price forecasts two periods ahead. That is, they make a forecast for period $t+1$ after observing the price in period $t-1$. Market prices in period t are then calculated based on the computerized trading of the six companies that the six subjects in the group advise (each company bases its trading decision on the price forecast it receives from its adviser). Subjects are supposed to predict future prices as accurately as possible. Therefore, their earnings only depend on their forecasting accuracy, according to the following formula:

$$\pi_{i,t+1} = \max\left\{1300 \cdot \left(1 - \frac{(p^e_{i,t+1} - p_{t+1})^2}{100}\right), 0\right\}. \tag{6}$$

$\pi_{i,t+1}$ is the payment for a subject's forecast for period $t+1$. Subjects receive this formula along with a payoff table summarizing their earnings for different forecasting errors (this information is reproduced in Online Appendix C.4). Subjects' earnings from a round are the sum of their earnings in each period of a round.

Subjects receive qualitative but not quantitative information about the environment in which they operate. To be more precise, they do not know that the market price is determined by (5), but they know that the price depends positively on the submitted forecasts. Furthermore, they know r and the details of the dividend process (which allows them to calculate the fundamental value).[8]

[7] The assumed myopic mean-variance optimization and the homogeneous expectations about the variance are standard assumptions in the LtFE literature. Relaxing these assumptions makes the model less tractable. The mean-variance assumption is intuitively convincing, as it is a straightforward formalization of the trade-off agents face, when they try to increase their expected wealth while disliking risk. There is empirical evidence that there is a larger agreement in volatility expectations than in mean expectations (see, for example, Merton, 1980).

[8] Not providing subjects with the market equations is standard in the learning-to-forecast literature. In

To reduce the effects of extreme forecasts and to mimic possible liquidity constraints, companies are programmed to base their decisions on subjects' forecasts only up to a certain deviation from the last observed price. If a price forecast deviates from the last observed price by more than a third of it and by more than 40, the company trades as if the prediction deviated by exactly one third of the last observed price or by 40 (whichever of the two deviations is greater in absolute terms). Subjects know these limits. Furthermore, we implement an upper limit of 1500 on the forecasts (similarly to the call market experiment, where we prohibit bids and offers above 1500), which is also common knowledge.

In each period, subjects have access to a history table and a history graph. In the table they can track past prices, forecasts, and earnings, as well as cumulative earnings. The graph shows past prices and own predictions. Subjects do not receive any information about other subjects' forecasts. A screenshot of a subject's decision situation can be found in Online Appendix A.

We impose the same time limit as in the call market experiment. That is, subjects have two minutes in the first 10 periods of the first round and one minute in all other periods to make their decision. If subjects do not make a decision on time, the computer automatically proceeds to the next period. If a subject does not submit a forecast, the corresponding company remains inactive and the subject earns no points for the given period. The average forecast in Equation (5) is then calculated as the average of submitted forecasts (which are adjusted as explained above if they are outside the mentioned limits).

real markets, agents do not know the underlying equations either, but they need to learn how the market works from participating in it (or from simply observing it). Even though subjects do not know quantitative information about the market, it is possible that they learn the equilibrium price. In negative feedback settings, when higher expectations lead to lower prices, subjects usually learn the equilibrium price (e.g., Bao et al., 2012). There are also more complex, two dimensional systems, where subjects can learn the fundamentals without knowing the exact equations (e.g., Assenza et al., 2019; Hommes et al., 2019). Sonnemans and Tuinstra (2010) show that variations in feedback strength determine whether or not learning of the fundamental takes place, in markets without common knowledge of the equations.

1.3 Treatments and hypotheses

In both experiments, we implement three information treatments. The treatment differences consist in the information that subjects receive about the fair price of the asset (that is, the fundamental and buyout price). Subjects always have full information about the interest rate and the dividend process, so that they can always calculate the fundamental value.

In the NO_INFO treatments, subjects receive no explicit information about the buyout price. In the call market experiment, they know that the asset will be bought back for a fair price, but they receive no information about what this price is until the third and last round of the experiment is finished. In the learning-to-forecast experiment, we tell subjects that the company that they advise receives a fair price for the asset (subjects also know that the price that the company receives does not affect their earnings).

In the INFO_AFTER treatments, we communicate the buyout price (i.e., the fundamental value) of a round after the round ends. Of course, the fundamental value is the same in the different rounds, but we nevertheless repeat giving this information.

In the FULL_INFO treatments, we communicate the buyout price (i.e. the fundamental value) already in the instructions before the experiment starts.

The design of the experiments is summarized in Table 1. The number of subjects per treatment is indicated in the cells of the table (with the number of markets given in parentheses). The summary table shows many similarities to a two-by-three design. We prefer to speak of two experiments with three treatments each instead, as there are several differences between the call market experiment and the learning-to-forecast experiment (these are two different market paradigms rather than a treatment variation).

Our ex-ante hypotheses were that bubbles in both experiments would disappear with experience in FULL_INFO, while they would not disappear in NO_INFO. The treatment INFO_AFTER lies between these two treatments and ex ante we predicted that already this

Table 1: Design summary

	NO_INFO	INFO_AFTER	FULL_INFO
Call market experiment	54 (9)	42 (7)	54 (9)
Learning-to-forecast experiment	48 (8)	42 (7)	54 (9)

This table summarizes the design and shows the number of subjects per treatment and the number of markets in parentheses.

way of providing information may be enough for bubbles to mostly disappear with experience. Considering developments of pricing accuracy more generally, our prediction similarly was that pricing accuracy across rounds would improve substantially in INFO_AFTER and FULL_INFO but not in NO_INFO (and that the pricing accuracy in INFO_AFTER would lie between the accuracy in the other two treatments). This means learning in the information treatments and no learning in the NO_INFO treatments. We provide a model to conceptualize these hypotheses in Section 3.

In addition to these treatments, we show an additional treatment conducted in response to comments by the reviewers of this journal. The additional treatment, which we call LOW_CASH or LOW_CASH (FULL_INFO) to be clear about the information provision, is identical to our original FULL_INFO treatment but with a lower cash-to-asset ratio of $1.4\bar{6}$, achieved through a lower initial endowment of 550 instead of 5500 points (such a cash-to-asset ratio is at the lower end of what is usually used but not an outlier: Holt et al., 2017, for instance, use a cash-to-asset ratio that increases from 0.42 in the first period to 3.51 in the tenth and last period; Duffy et al., 2019, who also use a constant fundamental value, have a cash-to-asset ratio of one). The exchange rate is adjusted accordingly to 140 points = 1 euro, so that the total earnings in a round remain constant. There are 7 groups with a total of 42 subjects in the additional treatment.

Note that in the four INFO_AFTER and FULL_INFO treatments (in both experiments), as well as in the additionally conducted LOW_CASH treatment in the call market experiment, the asset redemption value is completely clear (in the two FULL_INFO treatments and the new treatment) or at least very clear after the first one or two rounds (in the INFO_AFTER treatments), so that the calculation of the fundamental value is straightforward. In the NO_INFO treatments, subjects can find the fundamental value in at least two ways. First, they may find the price of the asset that generates the same expected profit for a holder of the asset as for somebody holding cash instead (this is the easiest way to find the fundamental value). The expected earnings from the dividend payments are 5 points per period, whereas the interest on cash is 4%. The price that leads to the same expected earnings when buying or not buying the asset is thus the solution of the equation $5 = FV \cdot 0.04$, which means $FV = 5/0.04 = 125$. Second, subjects could find the fundamental value by calculating the discounted expected cash flow of the asset, which is $FV = \sum_{t=1}^{\infty} \frac{5}{(1.04)^t}$, which can be simplified using the properties of the geometric series (to the standard formula for pricing a perpetuity), $FV = 5/00.4 = 125$.[9]

1.4 Procedures

The experiments were programmed in `PhP/MySql` and run in the CREED laboratory of the University of Amsterdam. In total, 336 subjects participated in 14 sessions, with two sessions per treatment in each experiment (these numbers include the additional CME LOW_CASH treatment).[10] Subjects were mainly economics undergraduate students. None of them participated more than once. Subjects read the instructions on paper and had to answer multiple comprehension test questions on screen. The experimental instruc-

[9] If some participants mistakenly thought that the asset would be worthless after period 40, which is the latest termination point of a round, the fundamental value of the asset would be decreasing instead of constant. However, in this case, the perceived fundamental value of the asset would always be below the actual fundamental value of 125, so that the bubbles that appear in the experiment would (in relation to this perceived fundamental value) be even larger than what we report.

[10] Initially, two additional groups started the experiment. One of these groups was excluded due to a serious software failure during the experiment (in CME INFO_AFTER). One group (in LtFE NO_INFO) was excluded as a participant refused to sign the data consent form. Minimal software failures appeared in three of the groups that we did not exclude. In one group, this consisted in a subject proceeding to the third round after the first round ended. This was realized almost immediately and the subject was moved to the correct second round. This group, in LtFE FULL_INFO, is represented by a light blue to turquoise line in Figures 1 to 3 below. In two further groups, one subject skipped one period in one round. These groups are represented by the pink (LtFE INFO_AFTER) and purple (CME INFO_AFTER) lines in Figures 1 to 3.

tions and the comprehension test questions are presented in Online Appendix B for the call market experiment and in Online Appendix C for the learning-to-forecast experiment. Subjects were provided with pocket calculators, pens, and scratch paper. The experiment took about 160 minutes. Average earnings were about 26 euros, including a participation fee of 10 euros.

2 Results

In this section we present the results of both experiments jointly. For the call market experiment, our data contains 9 groups in NO_INFO, 7 in INFO_AFTER, and 9 in FULL_INFO. There are 7 further groups in the additional LOW_CASH treatment that will be discussed in Section 2.5 (results of the call market experiment before Section 2.5 always refer to the original call market experiment without the additional treatment). In the learning-to-forecast experiment, there are 8 groups in NO_INFO, 7 in INFO_AFTER, and 9 in FULL_INFO. As the different groups do not interact with each other, observations at the group level are statistically independent. All tests that we conduct are two-sided. Additional data can be found in Online Appendix D.

Figure 1 shows the market prices in both experiments in the first round of the experiment. The prices in the call market experiment are shown on the left side. Each color and line type represents one group. The circles show realized market prices. The crosses show the midpoints between the highest submitted bid price and the lowest submitted ask price if there is no trade in a period (while both bids and offers are present). Circles and crosses in subsequent periods are connected (if the line representing one group is interrupted, this represents one or more periods without trade and without bids or offers). The prices of the learning-to-forecast experiment are shown on the right. In that experiment, there are no periods without trade, so that there is a circle representing the realized market price in each period. Figures 2 and 3 show the market prices for both experiments in the second and third rounds, respectively.

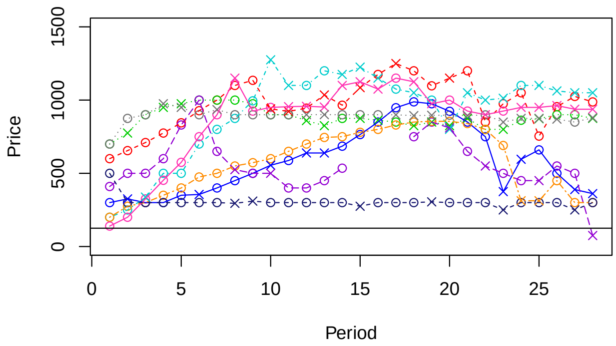
2.1 Experience and bubbles

Our main research question is whether bubbles disappear with experience. As can be seen from the graphs of the market prices in Figure 3, this is not the case.

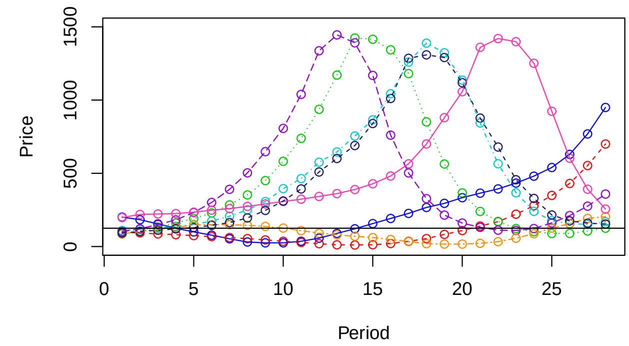
In our case, a good measure for the mispricing in a given round is the mean price. In general, other measures of mispricing may be more suitable, such as the relative absolute deviation (RAD; see Stöckl et al., 2010, and for an adaption to call markets Weber et al., 2018). However, as the fundamental value is constant in our experiment, and as we observe a lot of overpricing and hardly any underpricing, using the mean or RAD for the analysis are almost equivalent (they are fully equivalent for constant fundamentals when only overpricing is observed). We therefore only use mean values. There is no generally accepted definition of what a bubble is, but the precise definition of does not influence our conclusions (as long as this definition is somewhat reasonable). When the average price across all periods of a round is at least twice the fundamental value, one can certainly speak of (at least one) bubble being present in that round.[11] In the call market experiment, we only consider realized market prices for our analyses (that is, only the prices represented by circles in Figures 1 to 3, not the prices represented by crosses).

Figure 4 depicts the mean prices across all periods of a round. Each line corresponds to the mean prices in one group (the round number is on the horizontal axis). Which treatment a group belongs to is indicated by color and line type. The thick black lines correspond to the mean across all groups of a treatment. Table 2 summarizes the graph by showing the average value of the mean prices across all groups of a treatment (the values

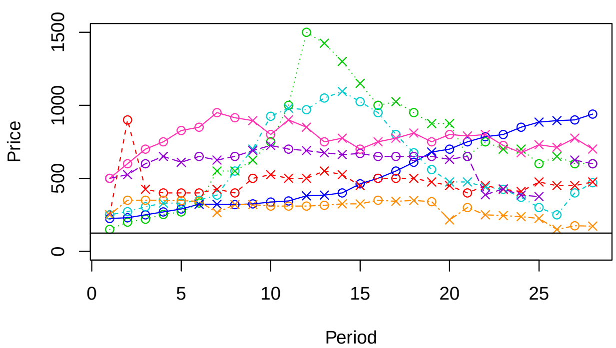
[11]This is a rather strict criterion in the sense that there could be price developments that one may consider to be a bubble that do not fulfill this criterion. Imagine, for example, a price that increases sharply to a multiple of the fundamental vale in the first few periods and collapses after, staying close to the fundamental value for the rest of the round. There would clearly be a bubble, while the mean price may still fail to be twice the fundamental due to the many periods with accurate pricing after the bursting of the bubble.



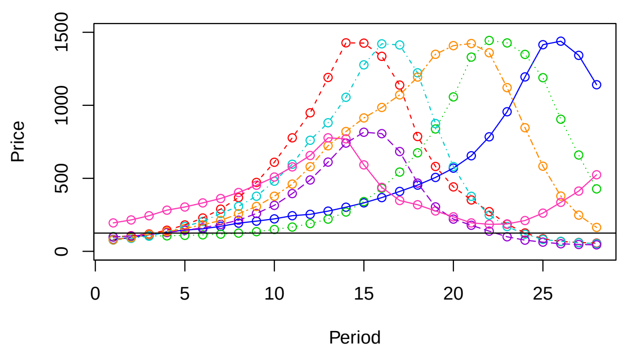
(a) CME NO_INFO Round 1



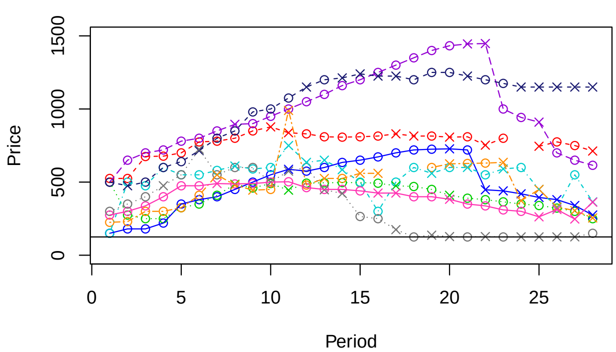
(b) LtFE NO_INFO Round 1



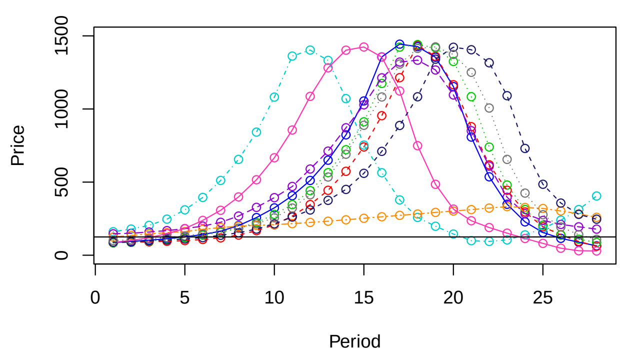
(c) CME INFO_AFTER Round 1



(d) LtFE INFO_AFTER Round 1



(e) CME FULL_INFO Round 1

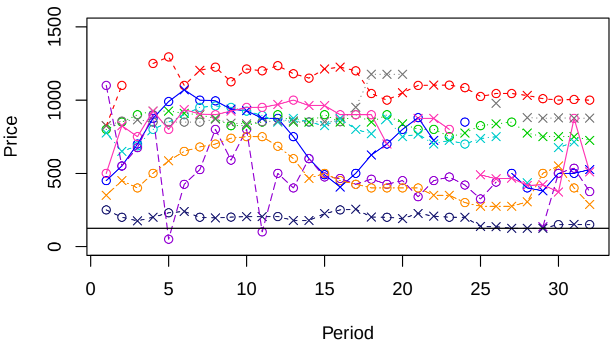


(f) LtFE FULL_INFO Round 1

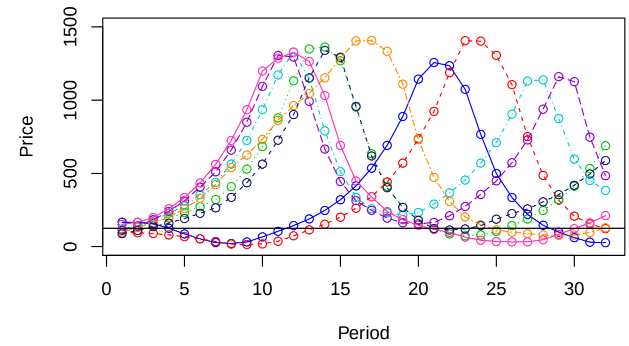
Figure 1: First round prices in all treatments in both experiments

---

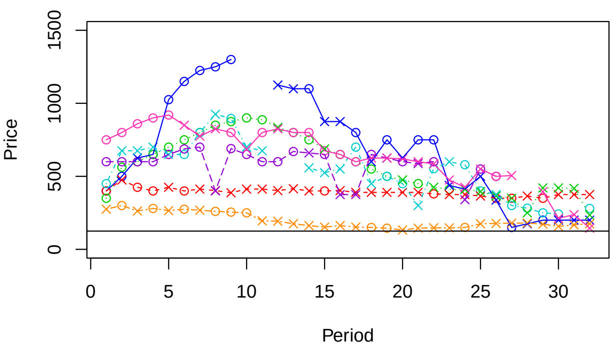
This figure shows prices in the first round in the treatments of the call market experiment (left) and the learning-to-forecast experiment (right). Market prices are indicated with circles. In the CME, crosses indicate midpoints between highest bids and lowest asks in periods without trade (but with both bids and asks present). Each color represents one group.



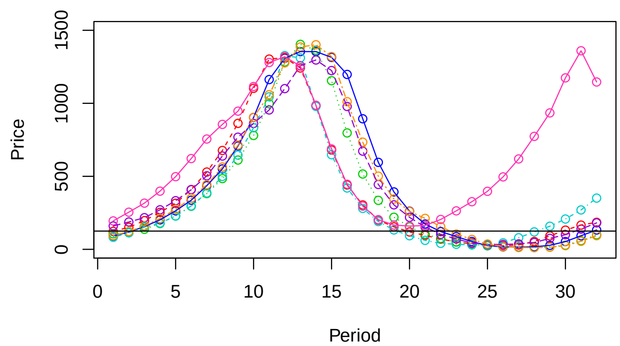
(a) CME NO_INFO Round 2



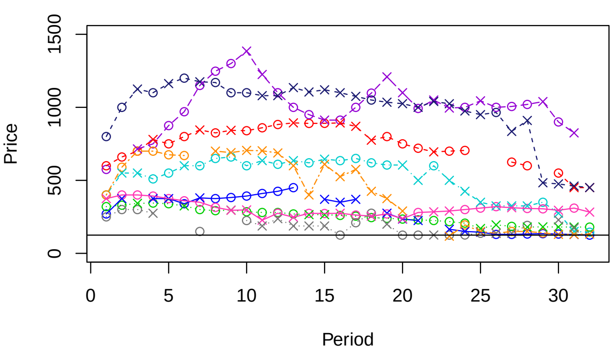
(b) LtFE NO_INFO Round 2



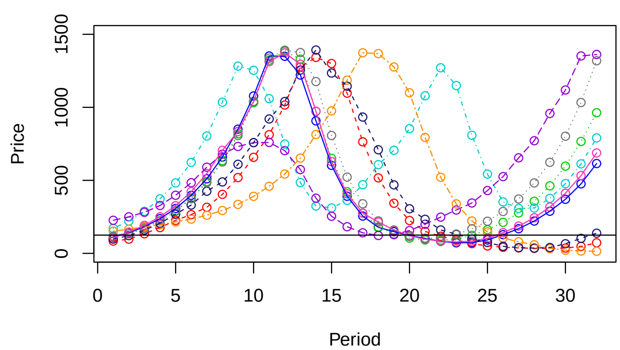
(c) CME INFO_AFTER Round 2



(d) LtFE INFO_AFTER Round 2



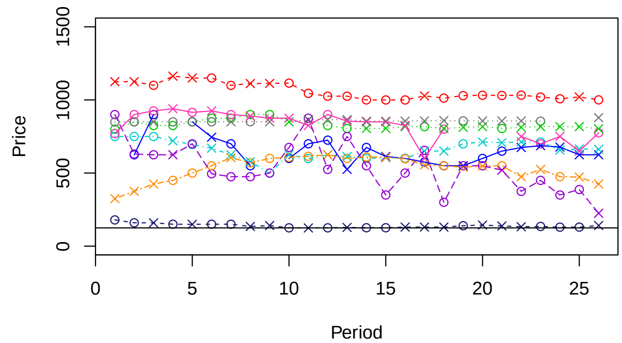
(e) CME FULL_INFO Round 2



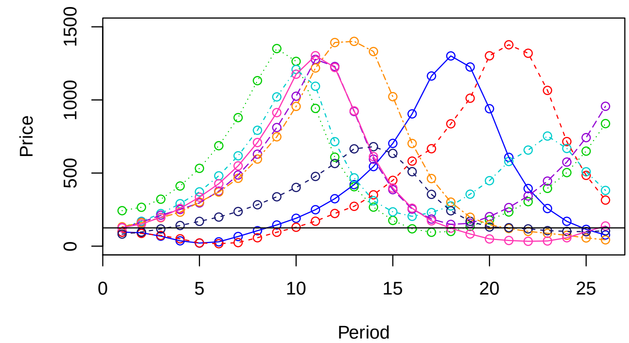
(f) LtFE FULL_INFO Round 2

Figure 2: Second round prices in all treatments in both experiments

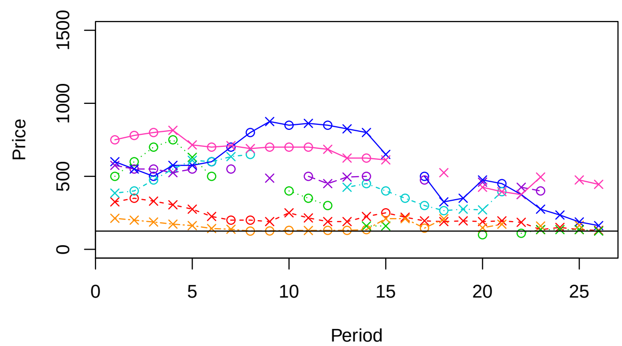
This figure shows prices in the second round in the treatments of the call market experiment (left) and the learning-to-forecast experiment (right). Market prices are indicated with circles. In the CME, crosses indicate midpoints between highest bids and lowest asks in periods without trade (but with both bids and asks present). Each color represents one group.



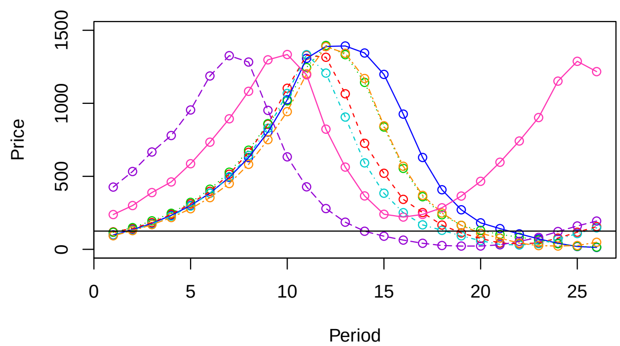
(a) CME NO_INFO Round 3



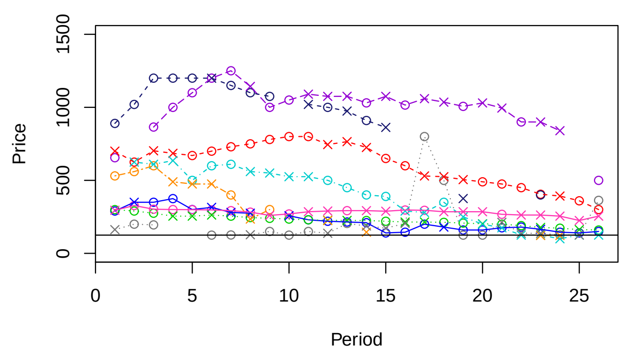
(b) LtFE NO_INFO Round 3



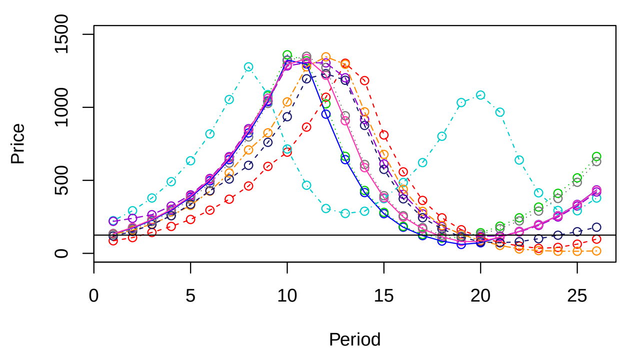
(c) CME INFO_AFTER Round 3



(d) LtFE INFO_AFTER Round 3



(e) CME FULL_INFO Round 3

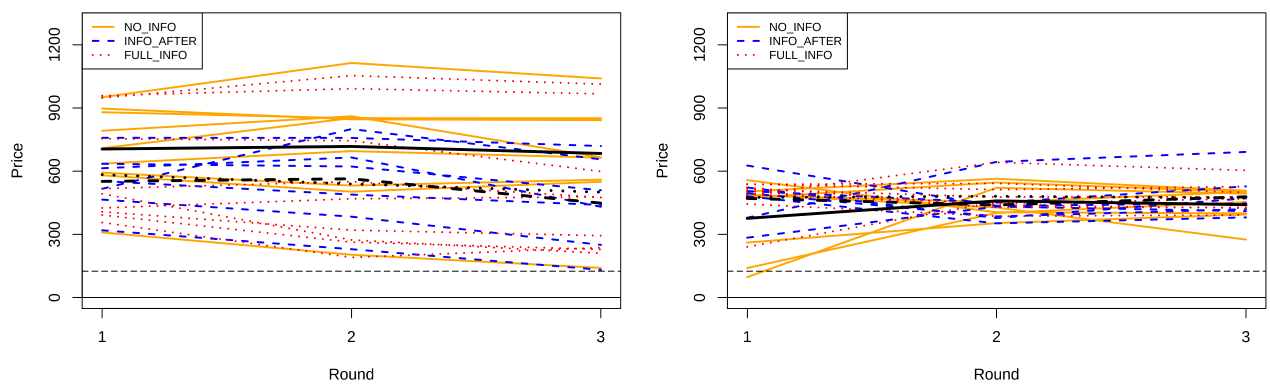


(f) LtFE FULL_INFO Round 3

Figure 3: Third round prices in all treatments in both experiments

This figure shows prices in the third round in the treatments of the call market experiment (left) and the learning-to-forecast experiment (right). Market prices are indicated with circles. In the CME, crosses indicate midpoints between highest bids and lowest asks in periods without trade (but with both bids and asks present). Each color represents one group.

of the thick black lines in Figure 4). Figure 4 shows that in almost all groups and rounds, mean prices are considerably above the fundamental value (that is, more than twice the fundamental) in both experiments. It is also notable that there is hardly any trend in the mean prices across the rounds in all treatments in both experiments. There is at best a very slight downward trend in the INFO_AFTER and FULL_INFO treatments of the call market experiment, but even such a trend is hardly visible.[12] Note that the results in the call market experiment are not driven by a single share selling at high values. Considering only market prices from periods with at least two trades gives a similar picture (see Online Appendix D.3).



(a) CME (b) LtFE

Figure 4: Mean prices in all rounds and treatments in both experiments

This figure shows the mean market prices across all periods of a round. Each thin colored line corresponds to one group. Thick black lines show the mean values of these lines per treatment.

For the question of whether bubbles disappear with experience, the results are clear-cut. They do not disappear, independent of the amount of information that subjects receive about the fundamental value (the treatments) and independent of the market paradigm employed (call market or learning-to-forecast setting). We state these results in the fol-

[12]The exact numbers of bubbles (according to the definition stated above) is as follows. In the call market experiment, the number of bubbles in NO_INFO is 9 in the first round, 8 in the second round, and 8 in the third round (out of 9 markets). In INFO_AFTER bubbles occur in the three rounds in 7, 6, and 6 markets (out of 7). IN FULL_INFO, these numbers are 9, 8, and 6 (out of 9). In the learning-to-forecast experiment the respective numbers are 6, 8, and 8 (out of 8) in NO_INFO, 7, 7, and 7 (out of 7) in INFO_AFTER, and 8, 9, and 9 (out of 9) in FULL_INFO.

Table 2: Mean prices

	Treatment	Round 1	Round 2	Round 3	Fundamental
CME	NO_INFO	705	717	684	125
	INFO_AFTER	552	564	448	125
	FULL_INFO	583	540	500	125
LtFE	NO_INFO	376	459	441	125
	INFO_AFTER	471	440	478	125
	FULL_INFO	475	481	474	125

This table shows the mean prices across groups and periods in all treatments of the experiment (rounded to integers and corresponding to the thick black lines in Figure 4).

lowing and briefly discuss and situate them within the literature.

Result 1: In the call market experiment, bubbles do not disappear with experience.

This result, found in all three treatments, stands in contrast to the literature concerning similar call market or double auction experiments.[13] Of course, we cannot say that bubbles would never disappear; they might disappear if we repeated the market many times (we discuss this in more detail in Section 2.2). Nevertheless, the literature on such markets usually shows the disappearing of bubbles after already one or two repetitions of an identical market.

There are three main differences between our FULL_INFO treatment and the majority of the literature: (1) we use an indefinite horizon instead of a fixed horizon, (2) we use a longer time horizon, and (3) we use a higher cash-to-asset ratio.[14] No matter which

[13]There are a few studies with considerable deviations from the standard designs, that do find bubbles with experienced traders. Oechssler et al. (2011) consider the trading of multiple assets simultaneously and find repeated bubbles when they introduce asymmetric information about dividend payments. Shestakova et al. (2019) investigate bubble formation in markets with a mix of experienced and inexperienced traders and find some reoccurring bubbles (with a decreasing fundamental value; the bubbles that reoccur are of moderate magnitudes). Weber et al. (2019) consider trade in bonds and credit default swaps and find that bubbles disappear with experience in the bond markets but not in the credit default swap markets. Weitzel et al. (2020) show that bubbles appear when experimental subjects are experienced financial professionals (they do not consider repeated markets but provide evidence that outside experience does not lead to accurate pricing in experimental markets).

[14]As a minor difference, the typical markets in the literature do not have an upper price limit (which

of these drive the results, a longer horizon and an indefinite end time seem to be the most relevant setting with actual equity markets in mind, and the same holds for a high cash-to-asset ratio (it turns out that the cash-to-asset ratio is what makes the crucial difference between our paper and the literature: we discuss the new treatment showing this in Section 2.5).

Result 2: In the learning-to-forecast experiment, bubbles do not disappear with experience.

This is a novel finding. As there is thus far no literature investigating how the pricing behavior changes when the markets are repeated, we cannot compare our findings to the existing literature. The finding arises in all three treatments.

Taking both of these findings together, we believe that it is reassuring for the experimental method that the results mirror each other. If many features are kept similar between the two experiments, relying on the one or the other market paradigm does not lead to strikingly different results concerning such an important characteristic as whether bubbles occur (with or without experience). However, given that markets outside the laboratory are basically never repeated in an identical manner, the fact that we do not observe the disappearance of bubbles even when repeating the same market in such simple settings sheds doubt on the view that the classical finding of bubbles disappearing fast with experience carries over to the field.

2.2 Development of pricing accuracy across the rounds

Bubbles do not disappear with experience in our experiments. However, we have not yet discussed whether or to what extent the pricing of the asset improves over the rounds. Figure 4 and Table 2 suggest that pricing improves slowly in the call market experiment

our market features for reasons of comparability with the LtFE). In addition, the provision of information is mildly different in the INFO_AFTER treatment and very different in the NO_INFO treatment.

in the information treatments, while it stays roughly similar in the NO_INFO treatment. In the learning-to-forecast experiment, pricing seems to remain similarly accurate across the rounds in the information treatments while it even seems to worsen over time when subjects receive no information on the fundamental value.

Testing whether mean prices are significantly different in the third and first rounds with a two-sided Wilcoxon signed-rank test leads to the following results. In CME NO_INFO pricing is not significantly different ($p = 0.426$). It is also not significantly different in CME INFO_AFTER ($p = 0.109$), but it is marginally different in CME FULL_INFO ($p = 0.098$). In the learning-to-forecast experiment differences are not significant in any treatment (p-values are 0.383, 0.938, and 0.570, in the order of increasing information provided to subjects).

We interpret these results overall as weak evidence for very slow learning in the treatments CME INFO_AFTER and CME FULL_INFO and as evidence for no learning in CME NO_INFO and all treatments of the learning-to-forecast experiment. How slow the learning is can be seen by the following thought-experiment. Imagining that one can extrapolate the linear trend between rounds 1 and 3 (this is of course highly problematic, it should be seen as no more than a thought-experiment), average pricing across groups would be no longer considered a bubble after 7 rounds in CME INFO_AFTER and 10 rounds in CME FULL_INFO (and much more or even never in the other 4 cases). Note that this only means that *average pricing across groups* would then not be considered a bubble anymore, not that no more bubbles would arise after this time period (in addition, remember that the definition of a bubble that we use is rather strict, as discussed in Footnote 11). Given this and given how simplistic these call markets are, the repetition of a perfectly identical market setting for 7 or 10 rounds until the average behavior would no longer be considered a bubble, seems very long (looking at markets outside of the laboratory, no situation ever repeats in exactly the same way and fundamental prices are often hard to estimate even for experts). We summarize the above discussion in the next two results.

Result 3: In the call market experiment, we observe no more accurate pricing in later rounds in NO_INFO, while we observe very slow improvements of pricing in the information treatments.

There are no comparable markets in the literature that do not provide the information about the fundamental value explicitly to subjects. As such, our result of no more accurate pricing in the later rounds of NO_INFO is novel. There are studies providing partial information about the fundamental value to subjects. Most closely related to our experiment is the work by Sutter et al. (2012), who provide partial information about dividend payments (other, but less comparable, experiments with a focus on information are Huber et al., 2008, and Stanley, 1997). With their treatments, Sutter et al. (2012) vary whether there is asymmetry across subjects in the information that is provided. They find that the assets are priced more accurately in the third and last round of the experiment in all treatments but find particularly accurate pricing in the asymmetric treatments where some subjects have better information than others. The second part of Result 3, which states that the accuracy of pricing only increases very slowly in the information treatments (which are most comparable to the standard literature), differs from the literature as the learning is slower in our experiment, while the tendency is the same. We attribute the slowness of learning to the fact that we have a high cash-to-asset ratio (that the end time is indefinite and that rounds are a bit longer than usually in the literature seems to play only a minor role, as we argue in Section 4), which should not matter according to economic theory, but which seems to be sufficient for subjects to have much bigger problems learning to price the assets accurately.

Result 4: In the learning-to-forecast experiment, we observe no more accurate pricing in later rounds in all treatments.

This is again a novel finding as no repeated learning-to-forecast asset markets have previously been conducted. We are surprised to observe absolutely no more accurate pricing in later rounds even in the information treatments.

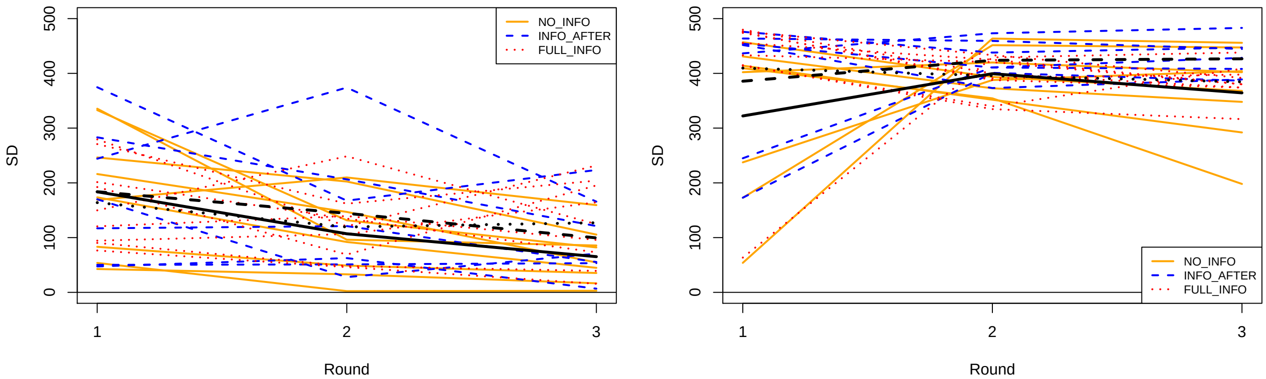
2.3 Shapes of bubbles

The first results are similar for the two market paradigms. However, as Figures 1 to 3 also show, there are also differences in the patterns of market prices across the experiments.

In the call market experiment, we often observe long periods of severe mispricing in which the market price does not change a lot from period to period. Such bubbles have been termed flat bubbles by Hoshihata et al. (2017). In our experiment, we observe different variations of such flat bubbles. The bubbles can burst, which means that after market prices have been high, there is an abrupt change in one period with no further trade or trade only close to the fundamental price in subsequent periods (e.g., the dark blue line in Figure 1e, where no more trade is observed after period 21). The bubbles can also deflate, which signifies a slow decrease of market prices toward the fundamental value (e.g., the red line in Figure 3e). In addition to these two types of bubbles, there can also be sustained flat bubbles that last until the market is terminated without showing prior signs of bursting or deflating (e.g., the red line in Figure 2a). In the learning-to-forecast experiment, on the other hand, we always observe boom-and-bust cycles. Prices increase and decrease smoothly, but with large amplitudes. The developments of market prices here look very homogeneous across groups.

This discussion can be quantified by considering the standard deviation of market prices per round. Flat bubbles go hand in hand with relatively low standard deviations of prices, while boom-and-bust cycles go together with a high standard deviation. This is the case as flat bubbles arise because many consecutive prices are similar; boom-and-bust cycles, on the other hand, have a high standard deviation as they feature a lot of very different prices. The mean standard deviations across groups are presented in Figure 5 and Table 3, split according to treatment and round.

The standard deviations confirm the results of the eye-inspection. Standard deviations in the call market experiment are much lower than in the learning-to-forecast experiment.



(a) CME (b) LtFE

Figure 5: Standard deviation of prices in both experiments

This figure shows the standard deviation of market prices in a round. Each thin colored line corresponds to one group. Thick black lines show the mean values of these lines per treatment.

Table 3: Standard deviation of prices

	Treatment	Round 1	Round 2	Round 3
CME	NO_INFO	184	107	65
	INFO_AFTER	184	144	100
	FULL_INFO	164	119	127
LtFE	NO_INFO	322	399	364
	INFO_AFTER	386	424	427
	FULL_INFO	410	396	385

This table shows the standard deviations of market prices in a round (rounded to integers and corresponding to the thick black lines in Figure 5).

These differences are also statistically significant.[15] This leads us to the next two results, which we subsequently compare to the existing literature.

Result 5: Market prices in the call market experiment usually exhibit flat bubbles.

Flat bubbles are also observed by Hoshihata et al. (2017). They consider a very long but fixed horizon of 100 periods. The fact that flat bubbles are observed in the call and

[15] Differences between CME and LtFE are statistically significant for all treatment-round combinations, tested with two-sided Wilcoxon-Mann-Whitney tests (p-values are 0.046 (NO_INFO R1), < 0.01 (NO_INFO R2), < 0.01 (NO_INFO R3), 0.011 (INFO_AFTER R1), < 0.01 (INFO_AFTER R2), < 0.01 (INFO_AFTER R3), < 0.01 (FULL_INFO R1), < 0.01 (FULL_INFO R2), and < 0.01 (FULL_INFO R3).

continuous double auction markets in Hoshihata et al. (2017) and in the call markets in this paper but not in the typical asset market experiments could be due to the fact that the horizon is longer in these two papers (much longer in the case of Hoshihata et al., 2017, and moderately longer and indefinite in our experiment). Comparing our results to those of Hoshihata et al. (2017), a difference consists in the fact that we also observe bubbles that continue until the market terminates. This does not happen in their study. The most likely explanation for this difference (at least when looking at our INFO_AFTER and FULL_INFO treatments) is that it is due to the indefinite end time. Some subjects may expect the market to continue for longer and therefore trade at higher prices (note that there are not many bubbles that do not burst or deflate before the market ends in the later rounds of INFO_AFTER and FULL_INFO). In NO_INFO and the first round of INFO_AFTER, the fundamental value has to be inferred from subjects instead of being presented directly to them; this may in addition drive such bubbles as subjects may have a wrong perception of the fundamental value.

Result 6: Market prices in the learning-to-forecast experiment follow boom-and-bust cycles.

Such boom-and-bust cycles are generally observed in financial market experiments using the learning-to-forecast paradigm. Subjects seem to coordinate on trend-following behavior, which results in large bubbles and eventually crashes (e.g., Bao et al., 2020). However, while we are not surprised to observe similar shapes of bubbles in later rounds (given that bubbles still appear in those rounds), the repetition of these dynamics has not been documented hitherto.

One reason for the bubble shape being different across the two experiments could be related to the fact that subjects have the option not to trade in the call market experiment, so that there is not necessarily a market price: if no trade occurs in a period, it is unclear how this affects subjects' strategies. A second reason might lie in the nature of the tasks. In the learning-to-forecast experiments, subjects' decisions are strategic complements: if subjects expect others to submit high forecasts, their best decision is to also submit high forecasts. When subjects trade assets, there are no such clear incentives to complement others' actions; at a time when prices are already high, subjects expecting higher prices might try to buy more assets in the hope to sell them for these higher prices in the future, but they might also sell the assets to secure a riskless profit.

2.4 Acceleration of bubble formation

Bubbles appear in all treatments and rounds of both experiments. The pricing of the assets hardly improves over time, if at all. However, the pricing behavior does change over time; the bubbles seem to speed up in both experiments, meaning that bubbles form earlier in later rounds (and burst or deflate earlier in the call market experiment) than in the first round. Figures 1 to 3 suggests this and we quantify it below.

There is no established measure of how early in a market a bubble occurs, but the following measure seems natural. In each round, we take the mean price in the first half of the round and divide it by the mean price over the whole round. This fraction measures how high prices are in the beginning as compared to the whole round. If bubbles indeed speed up over the different rounds (i.e., if they occur earlier in later rounds), this fraction should increase from the first to the third round. These data are reported in Table 4.

Table 4: Mean prices in the first half of a round as fraction of mean prices

	Treatment	Round 1	Round 2	Round 3
CME	NO_INFO	0.91	1.06	1.04
	INFO_AFTER	0.92	1.15	1.08
	FULL_INFO	0.98	1.14	1.07
LtFE	NO_INFO	0.74	1.04	1.03
	INFO_AFTER	0.73	1.58	1.42
	FULL_INFO	0.70	1.28	1.38

This table shows the mean across groups of mean prices in the first half of a round divided by mean prices in the same round.

The data confirm that bubbles appear earlier in the later rounds of both experiments. The fraction of mean prices increases sharply from the first to the second round in all treatments. However, thereafter, from the second to the third round, there is no additional increase in this measure. Numbers are similar in the second and third round, mostly with slightly lower numbers in the third round. The differences between the first and the second round are mainly statistically significant, the differences between the first and the third round are mainly (at least marginally) significant, while the differences between the second and the third round are mainly insignificant.[16] We summarize this in the following two results.

Result 7: Bubbles appear earlier in later rounds of the call market experiment than in the first round.

This result is also observed in the previous literature. Several studies find that bubbles are smaller and shifted to the left (i.e., they appear earlier) when subjects have already experienced one round (e.g., King et al., 1993; Dufwenberg et al., 2005; Haruvy et al., 2007).

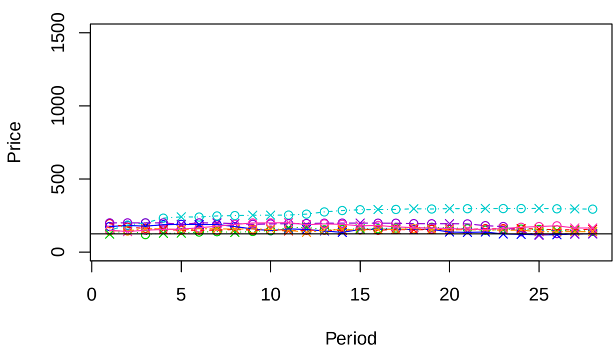
Result 8: Bubbles appear earlier in later rounds of the learning-to-forecast experiment than in the first round.

This result, which mirrors the corresponding result for the call market experiment, can again not be compared to similar literature, as we provide the first repeated markets in the learning-to-forecast literature.

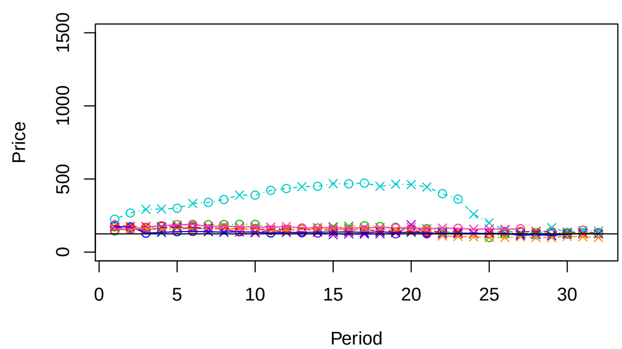
[16] *p*-values from two-sided Wilcoxon signed-rank tests are < 0.01 (R1-R2), 0.012 (R1-R3), and 0.426 (R2-R3) in CME NO_INFO. The respective numbers for CME INFO_AFTER are 0.016, 0.078, and 0.219, and for CME FULL_INFO 0.074, 0.164, and 0.910. For LtFE NO_INFO these numbers are 0.148, 0.148, and 0.844, for LtFE INFO_AFTER they are 0.016, 0.031, and 0.078, and for LtFE FULL_INFO they are 0.027, 0.012, and 0.203.

2.5 Effects of the cash-to-asset ratio in the call market experiment (additional treatment)

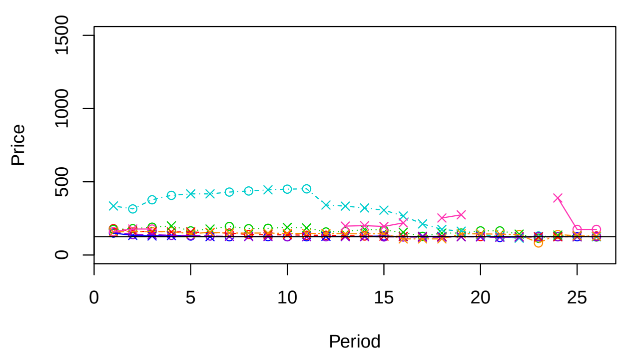
Here, we present the results of the new treatment with a low cash-to-asset ratio (conducted after the original experiment, based on the feedback from the editor and the reviewers of this journal). Figure 6 shows the market prices in all rounds of the new treatment. Mean prices in the new treatment and in the comparable treatment FULL_INFO are shown jointly in Figure 7 and Table 5.



(a) LOW_CASH (FULL_INFO) Round 1



(b) LOW_CASH (FULL_INFO) Round 2

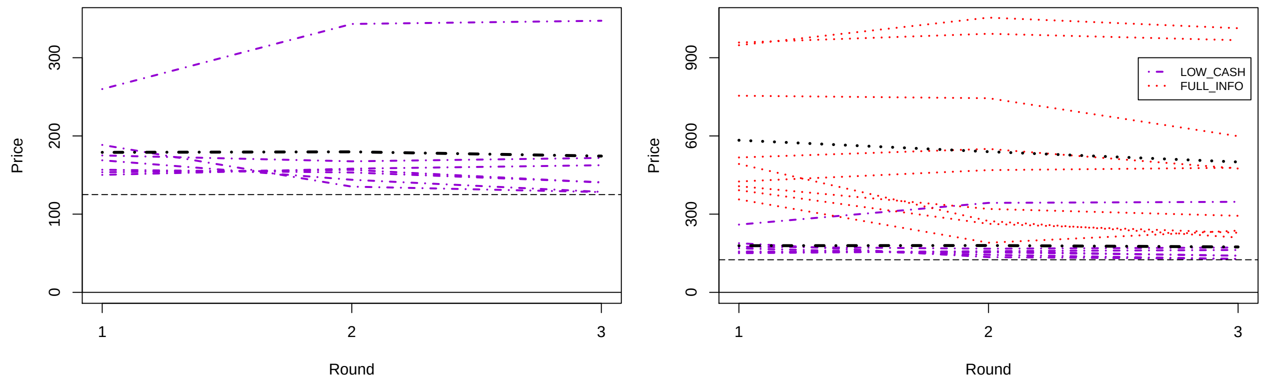


(c) LOW_CASH (FULL_INFO) Round 3

Figure 6: Market prices in treatment LOW_CASH

This figure shows prices in treatment LOW_CASH. Market prices are indicated with circles, crosses indicate midpoints between highest bids and lowest asks in periods without trade (but with both bids and asks present). Each color represents one group.

It can be seen that prices are considerably lower in the LOW_CASH (FULL_INFO) treatment than in the original FULL_INFO treatment. Figure 6 shows that market prices are



(a) LOW_CASH (FULL_INFO) (b) LOW_CASH (FULL_INFO) and FULL_INFO

Figure 7: Mean market prices

This figure shows the mean market prices across all periods of a round (left: only LOW_CASH; right: LOW_CASH and FULL_INFO). Each colored line corresponds to one group. Black lines show the mean values per treatment.

Table 5: Mean prices

	Treatment	Round 1	Round 2	Round 3	Fundamental
CME	LOW_CASH (FULL_INFO)	179	180	174	125
	FULL_INFO	583	540	500	125

This table shows the mean prices across groups and periods in the new treatment LOW_CASH and in the comparable treatment FULL_INFO (rounded to integers and corresponding to the black lines in Figure 7).

very close to the fundamental value in six out of the seven groups. Figure 7a zooms in on the prices, confirming this finding and further showing that there is some learning in most groups, with prices moving closer to the fundamental value (to be precise, five out of seven groups price the asset better in the third round than in the first). In the third round, mean prices in six out of the seven groups are less than one-and-a-half times the fundamental value. Note that even for the group with prices considerably above those in the other groups and no learning, prices are still considerably below the average prices across all groups in FULL_INFO, as can be seen in Figure 7b. The differences between prices in LOW_CASH and FULL_INFO are statistically significant for all rounds, with p-values $< 10^{-3}$ in the first round and < 0.01 in the second and third rounds, tested with two-sided Wilcoxon-Mann-Whitney tests. This leads us to the last result:

Result 9: With a low cash-to-asset ratio, call markets exhibit considerably fewer and smaller bubbles.

Our findings with the low cash-to-asset ratio are much more in line with the literature than the findings in the original experiment. In the majority of groups, pricing improves and is relatively close to the fundamental value, in particular in the last round. The stark difference to the literature of the results in our original experiment is thus driven by the high cash-to-asset ratio in our experiment (introduced for comparability with the learning-to-forecast experiment, among other reasons). A schematic summary of the relation of our paper to the existing literature is shown in Table 6.[17]

Note that, if the outlier is removed, mean prices in LOW_CASH change from 166 in the first round to 152 in the second round and 145 in the third round. That is, the distance of the average price from the fundamental value is reduced by about half from the first to the third round. This compares to a decrease of less than 20 percent in FULL_INFO. In that sense, there is also more learning in the new treatment with a low cash-to-asset ratio (although one might think that it is easier to decrease the distance from the fundamental value, both in absolute and relative terms, when starting out with a large distance). These differences are not statistically significant, however.

Observed behavior is very similar across the three regular (high cash-to-asset ratio) treatments of the call market experiment. It is, on most dimensions, also similar to observed behavior in the learning-to-forecast experiment, where cash constraints are absent by design. One could thus say that, with the low cash-to-asset ratio, we break the similarity to the other call market treatments (and, where it exists, to the learning-to-forecast

[17]Comparing to the existing literature, one might argue that our new treatment hardly features bubbles in the first round, whereas the existing literature often shows bubbles in the first round but not in later rounds of the experiment. However, the cash-to-asset ratios in these papers are not fully comparable; many of these papers use decreasing fundamentals with an increasing cash-to-asset ratio that usually increases to levels above that in our LOW_CASH treatment (or which is even above it throughout). Considering the only other paper we know of with a constant fundamental value and a constant cash-to-asset ratio at a level below or close to ours, Duffy et al. (2019), that paper also shows no bubbles (in the first and only round).

Table 6: Overview of repeated markets with trade in the laboratory

	No or very few bubbles in 2nd and 3rd round	Many bubbles in 2nd and 3rd round
Low to intermediate C/A ratio	Smith et al. (1988) King et al. (1993) Van Boening et al. (1993) Dufwenberg et al. (2005) Haruvy et al. (2007) Hussam et al. (2008) Weber et al. (2018) Füllbrunn et al. (2019) CME LOW_CASH	
High C/A ratio		CME NO_INFO CME INFO_AFTER CME FULL_INFO

This table schematically summarizes the relation of our treatments to literature on repeated markets. Note that this overview is necessarily imperfect, as all of these papers are different (e.g., some studies feature non-constant fundamental values and cash-to-asset ratios; Weber et al., 2018, and Füllbrunn et al., 2019, use non-trivially different settings, in which assets are first sold in an initial public offering).

experiment).

3 Modeling Behavior in the Learning-to-Forecast Experiment

Here, we provide a model for the learning-to-forecast experiment (developed after the experiments were conducted). The learning-to-forecast experiment is easier to analyze than the call market experiment, because it separates forecasting and optimization problems. It is thus possible to model forecasting decisions without having to deal with how forecasts translate into posted bids and asks. We first provide a version that conceptualizes our ex-ante hypotheses and then a version that describes the behavior actually observed in the experiment. The difference between the models lies in where learning takes place.

The model we propose is based on level-k reasoning. We assume that level-k agents with $k \geq 1$ act as price takers and react optimally assuming a market populated by agents of level $k-1$ (the assumption that agents are price takers is necessary to keep the model tractable; the assumption is in line with experimental evidence that participants in groups of four or more subjects act as in large groups; e.g., Huck et al., 2004). With the pricing equation of the asset market, one can calculate the behavior of level-k agents for $k \geq 1$, assuming a given behavior of level-0 agents.[18] Here, we omit constraints on forecasts or price formation (we discuss how these constraints can be taken into account after the derivation).

We define f as the function mapping forecasts into actual prices in the pricing equation:

$$p_t = p^f + \frac{1}{R}\left(\overline{p}^e_{t+1} - p^f\right) =: f\left(\overline{p}^e_{t+1}\right). \tag{7}$$

Furthermore, we use the following notation: prices in a market populated by agents of level k in period t are denoted by p_t^{Lk}, and forecasts of prices in period $t+1$ in a market

[18]As usually assumed in level-k models, we assume that agents with $k \geq 1$ respond perfectly to level $k-1$. While subjects in the experiment do not have perfect knowledge of the pricing equation, they can infer the essence of the equation after the first forecasts.

populated by agents of level k are denoted by $p_{t+1}^{e_{Lk}}$ (these forecasts are also the average forecasts in the market, as the market is populated by agents of the same level).

Level-1 forecasts are the forecasts that optimally react to forecasts in a market of level-0 agents. This can be written as $p_{t+1}^{e_{L1}} = p_{t+1}^{L0} = f(p_{t+2}^{e_{L0}})$. Thus, level-1-forecasts of prices in period $t+1$ depend on level-0 forecasts of prices in period $t+2$. Note that when level-1 agents make their forecasts for period $t+1$, only information of prices prior to period t is available; that is, if level-0 agents use a forecasting strategy in which forecasts of prices in period $t+1$ depend on past prices, the level-0 forecasts of prices in period $t+2$ are expected forecasts in period t (with the same information available as when forecasts in period t for period $t+1$ are formed). An additional superscript can indicate that only information prior to t is available, $p_{t+1}^{e_{L1}} = f(p_{t+2}^{e_{L0},t})$, but this is not essential (the expected forecasts in a market populated by agents of a given level equal the actual forecasts later, as there is no randomness in the model).

The same argument can be applied to higher level reasoning. Level-2 forecasts are forecasts optimally reacting to forecasts in a market of level-1 agents. Thus, $p_{t+1}^{e_{L2}} = f(p_{t+2}^{e_{L1},t})$. Of course, these level-1 forecasts for period $t+2$ depend on level-0 forecasts in period $t+3$. Thus, $p_{t+1}^{e_{L2}} = f(p_{t+2}^{e_{L1},t}) = f^2(p_{t+3}^{e_{L0},t})$. By induction, this leads to the general formula for level-k agents, $k \geq 1$:

$$p_{t+1}^{e_{Lk}} = f^k\left(p_{t+1+k}^{e_{L0},t}\right). \tag{8}$$

If behavior of level-0 agents is clearly defined (e.g., recursively in dependence of past prices), forecasts of future prices from agents of all levels can be obtained easily after calculating future market prices and forecasts in a market populated by level-0 reasoners.

The behavior of level-0 agents thus plays a crucial role in the model. We make the assumption that level-0 agents extrapolate trends (this assumption is fundamental). A trend follower's price forecast is of the form $p_{t+1}^{e_{TF}} = p_{t-1} + b(p_{t-1} - p_{t-2})$, where b is a parameter determining the strength of the trend extrapolation.

3.1 Modeling the ex-ante hypotheses

To model the ex-ante hypotheses, we assume that if the agents have knowledge about the fundamental value of the asset, they slowly incorporate this knowledge into their price forecasts. Level-0 agents start out with trend-following behavior and slowly reduce the weight placed on trend extrapolation while slowly increasing the weight placed on their knowledge about the fundamental value, from the moment onward in which the knowledge becomes available. That is, forecasts of level-0 agents can be written as

$$p_{t+1}^{e_{L0}} = \alpha(t)\left(p_{t-1} + b(p_{t-1} - p_{t-2})\right) + (1 - \alpha(t))p^f, \tag{9}$$

where $\alpha(t)$ depends on time and on whether and when information about the fundamental value is available.

Forecasts further in the future, assuming a market of level-0 agents, can be found recursively, as the price dynamics are specified in such a market. The price forecast for period $t+2$ is given by $p_{t+2}^{e_{L0};t} = p_{t+2}^{e_{L0}} = \alpha(t+1)\left(p_t + b(p_t - p_{t-1})\right) + (1 - \alpha(t+1))p^f = \alpha(t+1)\left(f(p_{t+1}^{e_{L0}}) + b(f(p_{t+1}^{e_{L0}}) - f(p_t^{e_{L0}}))\right) + (1 - \alpha(t+1))p^f$. Generally for period $t+1+n$, forecasts are

$$p_{t+1+n}^{e_{L0};t} = p_{t+1+n}^{e_{L0}} = \alpha(t+n)\left(f(p_{t+n}^{e_{L0}}) + b(f(p_{t+n}^{e_{L0}}) - f(p_{t-1+n}^{e_{L0}}))\right) + (1 - \alpha(t+n))p^f. \tag{10}$$

When applying the model to different rounds, we restart each round with new initial price forecasts (such restarts can also be observed in the experiment; that is, market participants do not extrapolate the last prices of the previous round into a new round). However, we assume that the learning that takes place in one round does not disappear in the next round, agents just continue learning. If no information is available, as in our NO_INFO treatment, $\alpha(t) \equiv 1$ in all rounds. In the first round of INFO_AFTER, $\alpha(t) = 1$ similarly holds. In the rounds in which learning takes place (the last two rounds in INFO_AFTER and all rounds in FULL_INFO), $\alpha(t) = (1-\beta)^{t+t_x}$, where β is the learning parameter, and t_x, which is different across rounds, ensures that the learning is carried over from round to round.[19]

As mentioned, the formulas spelled out above do not take into account any constraints on forecasts or price formation. However, these constraints can easily be taken into account: future prices and forecasts in a market of level-0 agents can just be computed with these constraints (the formulas become more convoluted without being more instructive, therefore we omit them here), and higher-level forecasts can be calculated from those. For the simulation results that we show, the constraints are accounted for exactly as in the experiment.[20]

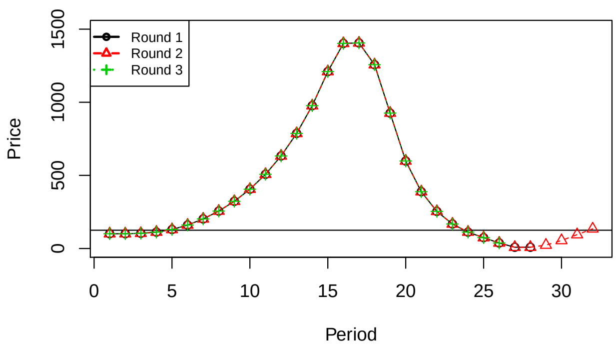
We show results of simulations from this version of the model in Figure 8. In these simulations, three out of six agents are modeled as level-0, two as level-1, and one as level-2 (note that it is in general possible to model agents as mixes of two or more levels). We have chosen to use levels zero, one, and two, because this is in line with previous empirical findings on level-k reasoning (in the simple guessing game; Nagel, 1995). The trend-extrapolation coefficient is $b = 1.2$ and the learning parameter is $\beta = 0.005$.[21] We initialize

[19]To be precise, we simulate the model as follows (minor modifications of when exactly $\alpha(t)$ starts to decrease do not affect our conclusions). In the first round of FULL_INFO, $\alpha(t) = 1$ for $t = 1,\ 2,\ 3$ to account for the fact that the first forecast using trend extrapolation is made in period 3 for period 4. For $t > 3$ in that round, $\alpha(t) = (1-\beta)^{t-3}$. In the second round of FULL_INFO, $\alpha(t) = 1$ for $t = 1,\ 2$, where the starting values of the forecasts are relevant, while $\alpha(t) = (1-\beta)^{t+28-3-2}$ from the third period onward, where 28 is the number of periods in the first round and the 3 and 2 that are subtracted from it are the numbers of periods with $\alpha(t) = 1$ in the beginning of the rounds. In the third round, $\alpha(t) = 1$ for $t = 1,\ 2$ again, and $\alpha(t) = (1-\beta)^{t+28+32-3-2-2}$ for the other periods, with a similar explanation as for the second round. In INFO_AFTER, we similarly have $\alpha(t) = 1$ for $t = 1,\ 2$ in the last two rounds, $\alpha(t) = (1-\beta)^{t-2}$ for $t > 2$ in the second round, and $\alpha(t) = (1-\beta)^{t+32-2-2}$ for $t > 2$ in the third round.

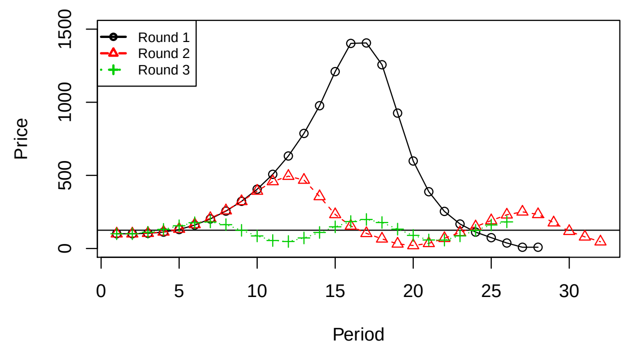
[20]In the experiment, forecasts cannot be below 0 or above 1500. Similarly, the constraints on the trading of the computerized agents imply that, in the pricing equation, forecasts that deviate from the previous price in an extreme way are replaced by the previous price plus or minus the specified maximally possible deviation. We consider it natural that level-k reasoners with $k \geq 1$ are aware of this.

[21]The trend-extrapolation parameter is below but close to the strong trend-extrapolation parameter used in several papers relying on a heuristic-switching model that includes both strong and weak trend followers (see Hommes, 2011). There is no such orientation in the literature for the learning parameter. However,

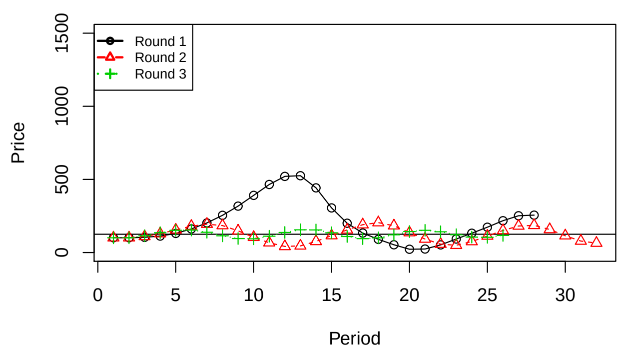
the model in each round with forecasts in periods 2 and 3 equal to 100, which is not far from what we observe in the experiment (as we deal with two-period ahead forecasts, the first forecast for which trend extrapolation is possible is the forecast for period 4, which determines the realized price in period 3). In these simulations, we use equal starting values, which is why the price paths in all three rounds of NO_INFO are identical. Figure 8 illustrates our ex-ante predictions: in NO_INFO no learning, in FULL_INFO learning and very accurate pricing of the assets in the last round, and in INFO_AFTER price paths that lie in between these two treatments (with a first round as in NO_INFO but considerable learning thereafter).



(a) NO_INFO



(b) INFO_AFTER



(c) FULL_INFO

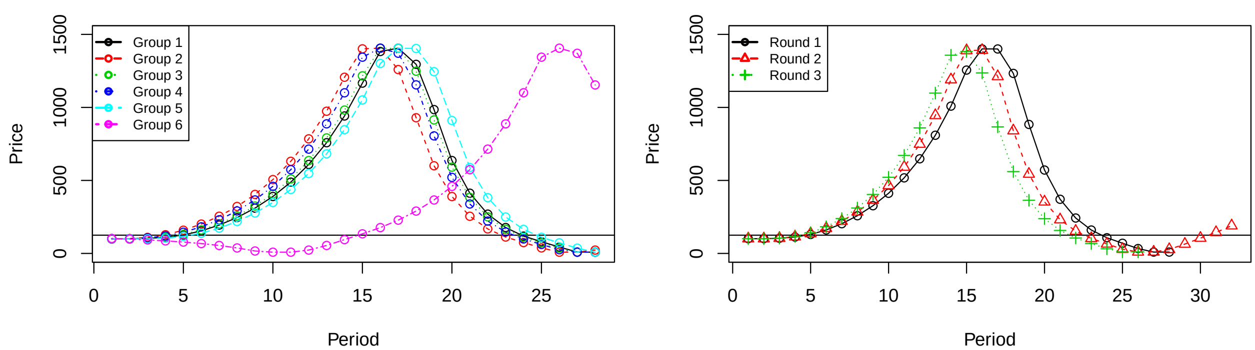
Figure 8: Model simulations of price dynamics in the three different treatments

This figure shows the results of the level-k-based model with learning of level-0 agents when applied to the different treatments in the learning-to-forecast experiment.

note that a wide variety of parameter values lead to qualitatively similar price dynamics.

3.2 Modeling behavior observed in the experiment

The experimental data do not show the ex-ante predicted treatment effects. In terms of the model, this suggests that level-0 agents do to not learn to incorporate the information on the fundamental value. In the following, we thus always consider the model without this type of learning. Other features of the data are described well by the model. The general shape of the bubbles in the model, for instance, is very similar to the bubbles observed in the experiment.[22] In addition, heterogeneity across groups concerning when the bubbles occur arises easily in the model by adding small noise terms to the starting values. Figure 9a shows simulations similar to the ones before (without learning; i.e., level-0 agents are pure trend-followers) but with very small noise terms added to the two starting values (the starting values are 100 plus i.i.d. $N(0, \sqrt{2})$-distributed error terms).



(a) Noisy starting values

(b) Agents increase their level over time

Figure 9: Model outcomes of price dynamics

This figure shows simulated price paths. Left: $N(0, \sqrt{2})$-error terms added to the starting values. Right: price paths in three rounds of the experiments when agents slowly increase their level over time.

We do not observe the learning of level-0 agents described in Section 3.1 in the data. However, another type of learning, agents learning to become more sophisticated over

[22]Note that a simple forecasting rule based on adaptive expectations does not describe the data well (while still describing the data less poorly than forecasts that are constantly at the fundamental value). The reason is that such an adaptive rule shows a lot of persistence, because forecasts are in general a weighted average of past observations. Large and rapidly forming bubbles, as we observe them in the experiment, can thus not be explained.

time, can lead to a speed-up of the bubbles over time as observed in the experiment. To be precise, we model this as all agents slowly changing their behavior in the direction of one level above their original level.

Higher levels of reasoning lead to stronger price bubbles because of the two-period ahead nature of forecasts and the strong positive feedback from price expectations to realized prices in the market (that is, because of the strong strategic complementarity). If, for example, a market populated with level-0 agents would result in the forecast of a very high price for period $t+2$ when a bubble is forming, this would lead to level-1 agents already forecasting a high price for period $t+1$ (this forecast would not be as high as the forecast of level-0 agents for period $t+2$, but it would be higher than level-0 forecasts for period $t+1$).

To explain the observed behavior in the experiment, we assume that each agent that is originally of level k forecasts $p_{t+1}^{e_{Lk'}} = \alpha_{k'}(t) p_{t+1}^{e_{Lk}} + (1-\alpha_{k'}(t)) p_{t+1}^{e_{L(k+1)}}$, which means that each forecast is a weighted average of the original level and one level above. We use $\alpha_{k'}(t) = (1-\beta_{k'})^{t-t_i}$, where $\beta_{k'}$ is the learning parameter for agents who are originally of level k. t_i determines when agents start to learn, which is at the beginning of the first round (when applying the model to different rounds, the learning continues across rounds, leading to different results for different rounds). Simulations with this model (again abstracting from any noise, so that prices would be identical across rounds without learning) are shown in Figure 9b.[23] It can be seen that the bubbles shift (somewhat) to the left over the rounds. Note that the simulations in Figure 9 can be considered as simulations for all treatments of the experiment, as the model does not distinguish between the different levels of information provision.

Viewing the ex-ante predictions for the experiment and the experimental results in light of the presented models, one could say that the ex-ante predictions are in line with

[23] Starting values are again 100. The learning parameter $\beta_{k'}$ equals 0.005 for all levels (also here, a wide variety of learning parameter values lead to qualitatively similar price dynamics). Other parameters are as for the simulations shown in Figure 8.

learning to incorporate information about the fundamental value into the decision making, while the experimental data are in line with agents learning to act in a more sophisticated fashion. Learning to be more sophisticated here means that agents learn to anticipate price changes, which leads to a speeding up of the bubbles, in contrast to learning to incorporate the provided information, which would have contributed to bubbles disappearing over time (in the information treatments).

4 Concluding Remarks

Bubbles do not disappear with experience in our experiments. These findings are novel for the learning-to-forecast experiment and stand in contrast to the literature for the call market experiment. In both experiments, we find reoccurring bubbles that appear earlier in later market repetitions. We can only observe slight improvements in pricing accuracy in the call market experiment with explicit information about the buy-out value. An interesting difference between the two experiments is the shape of the bubbles. While we observe relatively flat bubbles in the call market experiment, bubbles inflate and deflate fast in the learning-to-forecast experiment.

In our experiments, the presentation of information does not play an important role. Even when full information about the fundamental value is as clearly presented as possible, we observe very poor pricing of the assets repeatedly. This suggests that prices may not predominantly be driven by (correct or erroneous) computations of fundamental values but rather by behavior relying on trend-following (including versions in which subjects think that they can sell for more money later as long as prices are rising).

The reason why our findings in the call market experiment, in particular in the treatment with full information, differ from the literature lies in the high cash-to-asset ratio. We show this with a new treatment, in which the cash-to-asset ratio is lower. Pricing is much more accurate in this new treatment; this unites our contribution with the previous literature on experimental asset markets without repetition, as the cash-to-asset ratio has been shown to be a bubble driver there (e.g., Noussair and Tucker, 2016; Razen et al., 2017).[24]

We believe that a high cash-to-asset ratio is the most natural setting with equity markets outside the laboratory in mind (as total wealth is much greater than equity market capitalization). We find it surprising that the existing literature using high cash-to-asset ratios is so sparse; the economic theory that participants price assets at the fundamental value should hold for *any* sufficiently high cash level. Our specification with an indefinite end time and a longer horizon also seem natural with equity markets in mind, which do not posses a predetermined end time. Similarly, participants in real-world markets are not presented the fundamental value of the assets, as in our treatments without full information.

In the learning-to-forecast experiment, the data can be explained with a model based on level-k reasoning. In this model, level-0 agents extrapolate trends (and higher-level agents react to the actions one level below). In addition, all agents slowly become more sophisticated acting more and more like agents with a higher level of reasoning. This model cannot only explain the large and rapidly rising bubbles but also the fact that bubbles appear earlier in later rounds of the experiment.

Our work shows that the finding that bubbles disappear with experience is less robust than previously thought. Of course, our findings do not show that bubbles would never disappear. However, three repetitions of an absolutely identical market are already a lot, with respect to the prior literature and in light of the fact that markets outside the labora-

[24]Another difference between the design of our call market experiment and that of standard experiments is that the number of periods in the call market experiment is higher than in most other such experiments and the horizon is indefinite (these design choices were necessary to keep the two experiments similar and to facilitate the creation of a no-information treatment in the call market experiment). In a follow-up experiment (Kopányi-Peuker and Weber, 2020), we investigate the effects of the length and the definiteness of the horizon with the same high cash-to-asset ratio. It turns out that bubbles also do not disappear with experience when the horizon is short or definite or both. In those sessions there is also no upper bound on bids and asks, showing that this is not a particularly important difference.

tory never repeat in an identical way (market participants and the economic environment change continuously). Given how much more complicated markets outside the laboratory are and how much wealth there is enabling bubbles to form, it is likely that prices in actual markets can deviate substantially from fundamentals, no matter how experienced the traders are.

In general, it is unclear whether experiments with actual trade or with only forecasting in the laboratory (and computerized trade) yield findings that are more relevant for the markets outside the laboratory. In our view, it is good news for the experimental method that the two market paradigms yield similar outcomes with respect to such important characteristics as whether bubbles disappear with experience when the conditions in the two experiments are similar.

References

Arifovic, J. and Petersen, L. (2017). Stabilizing expectations at the zero lower bound: experimental evidence. *Journal of Economic Dynamics and Control*, 82:21–43.

Assenza, T., Bao, T., Hommes, C., and Massaro, D. (2014). Experiments on expectations in macroeconomics and finance. In *Experiments in Macroeconomics*, pages 11–70. Emerald Group Publishing Limited.

Assenza, T., Heemeijer, P., Hommes, C., and Massaro, D. (2019). Managing self-organization of expectations through monetary policy: a macro experiment. *Journal of Monetary Economics*, in press.

Bao, T., Duffy, J., and Hommes, C. (2013). Learning, forecasting and optimizing: An experimental study. *European Economic Review*, 61:186–204.

Bao, T., Hennequin, M., Hommes, C., and Massaro, D. (2020). Coordination on bubbles in large-group asset pricing experiments. *Journal of Economic Dynamics and Control*, 110:103702.

Bao, T., Hommes, C., and Makarewicz, T. (2017). Bubble formation and (in) efficient markets in learning-to-forecast and optimise experiments. *The Economic Journal*, 127(605):F581–F609.

Bao, T., Hommes, C., Sonnemans, J., and Tuinstra, J. (2012). Individual expectations, limited rationality and aggregate outcomes. *Journal of Economic Dynamics and Control*, 36(8):1101–1120.

Bosch-Rosa, C., Meissner, T., and Bosch-Domènech, A. (2018). Cognitive bubbles. *Experimental Economics*, 21(1):132–153.

Bossaerts, P. (2009). The experimental study of asset pricing theory. *Foundations and Trends in Finance*, 3(4):289–361.

Bossaerts, P., Ghirardato, P., Guarnaschelli, S., and Zame, W. R. (2010). Ambiguity in asset markets: Theory and experiment. *The Review of Financial Studies*, 23(4):1325–1359.

Bossaerts, P., Plott, C., and Zame, W. R. (2007). Prices and portfolio choices in financial markets: Theory, econometrics, experiments. *Econometrica*, 75(4):993–1038.

Caginalp, G., Porter, D., and Smith, V. (1998). Initial cash/asset ratio and asset prices: An experimental study. *Proceedings of the National Academy of Sciences*, 95(2):756–761.

Cheung, S. L., Hedegaard, M., and Palan, S. (2014). To see is to believe: Common expectations in experimental asset markets. *European Economic Review*, 66:84–96.

Cheung, S. L. and Palan, S. (2012). Two heads are less bubbly than one: Team decision-making in an experimental asset market. *Experimental Economics*, 15(3):373–397.

Colasante, A., Alfarano, S., Camacho, E., and Gallegati, M. (2018). Long-run expectations in a learning-to-forecast experiment. *Applied Economics Letters*, 25(10):681–687.

Colasante, A., Palestrini, A., Russo, A., and Gallegati, M. (2017). Adaptive expectations versus rational expectations: Evidence from the lab. *International Journal of Forecasting*, 33(4):988–1006.

Cornand, C. and M'baye, C. K. (2018). Does inflation targeting matter? An experimental investigation. *Macroeconomic Dynamics*, 22:362–401.

Duffy, J., Jiang, J., and Xie, H. (2019). Experimental asset markets with an indefinite horizon. Working Paper, University of California, Irvine.

Dufwenberg, M., Lindqvist, T., and Moore, E. (2005). Bubbles and experience: An experiment. *American Economic Review*, 95(5):1731–1737.

Füllbrunn, S., Neugebauer, T., and Nicklisch, A. (2019). Underpricing of initial public offerings in experimental asset markets. *Experimental Economics*, pages 1–28.

Füllbrunn, S., Rau, H. A., and Weitzel, U. (2014). Does ambiguity aversion survive in experimental asset markets? *Journal of Economic Behavior & Organization*, 107:810–826.

Hanaki, N., Koriyama, Y., Sutan, A., and Willinger, M. (2019). The strategic environment effect in beauty contest games. *Games and Economic Behavior*, 113:587–610.

Haruvy, E., Lahav, Y., and Noussair, C. N. (2007). Traders' expectations in asset markets: Experimental evidence. *American Economic Review*, 97(5):1901–1920.

Haruvy, E. and Noussair, C. N. (2006). The effect of short selling on bubbles and crashes in experimental spot asset markets. *Journal of Finance*, 61(3):1119–1157.

Hennequin, M. (2019). Experiences and expectations in asset markets: an experimental study. Working Paper, University of Amsterdam.

Holt, C. A., Porzio, M., and Song, M. Y. (2017). Price bubbles, gender, and expectations in experimental asset markets. *European Economic Review*, 100:72–94.

Hommes, C. (2011). The heterogeneous expectations hypothesis: Some evidence from the lab. *Journal of Economic Dynamics and Control*, 35(1):1–24.

Hommes, C., Kopányi-Peuker, A., and Sonnemans, J. (2020). Bubbles, crashes and information contagion in large-group asset market experiments. *Experimental Economics*, in press.

Hommes, C., Massaro, D., and Weber, M. (2019). Monetary policy under behavioral expectations: Theory and experiment. *European Economic Review*, 118:193–212.

Hommes, C., Sonnemans, J., Tuinstra, J., and Van de Velden, H. (2005). Coordination of expectations in asset pricing experiments. *The Review of Financial Studies*, 18(3):955–980.

Hommes, C., Sonnemans, J., Tuinstra, J., and Van De Velden, H. (2007). Learning in cobweb experiments. *Macroeconomic Dynamics*, 11(S1):8–33.

Hommes, C., Sonnemans, J., Tuinstra, J., and van de Velden, H. (2008). Expectations and bubbles in asset pricing experiments. *Journal of Economic Behavior & Organization*, 67:116–133.

Hoshihata, T., Ishikawa, R., Hanaki, N., and Akiyama, E. (2017). Flat bubbles in long-horizon experiments: Results from two market conditions. GREDEG Working Paper No. 2017-32.

Huber, J. and Kirchler, M. (2012). The impact of instructions and procedure on reducing confusion and bubbles in experimental asset markets. *Experimental Economics*, 15(1):89–105.

Huber, J., Kirchler, M., and Sutter, M. (2008). Is more information always better?: Experimental financial markets with cumulative information. *Journal of Economic Behavior & Organization*, 65(1):86–104.

Huck, S., Normann, H.-T., and Oechssler, J. (2004). Two are few and four are many: Number effects in experimental oligopolies. *Journal of Economic Behavior & Organization*, 53(4):435–446.

Hüsler, A., Sornette, D., and Hommes, C. H. (2013). Super-exponential bubbles in lab experiments: evidence for anchoring over-optimistic expectations on price. *Journal of Economic Behavior & Organization*, 92:304–316.

Hussam, R. N., Porter, D., and Smith, V. L. (2008). Thar she blows: Can bubbles be rekindled with experienced subjects? *American Economic Review*, 98(3):924–37.

Khaw, M. W., Stevens, L., and Woodford, M. (2019). Adjustment dynamics during a strategic estimation task. Mimeo, University of Maryland.

King, R. R., Smith, V. L., Williams, A. W., and van Boening, M. (1993). The robustness of bubbles and crashes in experimental stock markets. In Day, R. H. and Chen, P., editors, *Nonlinear Dynamics and Evolutionary Economics*, pages 183–200. Oxford University Press, New York.

Kirchler, M., Huber, J., and Stöckl, T. (2012). Thar she bursts: Reducing confusion reduces bubbles. *American Economic Review*, 102(2):865–883.

Kopányi-Peuker, A. and Weber, M. (2020). The role of the end time in experimental asset markets. Working Paper, University of St. Gallen.

Mauersberger, F. and Nagel, R. (2018). Levels of reasoning in keynesian beauty contests: A generative framework. In Hommes, C. and LeBaron, B., editors, *Handbook of Computational Economics*, volume 4, pages 541–634. Elsevier.

Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics*, 8:323–361.

Nagel, R. (1995). Unraveling in guessing games: An experimental study. *American Economic Review*, 85(5):1313–1326.

Noussair, C. N. and Tucker, S. (2013). Experimental research on asset pricing. *Journal of Economic Surveys*, 27(3):554–569.

Noussair, C. N. and Tucker, S. (2016). Cash inflows and bubbles in asset markets with constant fundamental values. *Economic Inquiry*, 54(3):1596–1606.

Noussair, C. N., Tucker, S., and Xu, Y. (2016). Futures markets, cognitive ability, and mispricing in experimental asset markets. *Journal of Economic Behavior and Organization*, 130:166 – 179.

Nuzzo, S. and Morone, A. (2017). Asset markets in the lab: A literature review. *Journal of Behavioral and Experimental Finance*, 13:42–50.

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

Palan, S. (2010). Digital options and efficiency in experimental asset markets. *Journal of Economic Behavior & Organization*, 75(3):506–522.

Palan, S. (2013). A review of bubbles and crashes in experimental asset markets. *Journal of Economic Surveys*, 27(3):570–588.

Pfajfar, D. and Žakelj, B. (2014). Experimental evidence on inflation expectation formation. *Journal of Economic Dynamics and Control*, 44:147–168.

Plott, C. R. and Sunder, S. (1988). Rational expectations and the aggregation of diverse information in laboratory security markets. *Econometrica*, 56(5):1085–1118.

Rabin, M. (2000). Risk aversion and expected-utility theory: A calibration theorem. *Econometrica*, 68(5):1281–1292.

Razen, M., Huber, J., and Kirchler, M. (2017). Cash inflow and trading horizon in asset markets. *European Economic Review*, 92:359–384.

Roxburgh, C., Lund, S., and Piotrowski, J. (2011). Mapping global capital markets 2011. McKinsey Global Institute Research Update.

Shestakova, N., Powell, O., and Gladyrev, D. (2019). Bubbles, experience and success. *Journal of Behavioral and Experimental Finance*, 22:206–213.

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

Sonnemans, J., Hommes, C., Tuinstra, J., and van de Velden, H. (2004). The instability of a heterogeneous cobweb economy: a strategy experiment on expectation formation. *Journal of Economic Behavior & Organization*, 54(4):453–481.

Sonnemans, J. and Tuinstra, J. (2010). Positive expectations feedback experiments and number guessing games as models of financial markets. *Journal of Economic Psychology*, 31(6):964–984.

Stanley, T. D. (1997). Bubbles, inertia, and experience in experimental asset markets. *The Journal of Socio-Economics*, 26(6):611–625.

Stöckl, T., Huber, J., and Kirchler, M. (2010). Bubble measures in experimental asset markets. *Experimental Economics*, 13(3):284–298.

Sutter, M., Huber, J., and Kirchler, M. (2012). Bubbles and information: An experiment. *Management Science*, 58(2):384–393.

Van Boening, M. V., Williams, A. W., and LaMaster, S. (1993). Price bubbles and crashes in experimental call markets. *Economics Letters*, 41(2):179–185.

Weber, M., Duffy, J., and Schram, A. (2018). An experimental study of bond market pricing. *Journal of Finance*, 73(4):1857–1892.

Weber, M., Duffy, J., and Schram, A. (2019). Credit default swap regulation in experimental bond markets. Tinbergen Institute Discussion Paper No 2019–039/I.

Weitzel, U., Huber, C., Huber, J., Kirchler, M., Lindner, F., and Rose, J. (2020). Bubbles and financial professionals. *The Review of Financial Studies*, 33(6):2659–2696.

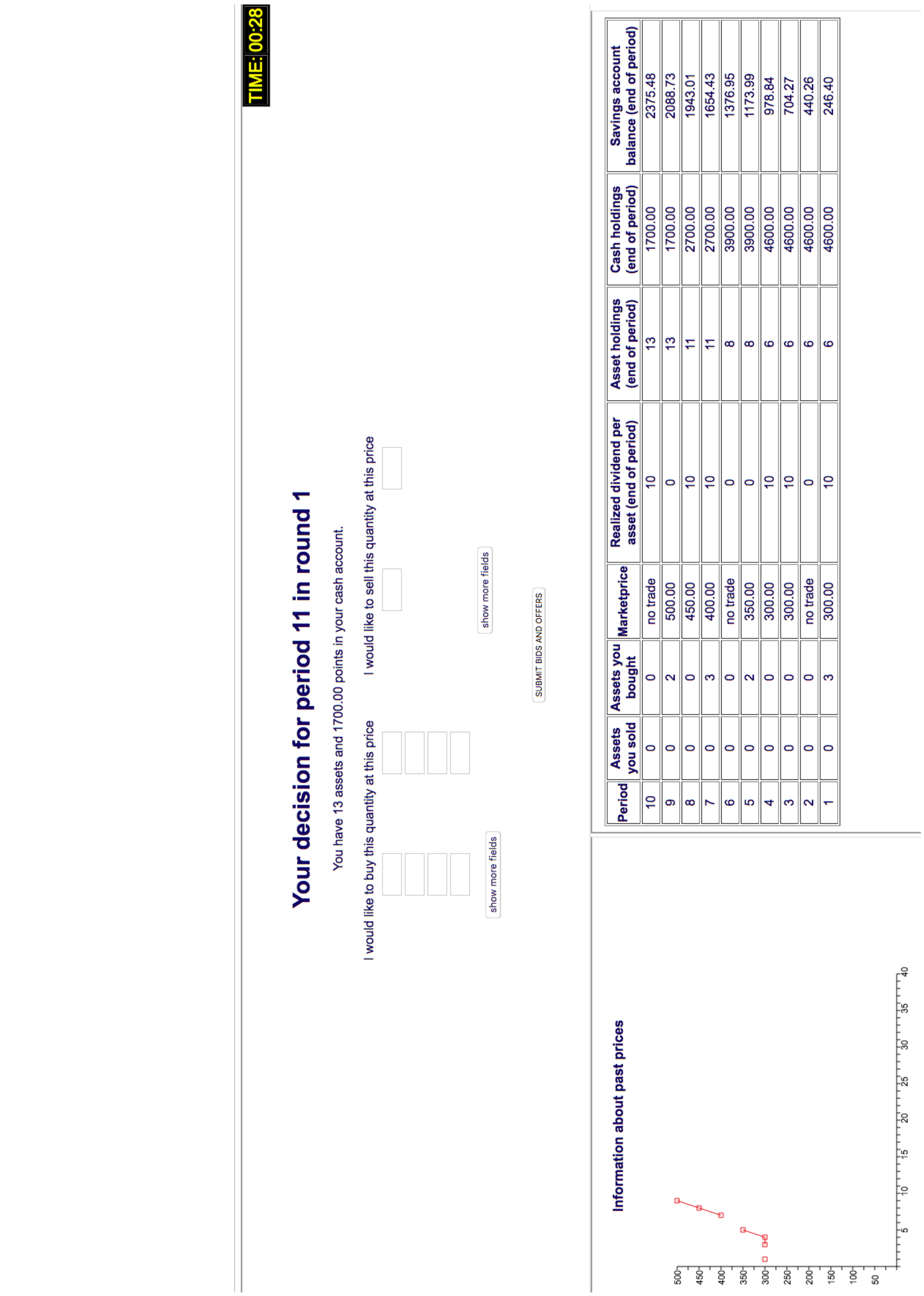
Online Appendix to ”Experience Does not Eliminate Bubbles: Experimental Evidence”

Anita Kopányi-Peuker Matthias Weber

This online appendix contains material in addition to the main text. Section A contains screenshots of the decision tasks in the experiments. Sections B and C reproduce the experimental instructions and comprehension test questions for the two experiments. Additional data can be found in Section D.

A Screenshots

Figures A.1 and A.2 show screenshots for subjects' decisions in the call market and learning-to-forecast experiments, respectively.



Period	Assets you sold	Assets you bought	Marketprice	Realized dividend per asset (end of period)	Asset holdings (end of period)	Cash holdings (end of period)	Savings account balance (end of period)
10	0	0	no trade	10	13	1700.00	2375.48
9	0	2	500.00	0	13	1700.00	2088.73
8	0	0	450.00	10	11	2700.00	1943.01
7	0	3	400.00	10	11	2700.00	1654.43
6	0	0	no trade	0	8	3900.00	1376.95
5	0	2	350.00	0	8	3900.00	1173.99
4	0	0	300.00	10	6	4600.00	978.84
3	0	0	300.00	10	6	4600.00	704.27
2	0	0	no trade	0	6	4600.00	440.26
1	0	3	300.00	10	6	4600.00	246.40

Figure A.1: Decision screen in the CME

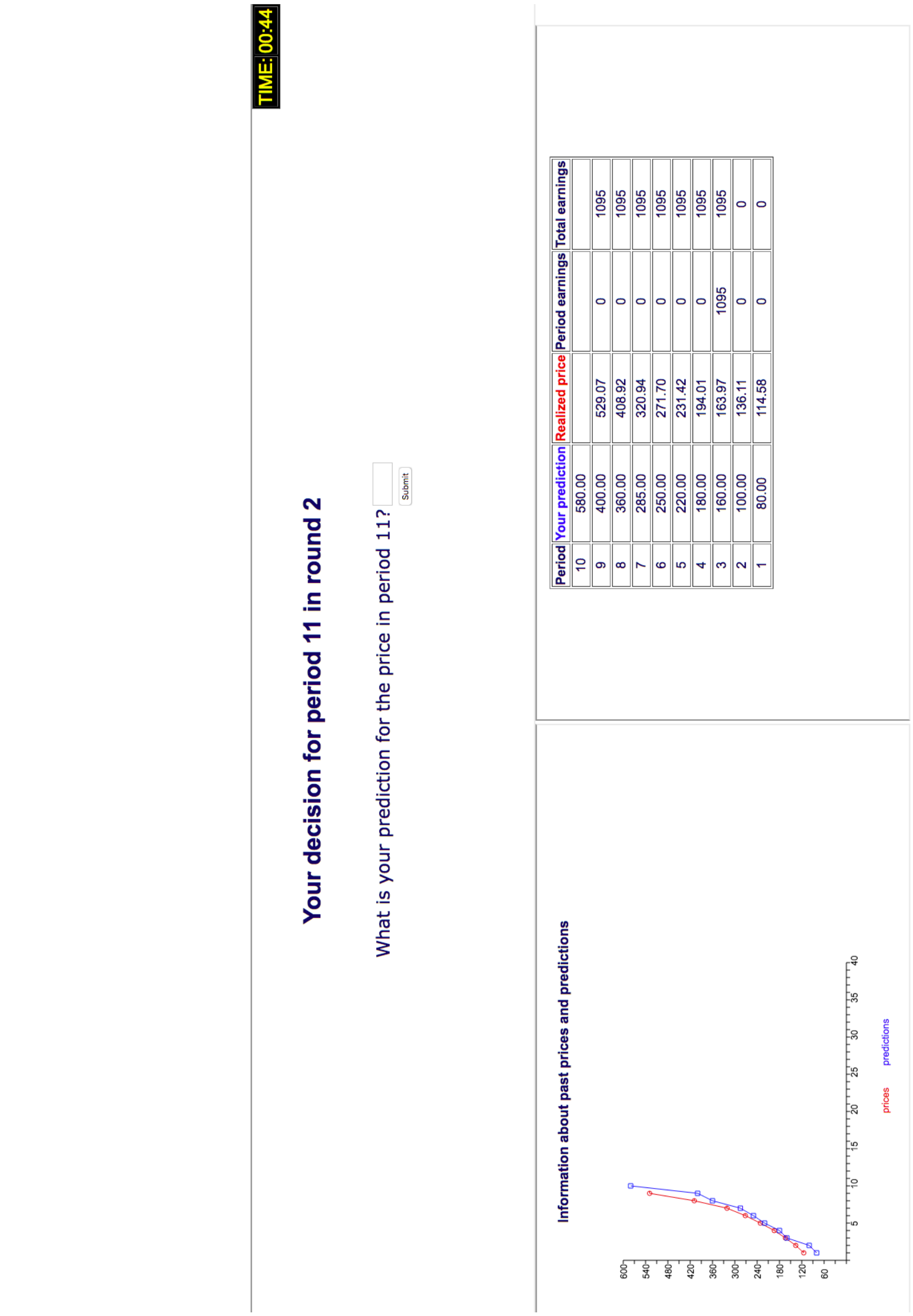


Figure A.2: Decision screen in the LtFE

B Experimental Instructions and Comprehension Test Questions for the Call Market Experiment

We reproduce the complete experimental instructions for the treatment NO_INFO of the call market experiment in Section B.1. Bold or italic text is also bold or italic in the original instructions and text in boxes is similarly in such boxes in the original instructions. In Section B.2 we discuss the differences in instructions between the treatments. Section B.3 reproduces the comprehension test questions as used in treatments NO_INFO and INFO_AFTER. Section B.4 reports the difference in the test questions used in FULL_INFO.

Note that the numbers used as examples in the instructions are more often above the fundamental value than below. However, the opposite is true in the comprehension test questions, so that no considerable anchoring bias should arise from the examples if instructions and comprehension test questions are considered jointly.

B.1 Instructions CME NO_INFO

Welcome to this experiment!

Please read these instructions carefully as they explain how you earn money from the decisions that you make. You will be paid privately at the end, after all participants have finished the experiment.

During the experiment you are not allowed to use your mobile phone or other electronic devices. You are also not allowed to communicate with other participants. If you have a question at any time, please raise your hand and someone will come to your desk to answer your question in private.

The experiment consists of 3 rounds. Each round consists of multiple periods. Except for the number of periods in each round, the rounds are identical. Your earnings for each of the 3 rounds will be in points. **At the end, only your earnings from one randomly selected round will be paid out to you! The points from the selected round will be exchanged into euros at the exchange rate 900 points = 1 euro.** In addition you will receive 10 euros for your participation.

All participants will be randomly divided into **groups of 6 people**. The group composition will not change during the experiment. You will not know the identity of any group member nor will they know your identity even after the experiment is over.

The following describes what you will be doing in **each** of the 3 rounds.

General information

You will be given an opportunity to trade in an asset with the other participants in your group. You will start each round with an endowment of 5500 points (booked on your "cash account") and with 3 assets. In total there are 18 identical assets that you can trade. Holding assets can give you earnings in a way that will be explained below. Each round consists of multiple time periods in which you can trade. **However, you do not know the exact number of time periods (it may be any number between 25 and 40 and this number will be different in different rounds).**

Trading

If you want to buy assets, you can enter the number of assets that you want to buy (bid for) at a certain price using the computer interface. You can state as many different bid prices and quantities as you like.

> Example (the numbers here provide no indication of what you should enter in the experiment): Imagine that you would like to buy no assets if the price per asset is more than 200 points. If the price is at most 200 but more than 150 points, you would like to buy one asset. If the price of the asset is at most 150 points, you would like to buy four assets altogether. Then you should enter the following information:
>
> – One bid for 1 asset with a price of 200

– One bid for 3 assets with a price of 150

Note: At a price of less than 150 you want to buy four assets – nevertheless, the quantity that you enter with the price of 150 should be only three in this case. This is so, because you are already bidding for one asset at a price of up to 200.

If you want to sell assets that you previously bought (or assets that you are endowed with in the beginning of a round), then you can do something similar. You enter the number of assets that you want to sell (offer quantity) and the ask price (or offer price), which is the minimum price that you would like to receive for those units of the asset. You can again enter multiple combinations of quantities and prices.

Example (the numbers here provide no indication of what you should enter in the experiment): Imagine that you would like to sell none of your assets if the price per asset is below 100 points. If the price is at least 100 points, but less than 700 points, you would like to sell two assets. If the price of the asset is at least 700 points, you would like to sell three assets altogether. Then you should enter the following information:

– One offer of 2 assets with a price of 100

– One offer for 1 asset with a price of 700

Note: At a price of at least 700 you want to sell three assets – nevertheless, the quantity that you enter with the price of 700 should be only one in this case. This is so, because you are already offering two assets at a price of at least 100.

In each period, you may enter both buy and sell orders, only buy orders, only sell orders, or no orders at all.

In each period you have enough (but limited) time to submit your bids and offers. If you do not submit bids or offers during this time frame, the computer will consider this as no bids or offers. This means that if you have entered bids or offers into the computer interface but not submitted them by the time the period ends, these bids or offers will be lost. A timer will show you the remaining time for each period (2 minutes in the first 10 periods of the first round, 1 minute in all other periods).

The bids and offers that you can enter into the computer interface are restricted as follows:

- You can only enter positive integer number as quantities.
- You can only enter positive numbers as prices, up to a maximum of 1500 (if you want to enter a decimal number, use a point and not a comma).
- You cannot try to sell more assets than you have at that moment. Similarly, you cannot try to buy more assets than there are available (which is 18 minus the number of assets you have).
- You cannot enter bids that you would not be able to pay for with the amount of cash that you have.
- All of your asks (offer prices) must be higher than your bids (that is, you cannot sell to yourself).

Market Price and Traded Quantity

The market price in each period is determined by supply and demand. This means that the price will be chosen that makes the most trades possible. All trades are then carried out at this single market price, which is centrally determined for your group in each period.

Explanation (this is a very simple example and the numbers here provide no indication of what you should enter in the experiment): Imagine you enter that you would like to buy 2 assets if the price is at most 550 points and one other participant enters that she would like to buy 4 assets if the price is at most 550. Imagine further that nobody else in the market enters a buying bid at 550 points or at a higher price. This means that *all participants of the market together* would like to buy 6 assets if the price is at most 550 points per asset. The aggregation of the buy orders can be done for all prices and yields the market demand schedule. This demand schedule contains the information of all buy orders for *all participants of the market together* and can be represented by a step function as below. On the horizontal axis you can see the total quantity demanded for each price on the vertical axis. In the graph of this simple example you can see that all participants of the market together are willing to buy up to 19 assets at a price of 80 points per asset, only 14 assets at a price of 300 points per asset, and only 6 assets at a price of 550 points per asset.

[Figure B.1 appears here in the experimental instructions.]

A similar schedule can be derived for the supply side of the market, aggregating all the sell offers. When drawn it in the same graph, the supply schedule is an increasing step function.

[Figure B.2 appears here in the experimental instructions.]

The market price is the price at which the two curves intersect (in this example 300). Similarly, the traded quantity is the quantity at which the two curves intersect (in this example 11). Note that at this price, 3 more assets are demanded than supplied (14 assets are demanded while only 11 are supplied). In this case a random selection of 3 bids *from all the bids at the market price* would not be fulfilled (it is similarly possible that there is more supply at the market price than demand).

In some rare cases there can also be a whole interval of prices at which the most trades can be carried out and the demand and supply schedules overlap vertically. In such cases the middle of the interval will be the market price. If no bids or offers are made at all or if all bids to buy are at lower prices than all offers to sell, there will be no trade and also no market price.

You will always see the market prices of previous periods in a round on your screen. Similarly, you will see how many assets you bought or sold at this price. You will not be told the total number of trades in the market (except if there are none).

Properties of the Asset and Interest Rate

The financial asset pays a random dividend in each time period. This dividend is 10 points per asset with 50% probability and 0 points with 50% probability. In each period either all assets pay the high dividend or all assets pay the zero dividend. The dividend earnings will be paid to a separate account called "savings account" – they are part of your earnings for the round, but you cannot use points in this separate account to buy more assets.

The money that you do not spend on buying assets (and the money that you receive when selling assets) is stored in your cash account. You can use this money to buy more financial assets if you so wish. For the money in the cash account you receive an interest rate of 4% per time period. These interest earnings are not paid to the cash account but to the savings account.

Both dividends and interest rates will be paid "overnight"; this means that if you buy an asset in one period, you will have received your dividend from this asset by the time you are trading in the next period (similarly, the money that you hold after the trades of one period have been conducted will have yielded the interest by the time the trading of the next period begins). In the information table that you will see during the experiment, the dividend and interest payments following the trading of one period will already be included in the fields showing cash and savings account balance at the end of this period.

The points in your savings account cannot be used to buy assets, but they still yield interest. The interest rate for the money in the savings account is the same as for the money in the cash account, namely 4%. The interest is paid to the savings account at the same moment as the interest for the money in the cash account.

A round ends abruptly at some point between period 25 and 40. **When a round ends, the financial asset ceases to exist and you receive a fair price for your holdings of the asset at that moment. Note, however, that you will not be told what this price is until all rounds of the experiment have finished.** That is, if you hold assets when a round is terminated, you will not get to know your exact earnings for this round until all rounds have been completed. A round always ends right after the dividend and interest payment for the last period in which you could trade.

You can now start to answer the comprehension questions on the screen.

B.2 Differences in instructions between the treatments of the call market experiment

The instructions in the treatments INFO_AFTER and FULL_INFO are identical to those in NO_INFO except for one sentence in the second to last paragraph (starting with "A round ends abruptly") after the sentence "When a round ends, the financial asset ceases to exist and you receive a fair price for your holdings of the asset at that moment." The sentence that is different between treatments reads as follows in the three treatments:

- NO_INFO: Note, however, that you will not be told what this price is until all rounds of the experiment have finished.
- INFO_AFTER: You will be told immediately what this price is when the round ends.
- FULL_INFO: This price is 125 points per asset.

The instructions in the new LOW_CASH treatment are identical to those of the treatment FULL_INFO except for the specification of the exchange rate ("140 points = 1 euro" instead of "900 points = 1 euro") and that of the initial endowment in each round ("550 points" instead of "5500 points").

B.3 Comprehension test questions CME NO_INFO and INFO_AFTER

We reproduce here the comprehension test questions of the call market experiment in the treatments NO_INFO and INFO_AFTER. The test questions are numbered on the screens and appear on two screens (the first four questions on the first screen). Note that subjects had to answer all questions on a screen correctly to proceed. If they did not answer

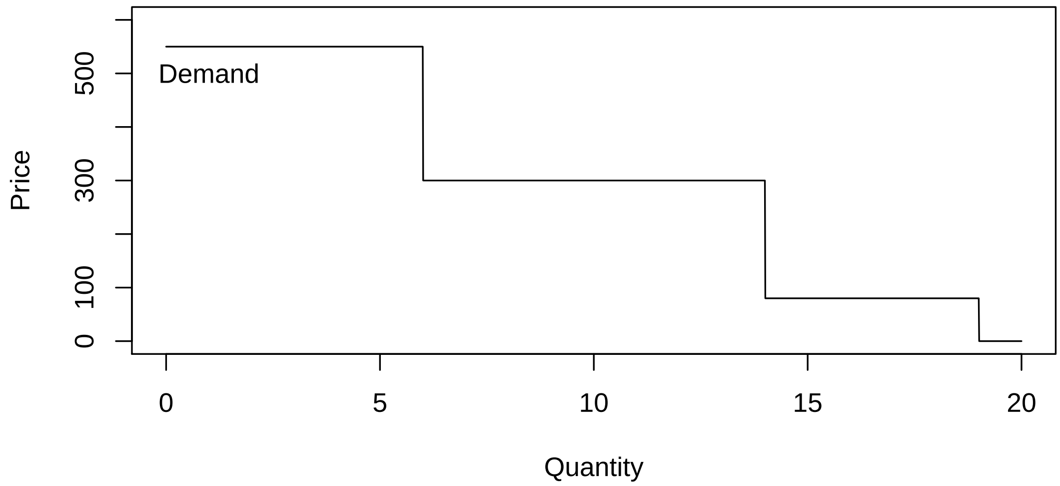


Figure B.1: Example of a demand curve (not labeled in the experimental instructions)

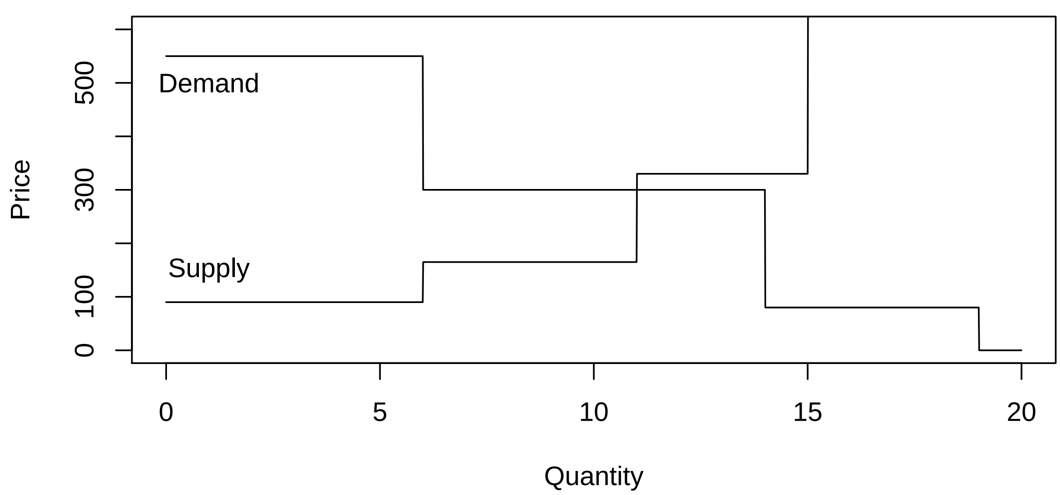


Figure B.2: Example of demand and supply curves (not labeled in the experimental instructions) all questions correctly and tried to proceed, they received the following error message: "You did not answer all questions correctly. Take another look at the instructions or raise your hand if you need help." We add a checkmark after each correct answer (or give the correct answer in brackets if the question is not a multiple choice problem). In Section B.4 we discuss how the test questions in treatment FULL_INFO and in the new treatment LOW_CASH differ from those shown here.

1. Imagine the following situation. You want to buy 8 assets in total if the price is at most 30 points per asset. You want to buy 5 assets in total if the price is above 30 points but at most 100 points. You want to buy 1 asset if the price is above 100 points but at most 311.5 points. What do you enter in the corresponding part of the computer interface?
   a. Quantity: 8, Price: 30; Quantity: 5, Price: 100; Quantity: 1, Price: 311.5.
   b. Quantity: 3, Price: 30; Quantity: 4, Price: 100; Quantity: 1, Price: 311.5. ✓
2. Imagine the following situation. All members in your group except for you offer to sell 2 assets at a price of 50. You bid to buy 5 assets at a price of 200. Which of the following is the result of this?
   a. The market price will be 50. You will buy 5 assets at this price. Which 5 of the 10 assets offered at this price will be traded is determined randomly. ✓
   b. The market price will be 200. You will buy 5 assets at this price. Which 5 of the 10 assets offered at this price will be traded is determined randomly.
   c. The market price will be 125. You will buy 10 assets at this price.
3. You can enter bids to buy assets and offers to sell assets. Imagine that you consider both, buying and selling assets. Which of the following is correct?
   a. You can try to bid for as many assets as you like at any price. If the market price turns out to be high, your cash holdings may become negative.
   b. You cannot try to buy assets at a higher price than the lowest price at which you are willing to sell assets. ✓

4. Suppose that you earn 27000 points in the round that is randomly selected for payment. How much is that in euros?
   - [Correct answer: 30]
5. Are the 3 rounds of the experiment different?
   a. No, they are absolutely identical.
   b. Yes, they are different in a variety of aspects.
   c. They only differ in the number of periods per round, otherwise they are identical. ✓
6. What happens if you have not submitted your bids and offers when the time of a period elapses?
   a. The computer will automatically submit the bids and offers that you have entered into the computer interface (but not yet submitted).
   b. The computer will not consider any bids or offers from you for this period. ✓
7. Which of the following is true about the savings account?
   a. Points in the savings account do not yield any interest.
   b. Points in the savings account cannot be used to buy assets. ✓
   c. Points in the savings account do not count towards your round earnings.
8. Each round is terminated abruptly between period 25 and 40. When the round is terminated, how are your round earnings determined?
   a. They depend on your points in the cash and savings accounts. Assets are worthless at the moment that the round terminates.
   b. They depend on your points in the cash and savings accounts and on the points that you receive for the assets that you hold when the round terminates. The latter depend on the fair price of the asset (this is not necessarily the same as the last market price of the asset). ✓
   c. They depend only on your points in the cash account and on the last market price of the assets that you hold when the round terminates.

B.4 Differences in comprehension test questions between the treatments of the call market experiment

The test questions and correct answers in the treatments NO_INFO and INFO_AFTER are identical. The test questions in FULL_INFO are almost identical and only differ in answer b to question 8 (which is still the correct answer). The difference between the treatments is as follows:

- NO_INFO and INFO_AFTER: They depend on your points in the cash and savings accounts and on the points that you receive for the assets that you hold when the round terminates. The latter depend on the fair price of the asset (this is not necessarily the same as the last market price of the asset).
- FULL_INFO: They depend on your points in the cash and savings accounts and on the points that you receive for the assets that you hold when the round terminates (125 points per asset).

The test questions in the new treatment LOW_CASH are identical to the ones in FULL_INFO with the only difference that in question 4, “27000 points” is replaced by “4200 points” to reflect the different exchange rates.

C Experimental Instructions and Comprehension Test Questions Learning-to-Forecast Experiment

We reproduce the complete experimental instructions for the treatment NO_INFO of the learning-to-forecast experiment in Section C.1. Bold text is also bold in the original instructions and text in boxes is similarly in such boxes in the original instructions. In Section C.2 we discuss the differences in instructions between the treatments. Section C.3 reproduces the comprehension test questions, which were identical in all treatments. Section C.4 reproduces a payoff information sheet (the payoff table) that subjects had on their desk.

C.1 Instructions LtFE NO_INFO

Welcome to this experiment!

Please read these instructions carefully as they explain how you earn money from the decisions that you make. You will be paid privately at the end, after all participants have finished the experiment.

During the experiment you are not allowed to use your mobile phone or other electronic devices. You are also not allowed to communicate with other participants. If you have a question at any time, please raise your hand and someone will come to your desk to answer your question in private.

The experiment consists of 3 rounds. Each round consists of multiple periods. Except for the number of periods in each round, the rounds are identical. Your earnings for each of the 3 rounds will be in points. **At the end, only your earnings from one randomly selected round will be paid out to you! The points from the selected round will be exchanged into euros at the exchange rate 900 points = 1 euro.** In addition you will receive 10 euros for your participation.

All participants will be randomly divided into **groups of 6 people**. The group composition will not change during the experiment. You will not know the identity of any group member nor will they know your identity even after the experiment is over.

The following describes what you will be doing in **each** of the 3 rounds.

General information

You are an **advisor** to a company that wants to optimally invest its money. The company has two investment options: a risk-free investment (on a bank account) and a risky investment (in a financial asset). As their financial advisor, you have to predict the price of the financial asset during a number of subsequent time periods. The more accurate your predictions are, the higher your total earnings will be.

Forecasting task

Your only task is to forecast the price of the financial asset in each time period as accurately as possible. The price of the financial assets has to be predicted two time periods ahead. You may only enter forecasts that are at least 0 and at most 1500. Prices of the asset are in experimental currency units (ECU); however, the unit of the prices is of no importance for your forecast. At the beginning of a round, you have to predict the price of the financial asset in the first two periods without information about past prices. It is very likely that the price of the asset will be between 0 and 150 ECU in the first two periods of the first round. After all participants have entered their predictions for the first two periods, the price of the financial asset for the first period will be revealed and, based upon your forecasting error, your earnings for period 1 will be determined. After that you have to make a prediction for the price of the financial asset in the third period. After all participants have given their predictions for the third period, the price of the asset in the second period will be revealed and, based upon your forecasting error, your earnings for period 2 will be determined. This process continues for a number of time periods. **You do not know the exact number of time periods (it may be any number between 25 and 40 and this number will be different in different rounds).**

The available information for forecasting the price of the financial asset in period t consists of

- all past prices up to period t – 2,
- your past predictions up to period t – 1, and
- your earnings up to period t – 2.

In each period you have enough (but limited) time to make your forecasting decision. If you do not submit a forecast during this time frame, you will not earn any points in that given period. A timer will show you the remaining time for each period (2 minutes in the first 10 periods of the first round, 1 minute in all other periods).

Earnings

Your earnings depend only on the accuracy of your predictions. The maximum possible points you can earn for each period (if you make no prediction error) is 1300, and the larger your prediction error is, the fewer points you earn. You will earn 0 points if your prediction error is greater than 10 (that is, if the absolute difference between the realized price and your prediction is greater than 10 ECU). There is a Payoff Table on your desk, which shows the points you can earn for different prediction errors.

Information about the financial asset and the decision making of the company

The price of the financial asset in each period is determined by its demand and supply. Supply and demand of the asset on the market are determined by the decisions of the companies in the economy (there are six companies per group in this experiment, each advised by one participant; no one else except for these six firms trades in this financial asset). The higher the companies' demand for the financial asset and the lower the supply, the higher will be the realized price. Whether companies want to buy or sell shares of the financial asset depends on the forecast of future prices by their financial advisor. If the financial advisor of a company expects the future price of the asset to be higher, the company is willing to hold more of the asset now at a given price; that is, the higher its demand or lower its supply for the asset will be. A company whose financial advisor does not enter a forecast neither buys nor sells assets in the corresponding period.

You have the following information about the financial asset and the decision situation of the company. The bank account of the risk free investment pays a fixed interest rate of 4% per time period. The financial asset pays a random dividend in each time period. This dividend is 10 ECU with 50% probability and 0 with 50% probability. The return that a company makes from investments of the financial asset from one time period to the next depends on the dividend and upon changes in the price of the asset.

A round ends abruptly at some point between period 25 and 40. **When a round ends, the financial asset ceases to exist and the company receives a fair price for its holdings of the asset at that moment. You will not be told what this price is.** This price has no influence on your earnings; as mentioned above, you are only payed according to the accuracy of your forecasts.

Note that the company that you advise can only buy and sell up to a maximum amount of the asset in each period. If your forecast of the price (two periods ahead) deviates from the last price by more than a third of the last price and by more than 40, the company will trade as if your prediction deviated by exactly one third of the last price or by 40 (whichever of the two deviations is greater). For example, if the last price is 240 and your forecast is 50, the company will act as if your forecast was 160 (because your forecast deviates by more than 240/3=80 from the last price and the last price minus a third of the last price is 240-80=160). However, if the last price is 60 and your price forecast is 85, the company will act regularly on your price forecast; the difference between forecast and last price is 25 and thus more than 60/3=20, but 60+25=85 is still less than 60+40=100.

You can now start to answer the comprehension questions on the screen.

C.2 Differences in instructions between the treatments of the learning-to-forecast experiment

The instructions in the treatments INFO_AFTER and FULL_INFO are identical to those in NO_INFO except for one sentence in the second to last paragraph in the box (starting with "A round ends abruptly") after the sentence "When a round ends, the financial asset ceases to exist and the company receives a fair price for its holdings of the asset at that moment." The sentence that is different between treatments reads as follows in the three treatments:

- NO_INFO: You will not be told what this price is.
- INFO_AFTER: You will be told what this price is.
- FULL_INFO: This price is 125 ECU per asset.

C.3 Comprehension test questions LtFE all treatments

We reproduce here the comprehension test questions of the learning-to-forecast experiment. These test questions are identical in all three treatments. The test questions are numbered on the screens and appear on two screens (the first four questions on the first screens). Note that subjects had to answer all questions on a screen correctly to proceed. If they did not answer all questions correctly and tried to proceed, they received the following error message: "You did not answer all questions correctly. Take another look at the instructions or raise your hand if you need help." We add a checkmark after each correct answer (or give the correct answer in brackets if the question is not a multiple choice problem).

1. Suppose that in one period, your prediction for the market price of the asset is 45.5, and the realized market price turns out to be 45.9, how many points do you earn in this period (please use the payoff table)?
    - [Correct answer: 1298]

2. Suppose that the price of the financial asset is the same in periods 8 and 18 and that a financial advisor predicts that the price increases from period 8 to 10 and decreases from period 18 to 20. In which of the periods 9 and 19 does the company want to hold more units of the asset (for each given price)?
   - [Correct answer: 9]
3. Imagine that all of the advisors predict that the market price will decrease substantially. What will happen to the market price?
   a. It will increase.
   b. It will decrease. ✓
4. Suppose that you earn 27000 points in the round that is randomly selected for payment. How much is that in euros?
   - [Correct answer: 30]
5. Are the 3 rounds of the experiment different?
   a. No, they are absolutely identical.
   b. Yes, they are different in a variety of aspects.
   c. They only differ in the number of periods per round, otherwise they are identical. ✓
6. Suppose that the price in the previous period (that is, p_{t-1}) is 93, and your price forecast for the next period (t+1) is 150. What is the price that the company bases its decision on? Remember that the company can only buy and sell assets up to a limit so that it may base its decision on a different price than the forecasted 150.
   - [Correct answer: 133]
7. Are your personal earnings affected by the amount of money that the company receives for its holdings of the financial asset when the market stops?
   a. Yes, you receive the same amount of money that the company receives.
   b. No, your earnings depend solely on the accuracy of your forecasts. ✓
8. What happens if you have not entered a price forecast when the time of a period

elapses?

a. A pop-up window will ask you for your forecast.

b. The software will proceed to the next period. You will not receive any earnings for this period. ✓

C.4 Payoff information sheet (LtFE)

Payoff Table

The earned points are based on the following formula:

$$\text{points} = \max\left\{1300 \cdot \left(1 - \frac{\text{error}^2}{100}\right), 0\right\},$$

where the error is the absolute difference between the realized and predicted price in period t.

[Table C.1 appears here on the payoff information sheet.]

Table C.1: Payoff table (not labeled in the experimental instructions)

error	point	error	point	error	point	error	point	error	point
0.1	1300	2.1	1243	4.1	1081	6.1	816	8.1	447
0.2	1299	2.2	1237	4.2	1071	6.2	800	8.2	426
0.3	1299	2.3	1231	4.3	1060	6.3	784	8.3	404
0.4	1298	2.4	1225	4.4	1048	6.4	768	8.4	383
0.5	1297	2.5	1219	4.5	1037	6.5	751	8.5	361
0.6	1295	2.6	1212	4.6	1025	6.6	734	8.6	339
0.7	1294	2.7	1205	4.7	1013	6.7	716	8.7	316
0.8	1292	2.8	1198	4.8	1000	6.8	699	8.8	293
0.9	1289	2.9	1191	4.9	988	6.9	681	8.9	270
1	1287	3	1183	5	975	7	663	9	247
1.1	1284	3.1	1175	5.1	962	7.1	645	9.1	223
1.2	1281	3.2	1167	5.2	948	7.2	626	9.2	200
1.3	1278	3.3	1158	5.3	935	7.3	607	9.3	176
1.4	1275	3.4	1150	5.4	921	7.4	588	9.4	151
1.5	1271	3.5	1141	5.5	907	7.5	569	9.5	127
1.6	1267	3.6	1132	5.6	892	7.6	549	9.6	102
1.7	1262	3.7	1122	5.7	878	7.7	529	9.7	77
1.8	1258	3.8	1112	5.8	863	7.8	509	9.8	51
1.9	1253	3.9	1102	5.9	847	7.9	489	9.9	26
2	1248	4	1092	6	832	8	468	error $\geq$10	0

D Additional Data

This section provides additional data on subjects' trading in the call market experiment. Section D.1 presents some overview of the data. Sections D.2 to D.4 show some data in more detail.

D.1 Overview trading activity

Table D.1 shows means of group-level data on the traded quantity in the first column and in the other columns normalized Herfindahl-Hirschman indices (HHI) of means of subject-level data on trading activity (mean number of trades a subject is involved in per period; we consider, e.g., a sale of m assets that a subject is involved in as this subject being involved in m trades), asset holdings (mean number of risky assets a subject holds per period), and performance (mean total round earnings in points).

The normalized Herfindahl-Hirschman index measures concentration, with zero signifying that a variable is equally distributed among all subjects, while one signifies that a variable is concentrated at one subject with zeros for the other subjects (for asset holdings in one period, a value of zero is obtained if all subjects hold exactly three assets, while a value of one is obtained if one subject holds all 18 assets). The formula for this index of a vector of non-negative variables $s = (s_1, \ldots, s_n)$ is given by

$$H^*(x) = \frac{\left(\sum_{i=1}^{n} x_i^2\right) - 1/n}{1 - 1/n},$$

with $x = (x_1, \ldots, x_n) = (s_1 / \sum_{j=1}^{n} s_j, \ldots, s_n / \sum_{j=1}^{n} s_j)$. Note that an HHI of one is not possible for trading activity, because there are always two parts involved in trading.

The first column shows that the average number of traded assets is about one per period. The numbers in the second and third columns, with relatively low Herfindahl-Hirschman indices, show that the trading activity and the asset holdings are not concen-

Table D.1: Summary of variables on trading behavior

	Treatment	Quantity	HHI Trading	HHI Holdings	HHI Performance
CME	NO_INFO	0.97	0.08	0.11	0.01
	INFO_AFTER	0.77	0.07	0.13	0.01
	FULL_INFO	0.93	0.09	0.14	0.01
	LOW_CASH	0.65	0.05	0.05	0.00

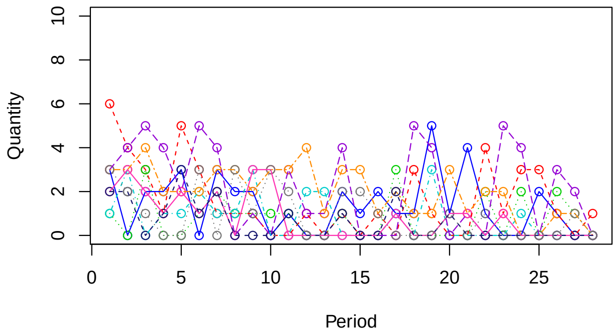
This table shows data aggregated across groups, rounds, and periods. The variable *Quantity* refers to group-level data on overall trades (mean number of assets traded per period). The variables starting with *HHI* denote normalized Herfindahl-Hirschman indices of subject-level data. *HHI Trading* concerns total trading activity, *HHI Holdings* concerns asset holdings, and *HHI Performance* concerns performance as measured by round earnings. *HHI Trading* and *HHI Holdings* show the mean across groups of the HHI of mean numbers across rounds and periods per subject; *HHI Performance* shows the mean across groups of the HHI of mean numbers across rounds). All variables are rounded to the second decimal position.

trated at one or two subjects, but that most subjects participate in the market. The HHI of performance is relatively low, but this is natural from the viewpoint that all subjects start out with exactly the same endowment (one could thus say that we start out with an HHI of zero) and also the subjects who lose money compared to not acting at all in a round still receive positive payments.

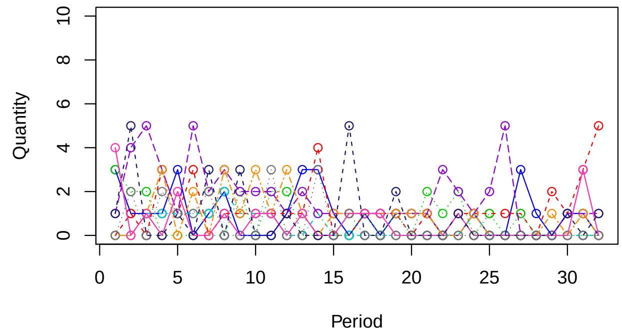
D.2 Quantities traded in the call market experiment

Figures D.1 and D.2 show the quantities of traded assets in the call market experiment in all rounds and treatments. The number of traded assets decreases across the rounds in all treatments. In NO_INFO, the mean number of traded assets per period decreases from 1.23 in the first round over 0.85 in the second to 0.82 in the third. In INFO_AFTER, the corresponding numbers are 1.03, 0.77, and 0.51. In FULL_INFO, the numbers are 1.31, 0.81, and 0.68.

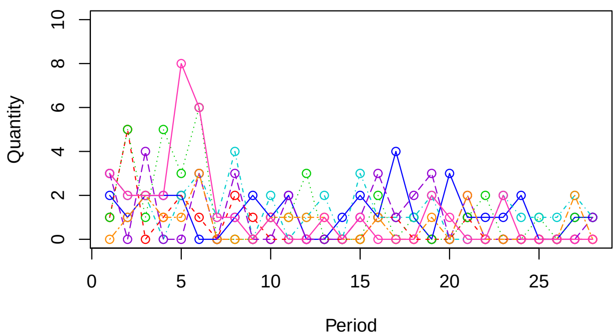
Figure D.3 shows the traded quantities in the additional treatment with low cash-to-asset ratio. The mean number of traded assets decreases also in this treatment, from 0.86 in the first round to 0.54 in the second and 0.53 in the third.



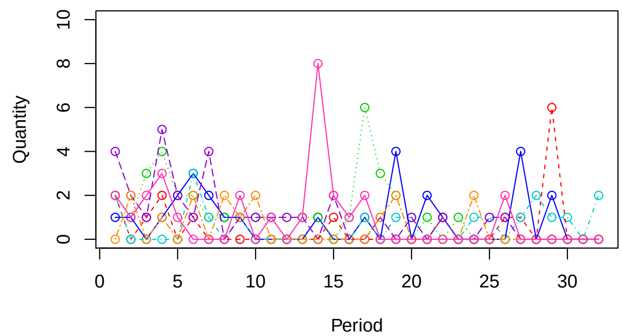
(a) CME NO_INFO Round 1



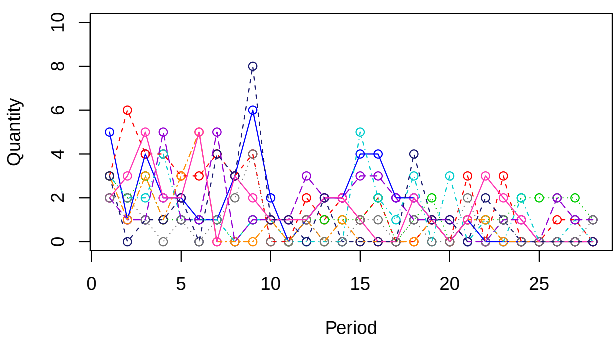
(b) CME NO_INFO Round 2



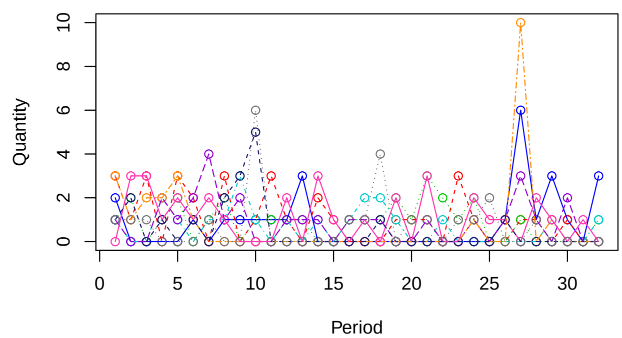
(c) CME INFO_AFTER Round 1



(d) CME INFO_AFTER Round 2



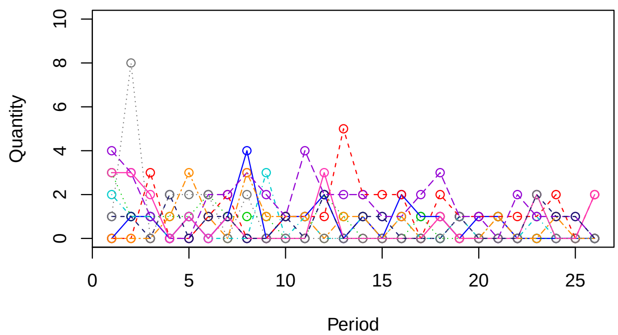
(e) CME FULL_INFO Round 1



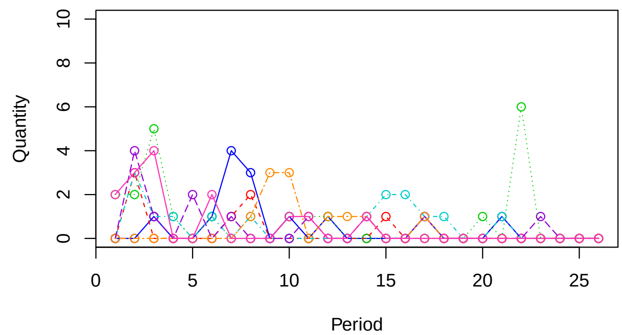
(f) CME FULL_INFO Round 2

Figure D.1: Quantities traded in rounds 1 and 2 in all treatments of the CME

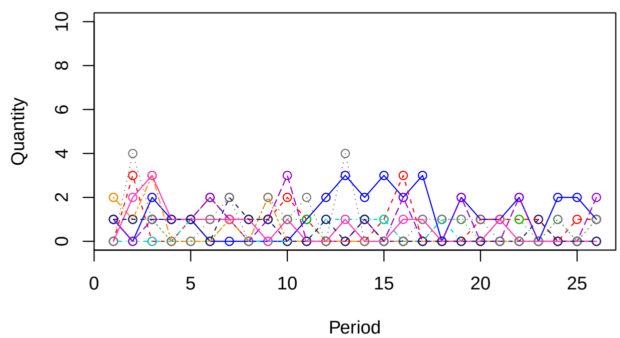
This figure shows traded quantities in the call market experiment in the first round (left) and the second round (right) of the experiment. Each color represents one group.



(a) CME NO_INFO Round 3



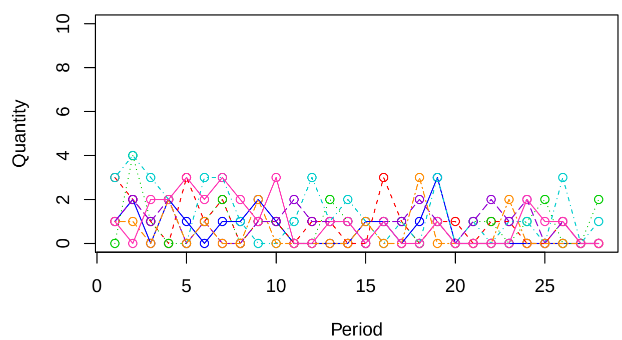
(b) CME INFO_AFTER Round 3



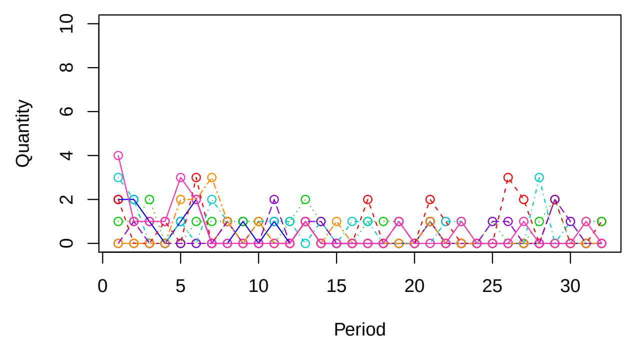
(c) CME FULL_INFO Round 3

Figure D.2: Quantities traded in round 3 in all treatments of the CME

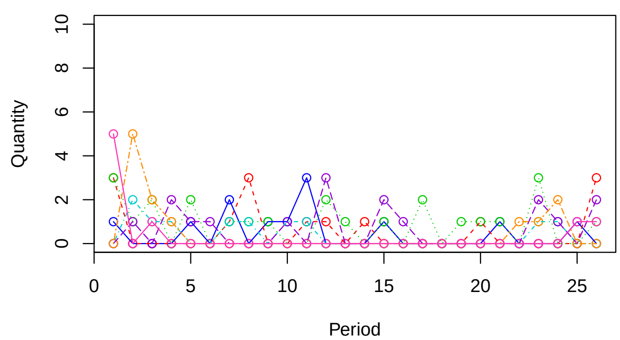
This figure shows traded quantities in the call market experiment in the third round of the experiment. Each color represents one group.



(a) CME LOW_CASH (FULL_INFO) Round 1



(b) CME LOW_CASH (FULL_INFO) Round 2



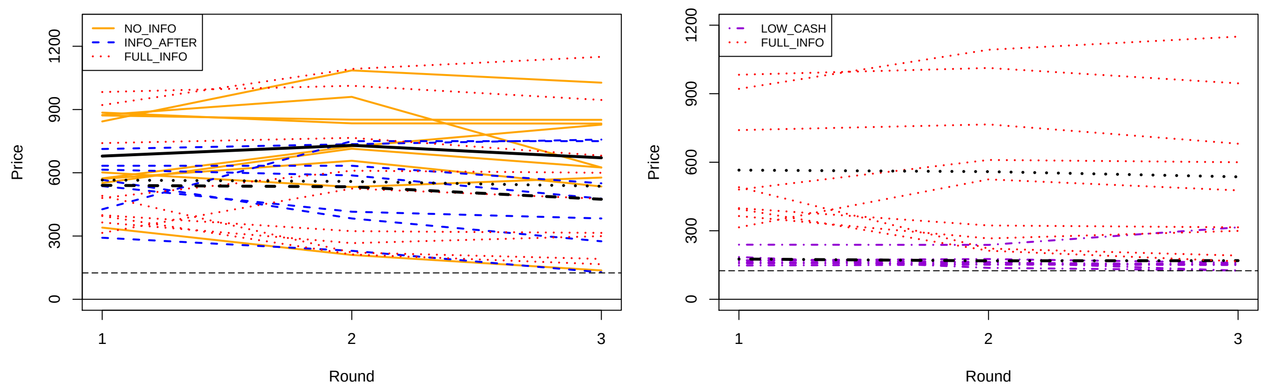
(c) CME LOW_CASH (FULL_INFO) Round 3

Figure D.3: Quantities traded in all rounds in the additional treatment LOW_CASH (FULL_INFO) of the CME

This figure shows traded quantities in the call market experiment in the additional treatment LOW_CASH (FULL_INFO) of the call market experiment. Each color represents one group.

D.3 Price means of market prices with more than one trade

Figure D.4 shows the means of market prices from periods with at least two trades (similarly to Figures 4 and 7). The corresponding means can be found in Table D.2.



(a) Original CME

(b) LOW_CASH

Figure D.4: Mean prices with at least two trades in all rounds and treatments of the CME

This figure shows the means of market prices with at least two trades across all periods of a round. Each thin colored line corresponds to one group. Thick black lines show the mean values of these lines per treatment.

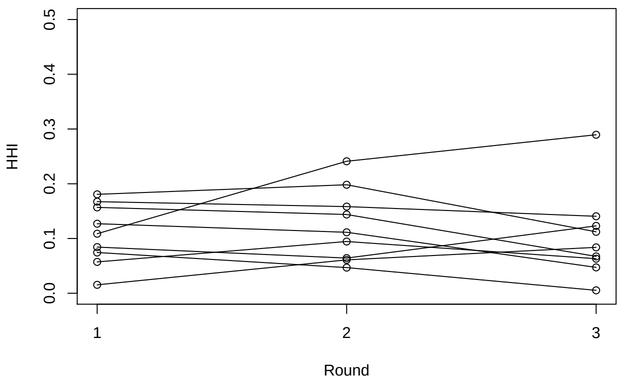
Table D.2: Mean prices with at least two trades in the CME

	Treatment	Round 1	Round 2	Round 3	Fundamental
CME	NO_INFO	679	730	671	125
	INFO_AFTER	540	534	474	125
	FULL_INFO	565	559	536	125
	LOW_CASH	176	168	169	125

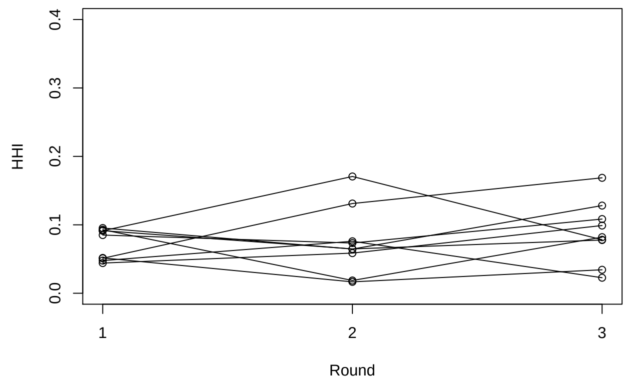
This table shows the means of market prices with at least two trades across all periods of a round and groups (rounded to integers and corresponding to the thick black lines in Figure D.4).

D.4 Herfindahl-Hirschman indices of asset holdings, trades, and performance

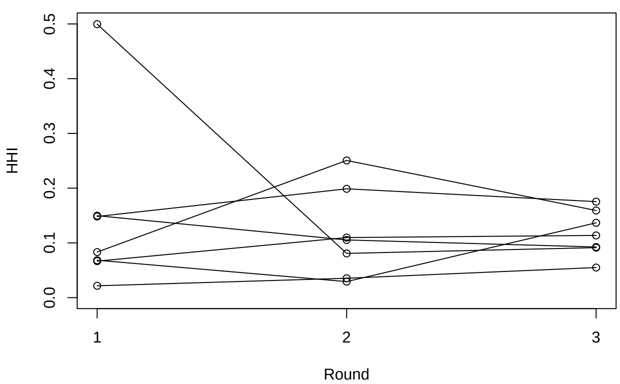
Figures D.5 to D.7 show normalized Herfindahl-Hirschman indices of asset holdings, trading activity, and performance in the experiment, first for the original call market experiment and then for the additional LOW_CASH treatment. The graphs show data per round, each line corresponds to one group.



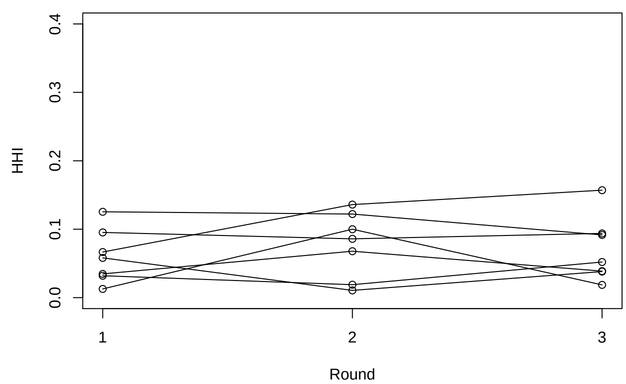
(a) CME NO_INFO Asset holdings



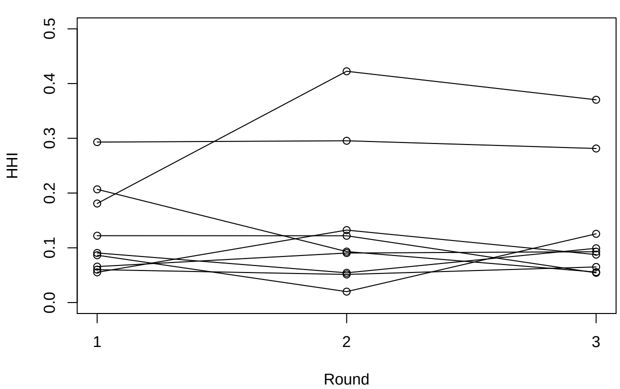
(b) CME NO_INFO Trades



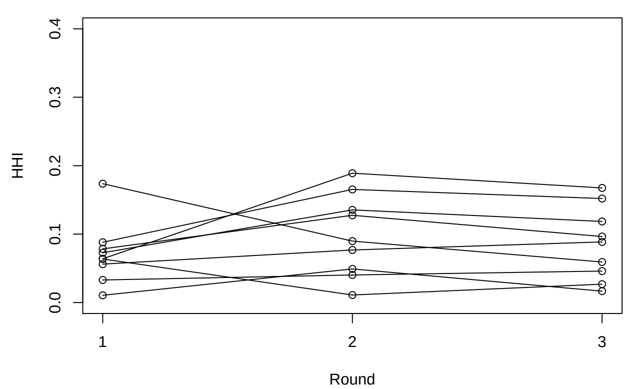
(c) CME INFO_AFTER Asset holdings



(d) CME INFO_AFTER Trades



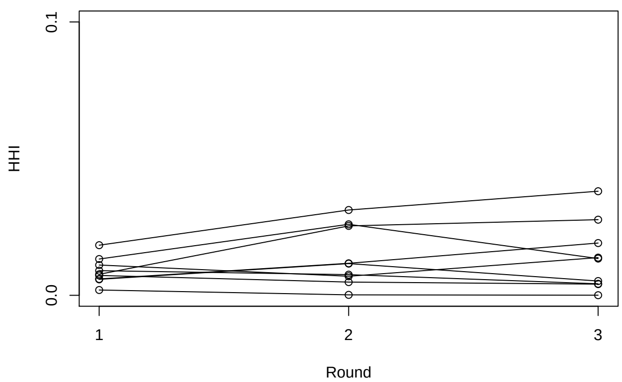
(e) CME FULL_INFO Asset holdings



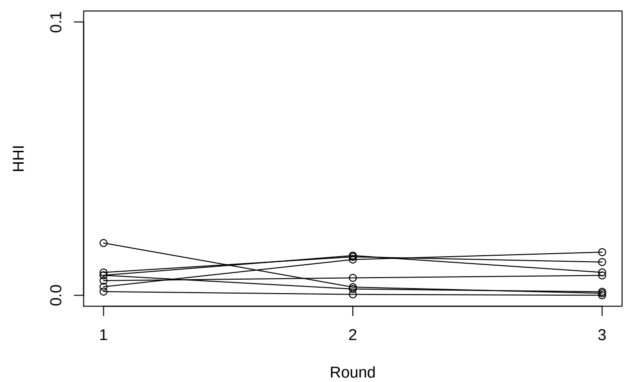
(f) CME FULL_INFO Trades

Figure D.5: Herfindahl-Hirschman indices of asset holdings and trades in the CME

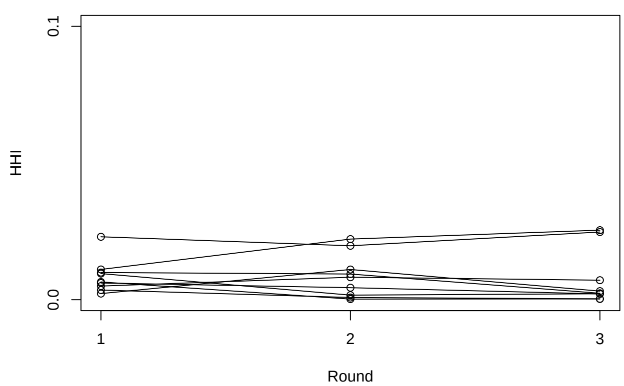
This figure shows normalized Herfindahl-Hirschman indices of asset holdings (left) and trading activity (right). Each line represents the index of the subjects of one group, where the subject-level data consists of the average asset holdings or trading activity across all periods of a round.



(a) CME NO_INFO Performance



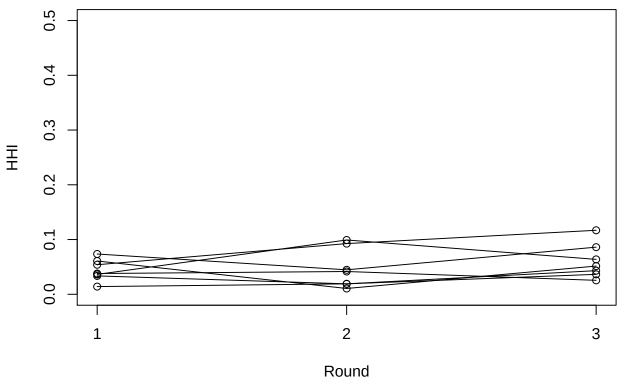
(b) CME INFO_AFTER Performance



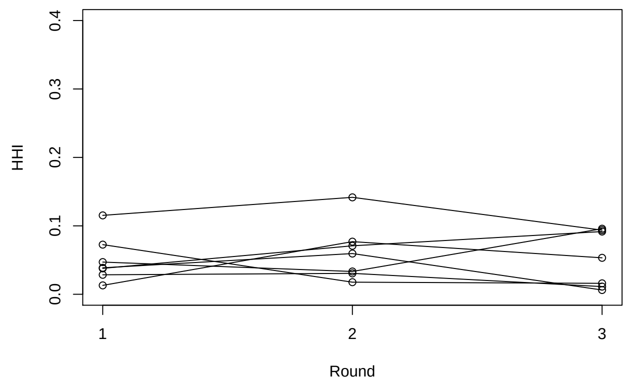
(c) CME FULL_INFO Performance

Figure D.6: Herfindahl-Hirschman indices of performance in the CME

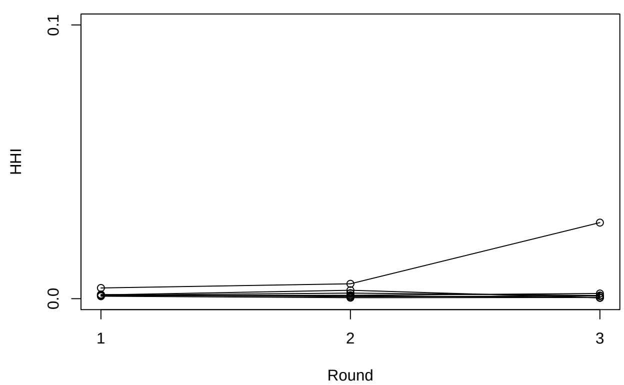
This figure shows normalized Herfindahl-Hirschman indices of performance (total round earnings). Each line represents the index of the subjects of one group.



(a) CME LOW_CASH (FULL_INFO) Asset holdings



(b) CME LOW_CASH (FULL_INFO) Trades



(c) CME LOW_CASH (FULL_INFO) Performance

Figure D.7: Herfindahl-Hirschman indices of asset holdings, trades, and performance in the additional treatment LOW_CASH

This figure shows normalized Herfindahl-Hirschman indices of asset holdings, trading activity, and performance (total round earnings). Each line represents the index of the subjects of one group; for asset holdings and trades, the subject-level data consists of the average asset holdings or trading activity across all periods of a round.