Bubble Formation and (In)Efficient Markets in Learning-to-Forecast and -Optimize Experiments*

Te Bao[a,b], Cars Hommes[b], and Tomasz Makarewicz[b]

[a]IEEF, Faculty of Economics and Business, University of Groningen
P.O.Box 800, 9700 AV Groningen, The Netherlands
[b]CeNDEF, School of Economics, University of Amsterdam
Valckenierstraat 65-67, 1018XE Amsterdam, The Netherlands

March 5, 2014

Abstract

This experiment compares the price dynamics and bubble formation in an asset market with a price adjustment rule in three treatments where subjects (1) submit a price forecast only, (2) choose quantity to buy/sell and (3) perform both tasks. We find that bubbles emerge in all these treatments, but to a larger degree in learning to optimize treatments (2) and (3). Bubble formation is therefore a robust finding in markets with positive expectation feedback. Some repeated "super bubbles" arise, where the price is 3 times larger than the fundamental value, which were not seen in former experiments.

JEL Classification: C91, C92, D53, D83, D84
Keywords: Financial Bubble, Experimental Finance, Rational Expectations, Learning to Forecast, Learning to Optimize

*The authors are thankful for stimulating discussion by participants at "Computing in Economics and Finance" 2013 conference, Vancouver. We gratefully acknowledge the financial support from NWO (Dutch Science Foundation) Project No. 40611142 "Learning to Forecast with Evolutionary Models" and other projects: the EUFP7 project Complexity Research Initiative for Systemic Instabilities (CRISIS, grant 288501), and from the Institute of New Economic Thinking (INET) grant project "Heterogeneous Expectations and Financial Crises" (INO 1200026). Email addresses: `t.bao@rug.nl`, `c.h.hommes@uva.nl`, `T.A.Makarewicz@uva.nl`.

1 Introduction

Financial bubbles are an economic phenomenon that may be as old as the history of financial markets, but has not been investigated extensively by modern economics and finance. One possible reason is that it contradicts the standard theory of rational expectations (Muth, 1961; Lucas Jr, 1972) and efficient markets (Fama, 1970). Recent finance literature however has shown growing interest in studies on bounded rationality (Farmer and Lo, 1999; Shiller, 2003) and 'abnormal' market movement such as over- and under-reaction to changes in fundamental (Bondt and Thaler, 2012) and excess volatility (Campbell and Shiller, 1989). The recent financial crisis and precedent boom and bust in the US housing market also highlight the importance of studying the mechanism of fast price appreciation, 'bubbles', and subsequent crashes in financial market. Without understanding the origins of such bubbles, the policy makers will be unable to identify and counter potential threats to stability of financial markets and national economies.

It is usually difficult to identify an empirical bubble on stock markets or housing markets, since people may substantially disagree about the underlying fundamental price of the asset. Laboratory experiments can help studying bubble dynamics, by taking full control over the underlying fundamental price. Smith et al. (1988) are among the first authors to reliably reproduce price bubbles and crashes of financial assets in a laboratory setting. They let the subjects trade an asset that pays a random dividend with a positive expected value in each of the 15 periods. Therefore the fundamental price at each period equals the sum of the remaining expected dividends and follows a decreasing step function. The authors find the price to go substantially above the fundamental level after some initial periods before it crashes towards the end of the experiment. This approach has been followed in many studies *i.e.* Lei et al. (2001); Noussair et al. (2001); Dufwenberg et al. (2005); Haruvy and Noussair (2006).[1] A typical result of these papers is that the bubbles are a robust finding despite several major changes in the experimental environment.

Nevertheless, Kirchler et al. (2012); Huber and Kirchler (2012) argue that the non-fundamental outcomes in this type of experiments are due to misunderstanding, which is induced on the subjects by the declining fundamental price. They support their argument by showing that no bubble appears when the fundamental price is not declining or when the declining fundamental price is further illustrated by an example of 'a depletable gold mine'. Another problem relevant to policy makers is that these experiments, due to typically short experimental sessions and

[1]For survey of the literature, see Sunder (1995); Noussair and Tucker (2013).

the declining fundamental, cannot test whether financial crashes are likely to be followed by new bubbles. This is an important problem, given for instance the evolution of the asset prices between the dot-com and the 2007 crises.

Besides the approach by Smith et al. (1988), a framework of 'learning to forecast' (henceforth LtF) experimental studies was introduced by Marimon et al. (1993) (see Hommes, 2011, for a comprehensive survey). In contrast to the LtF experiments, the Smith et al. (1988) experiment belongs to a class called 'learning to optimize' (henceforth LtO) experiments (see Duffy, 2008, for an extensive discussion). Hommes et al. (2005) design an experiment where subjects act as professional advisers (forecasters) for a pension fund: they submit a price forecast, which is transformed into a quantity decision of buying/selling by computing demand/supply from optimizing a standard myopic mean variance utility function. Subjects receive a payment based on the their forecasting accuracy. The fundamental price is defined as the discounted sum of expected future dividends over infinite horizon and in their experimental set-up remains constant over time. The result of this paper is twofold: (1) the asset price fails to converge to the fundamental, but rather oscillates and forms bubbles in several markets; (2) instead of having rational expectations, in most groups subjects coordinate on a price trend following strategies (*cf.* Bostian and Holt, 2009). Heemeijer et al. (2009) and Bao et al. (2012) investigate whether the non-convergence result is driven by the positive expectation feedback nature of the experimental market in Hommes et al. (2005). Positive/negative expectation feedback means that the realised market price increases/decreases when the average price expectation increases/decreases. The authors design two comparable treatments of positive and negative feedback. They find that the negative feedback markets converge quickly to the fundamental price, and also adjust fast to a new fundamental after a large shock to the system. In contrast, positive feedback markets usually fail to converge, and under-react to the shocks in the short run, while overreacting in the long run. This results in repeated bubbles and crashes.

The subjects in Hommes et al. (2005) and other 'learning to forecast' experiments do not directly trade, but are rather assisted by a computer program to translate their forecasts into optimal trading decisions. A natural question is what will happen if they submit explicit quantity decisions, i.e. if the experiment is based on the 'learning to optimize' design. Are the observed bubbles robust against the LtO design or are they just an artifact of the computerized trading in the LtF design?

In this paper we design an experiment, in which the fundamental price is constant over time (as in Hommes et al., 2005), but the subjects are asked to directly indicate the amount of asset they want to buy/sell. Different from the double auction mechanism in the Smith et al. (1988) design, the price in our experiment is determined by a price adjustment rule based on excess supply/demand (Beja and Goldman, 1980). There are many theoretical works on financial markets, where the asset price adjustment depends on the total excess demand/supply of assets (Beja and Goldman, 1980; Campbell et al., 1997; LeBaron, 2006). Our experiment is helpful in testing financial theory based on such demand/supply market mechanisms. Furthermore, our design allows us to have a longer time span of the experimental sessions, which will enable a test for the recurrence of bubbles and crashes.

We design three experimental treatments: (1) subjects make a forecast only, and are paid according to forecasting accuracy; (2) subjects make a quantity decision only, and are paid according to the profitability of their decision; (3) subjects make both a forecast and a quantity decision, and are paid by their performance of either of the tasks with equal probability. The first treatment is the basic 'learning to forecast' experimental economy, while the second and third form 'learning to optimize' markets. Our experimental design enables us to address the fundamental question of what causes of bubbles: is it the failure to learn to forecast or the failure to learn to optimize? We provide a rigorous proof that, when the subjects consider themselves as price takers, the payoff based on the trading profit is a monotonic transformation of the payoff based on the forecasting accuracy/error. Therefore, the Rational Expectations framework predicts that the three treatments are equivalent, and any differences between them directly show the effect of the task specification.

The main finding of our experiment is that the slow adjustment and persistent deviation from the fundamental price in Hommes et al. (2005) is a stylised fact in all treatments. We measure the size of the bubbles based on Relative Absolute Deviation (RAD) and Relative Deviation (RD) as defined by Stöckl et al. (2010), and find that the amplitude of the bubbles in treatment (2) and (3) is much higher than in treatment (1). We also find that coordination of decisions is weaker in treatment (2) and (3) than in treatment (1). In particular, coordination of traded quantities is weaker than coordination of individual price forecasts. We therefore argue that learning to optimize is even harder than learning to forecast and generates even larger deviations from rationality and efficiency.

An important finding of our experiment is that in the mixed, LtO and LtF designs we find some repeated 'super bubbles', where the price increases to more than 3 times the fundamental price. This was not observed in the former experimental literature. Considering that bubbles in stock and housing prices reached similar levels, our experimental design may provide a potentially better test bed for policies that deal with large bubbles.

Another contribution is that, to our best knowledge, we are the first to perform a formal statistical test on individual heterogeneity in forecasting and trading strategies in an asset pricing experiment. We find that individual heterogeneity does not diminish over the periods. Nevertheless, large bubble can emerge in the presence of persistent individual heterogeneity, because the subjects are still able to coordinate on buying or selling the asset (*c.f.* Heemeijer et al., 2009; Bao et al., 2012). In particular, in some trading markets we observe a large degree of heterogeneity in the quantity decision even when the price is rather stable. This implies furthermore that many subjects trade inconsistently with their own price predictions.

In order to study whether our results are (in)consistent with a perfectly rational framework, in addition to the perfect competition price-takers RE equilibrium we study the subjects' rational strategic behaviour when they realise their market power and (1) can collude on the trading quantity or (2) play a non-cooperative game. We show that the fundamental equilibrium is unique under price-taking assumption. When the subjects take their market power into account, they may coordinate on alternating between buying and selling to some maximum amount around the REE if they form (implicit) collusion. In addition, they can ride bubbles/crashes by submitting the largest buying/selling amount when the price is above/below the REE until the price hits the ceiling/floor when they play non-cooperatively. Taking into account the heterogeneity in the data, and the fact that the subjects seldom submit the maximum trading amount, we conclude that the bubbles and crashes in our experimental data are not explained so much by rational strategic thinking in non-cooperative games, but rather by boundedly rational behavioural factors such as trend following behaviour.

Our paper is related to Bao et al. (2013) who run an experiment to compare the LtF, LtO and Mixed designs in a cobweb economy. The main difference is that they consider a negative expectation feedback system, for which all markets converge to the RE fundamental price. Nevertheless, Bao et al. (2013) found, in line with our results, that LtF converges faster than the LtO and Mixed design, which results from different incentive schemes (forecasting accuracy vs. trading profit). Our paper is also related to a study by Haruvy et al. (2013) who follow the basic design of Smith et al. (1988), with an additional new issue or repurchase of stocks in order to increase/decrease the supply of stock shares on the market. Theoretically, since the fundamental price in this type of studies is based purely on the dividend process, and irrespective of the size of the share supply, the new issue and repurchase should generate no impact on the asset price. But the results suggest that the price level is actually negative related to the supply of asset. This outcome points in the same direction as the intuition behind the models based on excess supply/demand, which we used in our experiments. The difference is that we keep the asset supply constant in our experiment, and the price change is driven instead by the asset excess demand of the investors (played by subjects).

The paper is organised as follows: Section 2 presents the experimental design, Section 3 reports the experimental result, Section 4 discusses alternative rational benchmark solutions to the experimental economy and finally, Section 5 concludes.

2 Experimental design

2.1 Experimental economy

Our experiment is based on the same asset market as in Heemeijer et al. (2009). We focus on the simple myopic mean-variance optimization model with $I = 6$ agents, who invest over time in a risky asset or a risk-free bond. Each agent i at time t gains utility from her expected wealth in the next period $\tilde{W}_{i,t+1}$, but derives disutility from the perceived investment risk. The agent's i utility function takes the form of

$$(1) \qquad \tilde{U}_{i,t}(z_{i,t}) = \bar{E}_{i,t}\tilde{W}_{i,t+1} - \frac{a}{2}\bar{V}_{i,t}(\tilde{W}_{i,t+1}),$$

where a measures the relative risk aversion of the agent i and $\bar{E}_{i,t}$ and $\bar{V}_{i,t}$ are the individual perceived (and not necessarily perfectly rational) expectations and variance operators. The wealth of agent i evolves according to

$$(2) \qquad \tilde{W}_{i,t+1} = R\tilde{W}_{i,t} + z_{i,t}(p_{t+1} + y_{t+1} - Rp_t),$$

where $R = 1 + r$ is the gross interest rate of the risk-free bond (assumed constant over time), $z_{i,t}$ is the amount of asset which the agent i decides to buy or sell in period t, p_t and p_{t+1} are the prices of the asset from periods t and $t+1$ respectively, y_{t+1} is the assets dividend paid at the beginning of period $t + 1$ and a is the risk aversion factor. For simplicity, the risk associated with one unit of the asset is constant and homogeneous among agents, *i.e.* $\bar{V}_{i,t}(p_{t+1} + y_{t+1} - Rp_t) = \sigma_z^2$.

Since in period t $R\tilde{W}_{i,t}$ is given, we have that $V_{i,t}(R\tilde{W}_t) = 0$ and we consider a linear transformation of the utility function (1),[2] given by

$$U_{i,t} = 800 + 40\left(\bar{E}_{i,t}W_{i,t+1} - \frac{a}{2}\bar{V}_{i,t}\left(W_{i,t+1}\right)\right), \tag{3}$$

where W_{t+1} denotes the total return on the risky asset

$$W_{t+1} = z_{i,t}(p_{t+1} + y_{t+1} - Rp_t) \equiv z_{i,t}\rho_t. \tag{4}$$

$\rho_t = p_{t+1}+y_{t+1}-Rp_t$ can be interpreted as the net return of a unit of the risky asset at time t. Utility functions (3) and (1) are equivalent for the sake of optimization, and since (3) is time-invariant (it does not depend on the accumulated wealth), we can directly use it as the profit for the experimental subjects. The maximization problem over investments in z has a straightforward solution, conditional on price expectations. The FOC with respect to the choice variable $z_{i,t}$ yields

$$z^*_{i,t} = \frac{\bar{E}_{i,t}\{p_{t+1} + y_{t+1}\} - Rp_t}{a\sigma_z^2}. \tag{5}$$

The market price is set by a market maker using a simple price adjustment mechanism (Beja and Goldman, 1980),[3] given by

$$p_{t+1} = p_t + \lambda\left(Z_t^D - Z_t^S\right) + \varepsilon_t, \tag{6}$$

where $\varepsilon_t \sim NID(0,1)$ is a small idiosyncratic shock, $\lambda > 0$ is a scaling factor, Z_t^S is the exogenous supply and Z_t^D is the total supply. This mechanism guarantees that an excess demand/supply increases/decreases the price.

We choose the same parametrization for our experiment as in Heemeijer et al. (2009). We specify both dividend $y_t = y$ and exogenous supply $Z_t^S = Z = 0$ to be fixed over time. We take $R\lambda = 1$, specifically $R = 1 + r = 1.05 = 21/20$ and $\lambda = 20/21$, and also $a\sigma_z^2 = 6$. In contrast to Heemeijer et al. (2009), we take $y = 3.3$.[4] The price adjustment thus takes the form of

$$p_{t+1} = p_t + \frac{20}{21}\sum_{i=1}^{6} z_{i,t} + \varepsilon_t. \tag{7}$$

For an optimizing agent and the chosen parameters, the individual demand (5) equals

$$z^*_{i,t} = \frac{p^e_{i,t+1} + 3.3 - 1.05p_t}{6}, \tag{8}$$

[2]We introduce this linear transformation of the utility to ensure that the subjects can obtain a positive profit 800 under RE equilibrium, in which $z^*_{i,t} = 0$. See following discussion for the RE solution and Table 5 in Appendix B.

[3]See *e.g.* Chiarella et al. (2009) for a survey on the abundant literature about the price adjustment market mechanisms.

[4]This gives us a slightly higher fundamental price $p^f = 66$, instead of 60.

where $p^e_{i,t+1} \equiv \bar{E}_{i,t}\{p_{t+1}\}$ denotes the price forecast of the agent i. Given our parametrization of the economy, the price adjustment equation conditional on price expectations $p^e_{i,t+1}$ simplifies to

$$\begin{aligned} p_{t+1} &= p_t + \lambda \left(-Z^S_t + \sum_{i=1}^{6} \frac{p^e_{i,t+1} + y - Rp_t}{a\sigma^2_z} \right) + \varepsilon_t \\ &= \frac{20}{21} \left(\bar{p}^e_{t+1} + 3.3 \right) + \varepsilon_t \\ &= 66 + \frac{20}{21} \left(\bar{p}^e_{t+1} - 66 \right) + \varepsilon_t, \end{aligned} \tag{9}$$

where $\bar{p}^e_t = \frac{1}{6} \sum_{i=1}^{6} p^e_{i,t+1}$ is the average prediction of price p_{t+1}.

Eq. (9) represents the price adjustment in terms of deviations from the fundamental price. One can easily see that $p^f = 66$ is the unique Rational Expectations (RE) fundamental price (see Appendix E for a formal proof). If all the agents have rational expectations, the realised price becomes $p_t = p^f + \varepsilon_t = 66 + \varepsilon_y$, *i.e.* the fundamental price plus a white noise, and, on average, the price forecasts are self-fulfilling.

2.2 Experimental treatments

We are interested in how individuals predict prices and trade in our experimental economy. We focus on three treatments:

LtF Classical Learning-to-Forecast experiment. Subjects are asked for one-period ahead price predictions $p^e_{i,t+1}$, based on which the realised price is generated according to the price adjustment rule (9). The subjects' reward depends only on the prediction accuracy, defined by (see also Table 4 in Appendix B)

$$\text{Payoff}_{i,t} = \max \left\{ 0, (1300 - \frac{1300}{49} \left(p^e_{i,t+1} - p_{t+1} \right)^2) \right\}. \tag{10}$$

The law of motion of the treatment economy is given by (9).

LtO Classical Learning-to-Optimise experiment, where the subjects are asked to decide on the asset quantity $z_{i,t}$. They are not explicitly asked for a price prediction, but use a calculator to compute the asset return ρ_t as in equation (4). Subjects are rewarded based on the realised (profit) utility (3) given by

$$U_{i,t} = max \left\{ 0, 800 + 40(z_{i,t}(p_{t+1} + 3.3 - 1.05p_t) - 3z^2_{i,t}) \right\}, \tag{11}$$

that is on how close their choice was to the optimal choice regardless of their individual prediction (see Appendix B, Table 5 for the payoff table presented to the subjects). The law of motion of the LtO treatment is given by (7).

Mixed Each subject is asked first for his or her price forecast and second for the choice of the asset quantity (in that order). In order to avoid hedging, the reward for the whole experiment is with equal probability either the prediction performance (10) throughout the experiment or the (profit) utility (11) achieved throughout the experiment. The law of motion of the treatment economy is given by (7), the same as in LtO and does not depend on the submitted price forecasts.

We emphasise that we use the same payoff scheme as in the previous LtF experiments for the LtF and mixed treatments. The points achieved in each treatment are exchanged into Euro with the conversion rate 3000 points = 1 Euro.

Variable	**Notation**	**Parameter**
	Market parametrization	
Subjects	I	6
Risk penalty	$a\sigma_z^2$	6
Dividend	y	3.3
Interest rate	r	0.05
Exogenous supply	Z^S	0
Price adjustment	λ	$\frac{20}{21}$
	Stationary RE equilibrium	
Price	p^f	66
Excess demand	$z^*\left(p^f\right)$	0
Points per 1 Euro		3000

Table 1: Parametrization of the experiment.

Finally, we would like to emphasise that the LtF and LtO treatments are equivalent under the assumption of perfect rationality and perfect competition. For details, see Section 4.1.

2.3 Liquidity constraints

To limit the effect of extreme price forecasts or quantity decisions in the experiment, we impose the following liquidity constraints on the subjects. For the LtF treatment, price predictions such that $p^e_{i,t+1} > p_t + 30$ or $p^e_{i,t+1} < p_t - 30$ are treated as $p^e_{i,t+1} = p_t + 30$ and $p^e_{i,t+1} = p_t - 30$ respectively. For the LtO treatment, quantity decisions greater than 5 or smaller than -5 are treated as 5 and -5 respectively.

These two liquidity constraints are roughly similar, since the optimal asset demand (8) is close to one sixth of the expected price difference. Nevertheless, in the sessions we observed that the liquidity constraint in the LtF treatment was never binding, while under the LtO treatment subjects would sometimes trade at the edges of the allowed quantity interval.[5]

2.4 Number of observations

Experimental instructions with the computer screen presented to the subjects are shown in Appendix A. Our experiment was run December 14, 17, 18 and 20, 2012 at the CREED Laboratory, University of Amsterdam. 108 subjects were recruited. We used a group design with 6 subjects per the experimental market. We had 18 markets in total: 4 markets in LtF treatment, 6 markets for LtO and 8 markets for Mixed. No subject participates in more than one session. We have fewer observations for treatment 1 because a similar experiment has been already run by Hommes et al. (2005) and Heemeijer et al. (2009). The duration of the experiment is typically about 1 hour for the LtF treatment, 1 hour and 15 minutes for the LtO treatment, and 1 hour 45 minutes for the Mixed treatment.

3 Experimental results

3.1 Overview

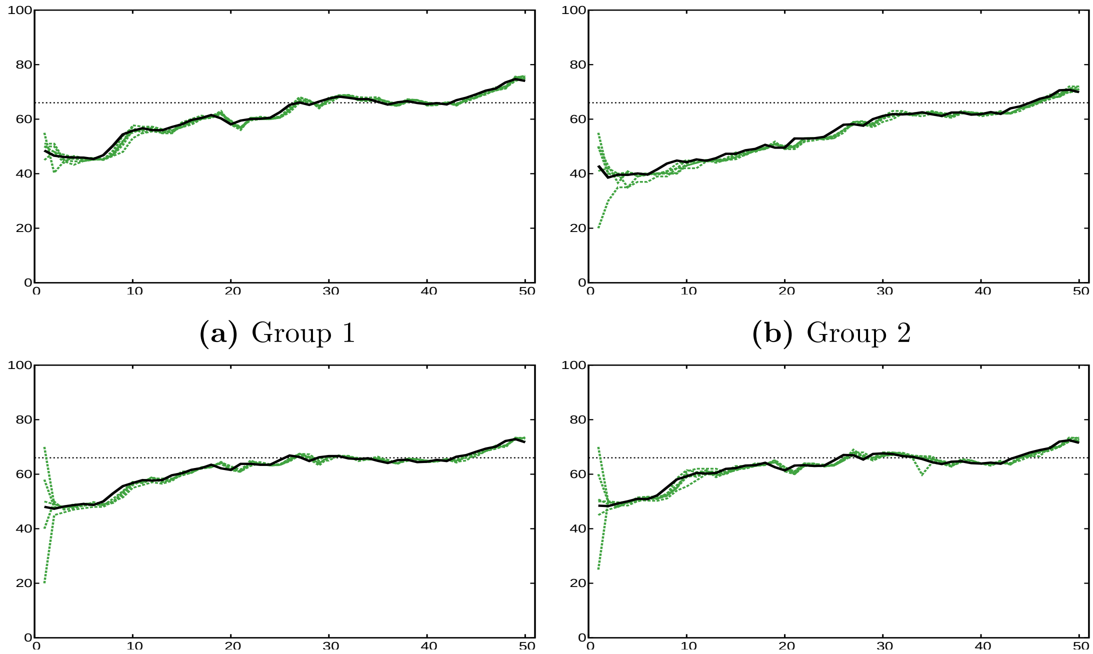
We report the experimental results in Figure 1 (LtF treatment, 4 groups), Figure 2 (LtO treatment, 6 groups) and Figure 3 (Mixed treatment, 8 groups). For most of the groups, the prices and predictions remained in the interval $[0, 100]$. The exceptions are the mixed treatment groups 1, 4 and 8 (Figures 3a, 3d and 3h). In the first two of these three groups, prices peaked at almost 150 (more than twice the fundamental price $p^f = 66$) and for the last group, the prices reached 225, almost 3.5 times the fundamental price.

It is clear that the price in most markets is far from the fundamental price. If we define convergence as the price moving into a small neighbourhood of the REE, *i.e.* $[61, 71]$,[6] and staying within it forever after, none of the markets, except market 2 in the Mixed treatment, satisfies this criterion.[7]

[5]We also imposed additional constraint that p_t has to be non-negative and not greater than 300. In the experiment, this constraint never had to be implemented.

[6]Note that the standard error of the small shock in the price determination function is only 1, which implies that the interval is ± 5 SD wide. In relative terms it is $\pm 7.6\%$ of the fundamental.

[7]Furthermore, this market actually converged after period 44.



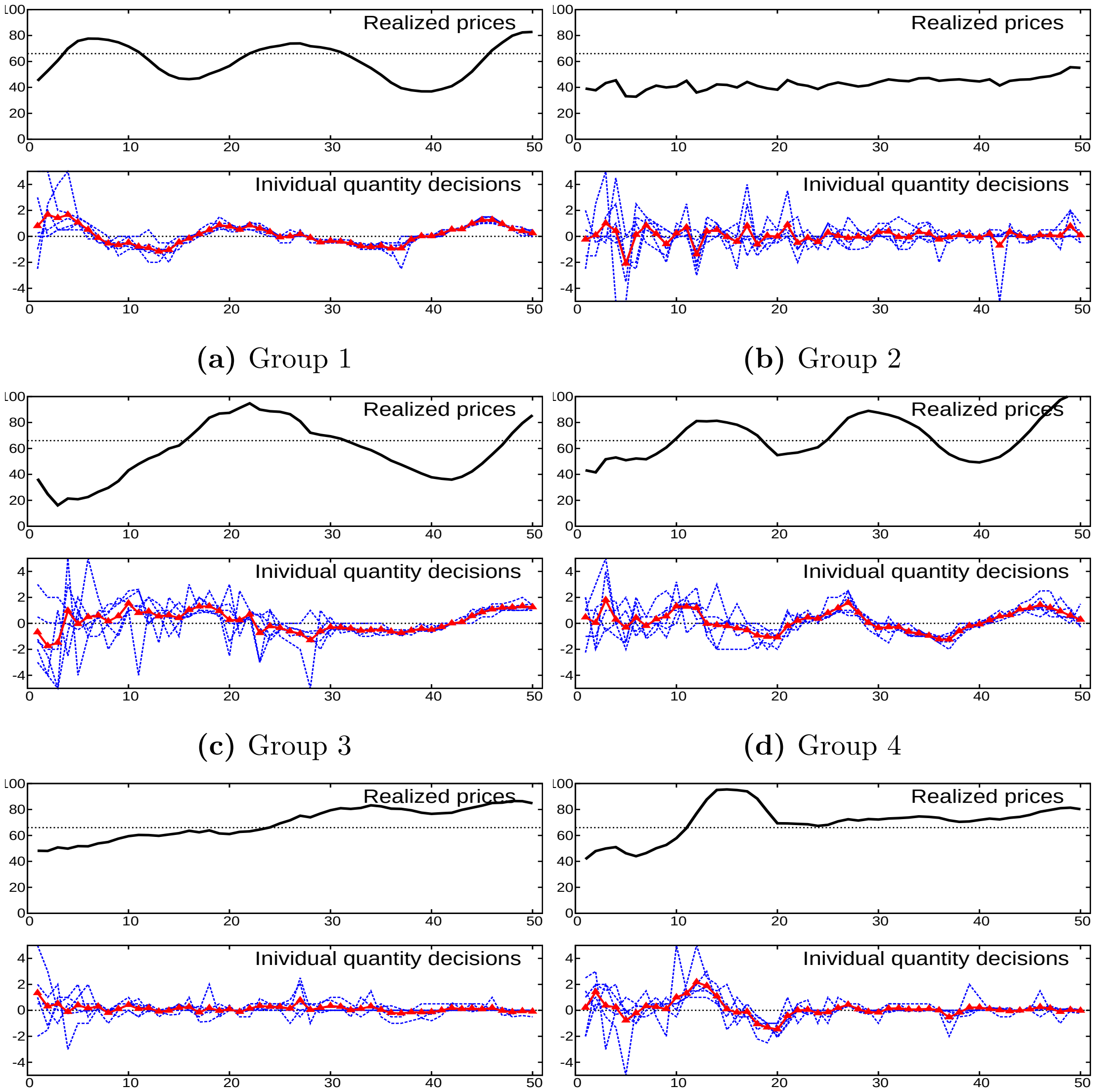
(a) Group 1 **(b)** Group 2

(c) Group 3 **(d)** Group 4

Figure 1: Groups 1-4 for the Learning to Forecast treatment. Straight line shows the fundamental price $p^f = 66$, solid black line denotes the realised price, while green dashed lines denote individual forecasts.

The LtF treatment has results similar to Heemeijer et al. (2009): individual forecasts in all four groups start below the fundamental price, quickly coordinate and hence smoothly move towards the fundamental. In groups 1, 3 and 4, predictions seemingly stabilise close to the fundamental for some time, but eventually overshoot it. In contrast to Heemeijer et al. (2009), we do not observe large oscillations. This may be due to fact that the fundamental price is higher ($p^f = 66$) in our experiment than in theirs ($p^f = 60$). Since the market price usually starts below 50, a higher p^f leads to a longer initial price growth. This may lead subjects to think that the asset price just follows some constant slow growth path, and the price overshoots only towards the end of the experiment, leaving no time for a market crash.

In the LtO treatment, the results are more diverse. Coordination between the agents does arise, but it requires time to emerge. Group 1 took around 15 periods to coordinate, while groups 3, 4, and 6 took more than 20 periods, and still with a relatively large degree of heterogeneity persisting towards the end of all six sessions. None of the groups converged to the RE equilibrium. Interestingly, group 2 (maybe with the exception of the last five periods) seems to have converged to a price which is around two thirds of the fundamental price. In this group, the subjects on average traded little, which resulted in a stable price. In group 5,



(a) Group 1 **(b)** Group 2

(c) Group 3 **(d)** Group 4

(e) Group 5 **(f)** Group 6

Figure 2: Groups 1-6 for the Learning to Optimize treatment. Each group is presented in two panels. The upper panel displays the fundamental price $p^f = 66$ (straight line) and the realised prices (solid black line), while the lower panel displays individual trades (dashed blue lines) and average trade (solid red line).

subjects were on average buying a small amount of the asset, which generated a small but persistent upward trend, that gradually lead the price to overshoot the fundamental by around 25%. Groups 1, 3 and 4 exhibited large price oscillations. Groups 1 and 4 over- and under-shot the fundamental three times, but the price usually stayed in interval $[40, 90]$ (between 60% and 150% of the fundamental). The oscillations in group 3 were slower, but of higher amplitude, with the smallest price close to 20 (less than 1/3 of the fundamental price). Finally, group 6 first oscillated, but later on stabilised on a small growth path similarly to group 5.

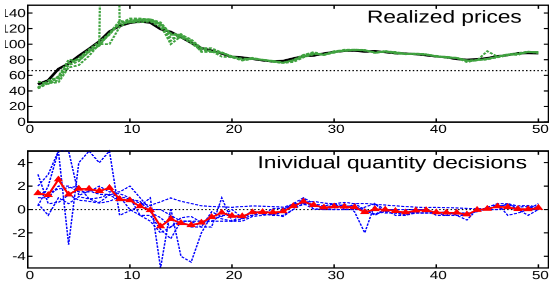
A surprising result is that the price oscillations do not really depend on the level of coordination in terms of the traded quantities. For example in groups 1 and 4, the magnitude of the oscillations does not change in the experiment, even though the subjects are clearly more coordinated in the second half of the sessions. However, during bubbles (crashes) subjects typically coordinate well on buying (selling), *i.e.* on the *sign* of the traded quantities, which is visible in the average demand in all markets.

The Mixed treatment shows similar results. As was the case in the LtF treatment, subjects are able to quickly coordinate their price forecasts, and perform this task with a high degree of success, even in the markets with large oscillations. The coordination of the quantity decisions is weaker than that of the price predictions, and occurs only after about 20 periods in groups 1, 4, 5, 6 and to some extent 7. For three groups (2, 3 and 8) there is no coordination at all even towards the end of the experiment. However, as in the LtO treatment, subjects coordinate on buying or selling, and the average quantity is persistently positive or negative as seen in the case of group 8.

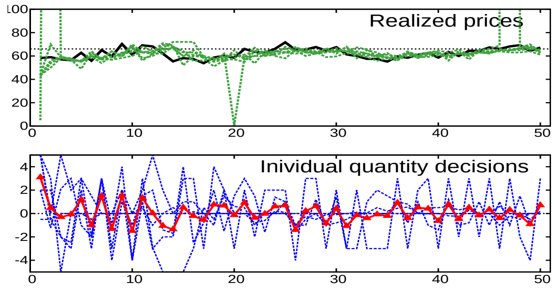
The behaviour of the prices is similar to that in the LtO treatment. In some of the groups (group 2, 6 and, until period 42, group 3), the market is stable, but the price is systematically different from the fundamental price. The behaviour of groups 5 and 7 is unruly – there are periods of stabilization of the price, which are interrupted by a sudden switch to a different price level or a smooth transition path.

Super-bubbles appeared in three markets (groups 1, 4 and 8). Despite relative heterogeneity of the traded quantity, subjects coordinated well on buying (selling), which made the average demand persistently high (negative) during bubbles (crashes). Market 4 exhibited oscillations common under the LtO treatment, but the amplitude of the market bubbles is significantly larger, with the maximum price slightly below 150. In fact, we observe three bubbles in this market. The first bubble reached almost 250% of the fundamental price, the second was only slightly smaller (twice the fundamental) and the third started to build up in the last periods of the session. Different behaviour was observed in group 1. Here there was a super-bubble with the peak price equal to about 250% of the fundamental. However, once the bubble crashed, the price did not fall below the fundamental, but instead exhibited mild oscillations in the interval $[80, 100]$.

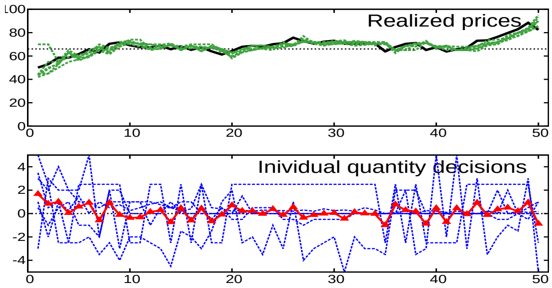
The largest bubble was observed in group 8, where the price was growing for around twenty periods until it reached a level around 215 (which is 3.5 times the fundamental!). Then it was plummeting for about 15 periods, when it reached a



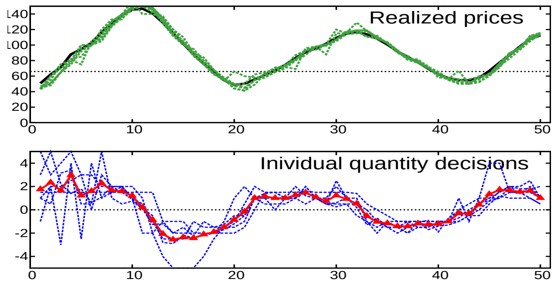
(a) Group 1, price scale $[0, 150]$



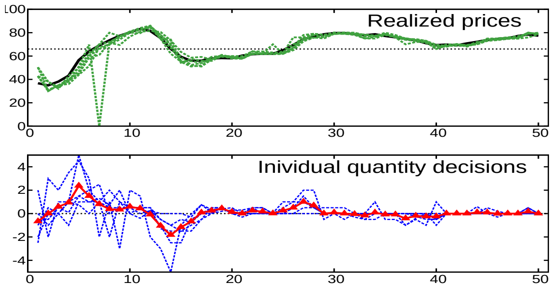
(b) Group 2



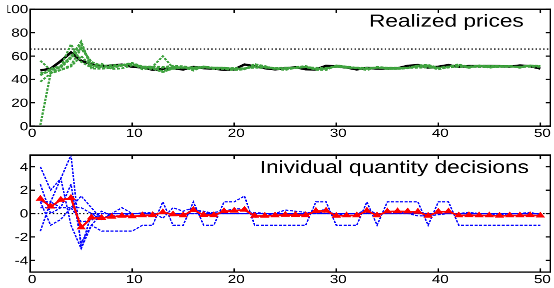
(c) Group 3



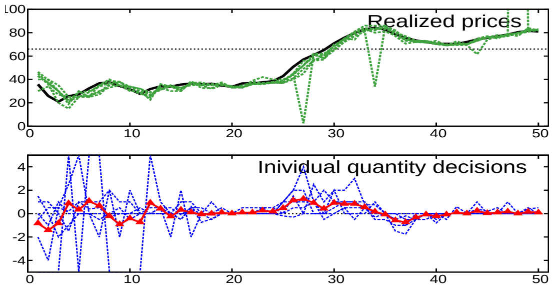
(d) Group 4, price scale $[0, 150]$



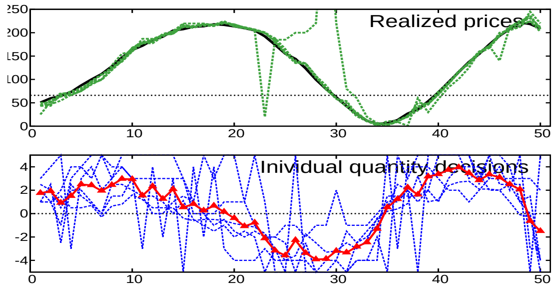
(e) Group 5



(f) Group 6



(g) Group 7



(h) Group 8, price scale $[0, 250]$

Figure 3: Groups 1-8 for the Mixed treatment with subject forecasting and trading. Each group is presented in a picture with two panels. The upper panel displays the fundamental price $p^f = 66$ (straight line), the realised prices (solid black line) and individual predictions (green dashed lines), while the lower panel displays individual trades (dashed blue lines) and average trade (solid red line). Notice the different y-axis scale for groups 1, 4 and 8 (pictures a, d and h respectively).

level of 5 (which is less than 10% of the fundamental) and bounced back. The new bubble steadily grew until period 48, when the price reached 220, a level even larger than 30 periods before. The last few rounds of this session saw the bubble starting to crash.

3.2 Quantifying the bubbles

We follow Stöckl et al. (2010) to evaluate the mispricing inefficiency and the size of the experimental asset price bubbles, using the Relative Absolute Deviation (RAD) and Relative Deviation (RD). These two quantities measure respectively the typical absolute and relative deviation from the fundamental and are given by

$$RAD_g \equiv \frac{1}{50}\sum_{t=1}^{50}\frac{|p_t^g - p^f|}{p^f} \times 100\%, \tag{12}$$

$$RD_g \equiv \frac{1}{50}\sum_{t=1}^{50}\frac{p_t^g - p^f}{p^f} \times 100\%, \tag{13}$$

where $p^f = 66$ is the fundamental price and p_t^g is the realised asset price at period t in the session of group g. (12) shows the typical distance between the realised prices and the fundamental, while (13) focuses more on the sign of this relationship. Groups with RD close to zero could either converge to the fundamental (in which case RAD is also close to zero) or oscillate evenly around the fundamental (with high RAD), while positive or negative RD signals that the group typically over- or under-priced the asset.

Treatment	**LtF**		**LtO**		**Mixed**	
Group	**RAD**	**RD**	**RAD**	**RD**	**RAD**	**RD**
#**1**	10.03	−7.011	18.26	−8.148	38.65	36.84
#**2**	17.98	−16.94	34.52	−34.52	7.27	−5.657
#**3**	8.019	−6.048	30.2	−12.95	8.025	4.014
#**4**	7.285	−5.196	20.63	3.844	42.86	35.46
#**5**			16.55	5.256	14.98	3.341
#**6**			17.51	7.056	23.08	−23.08
#**7**					32.14	−18.71
#**8**					120.7	96.5
Average	10.83	−8.798	22.95	−6.577	35.97	16.09

Table 2: Relative Absolute Deviation (RAD) and Relative Deviation (RD) of the experimental prices for the three treatments, in percentages.

The results are presented in Table 2. They confirm that the LtF groups were the closest to the fundamental (with an average RAD of about 10%), while Mixed groups exhibited largest bubbles with an average RAD of 35%. Interestingly, LtO groups had significant oscillations (on average high RAD of 23%), but centred close to the fundamental price (average RD of −6.5%, compared to average RD of −8.8% and 16.1% for the LtF and Mixed treatments respectively). LtF groups on average are below the fundamental price and Mixed groups typically overshoot it. Furthermore, the LtF groups are almost the same with the exception of group 2, LtO are varied but comparable to each other and the Mixed groups are diversified, ranging from rather stable (group 2) to super bubbles (groups 1, 4 and 8). We will argue that this is closely related to the observed individual heterogeneity. Under the LtF treatment, the subjects could easily coordinate, which implies that the price dynamics are relatively simple. On the other extreme, the Mixed treatment prices can 'be anything', and therefore the subjects have coordination problems.

Our experiment is comparable with the data investigated by Stöckl et al. (2010) (see specifically their Table 4 for the RAD/RD measures) in terms of the typical RAD values. Nevertheless, there are some important differences. First, group 8 from the mixed treatment (with RAD equal to 120.7%) exhibits the highest relative price bubble among the experimental data. Second, the four experiments investigated by Stöckl et al. (2010) have shorter spans (with sessions of either 10 or 25 periods) and so typically witness one bubble. Our data shows that the experimental bubbles are a robust and repeated finding. The crash of a bubble does not enforce the subjects to converge to the fundamental, but instead marks the beginning of a 'crisis' until the market turns around and a new bubble emerges. Thus even in the long-run prices oscillate around the fundamental and do not settle on it. This succession of over- and under-pricing of the asset is reflected in our RD measures, which are smaller than the typical ones reported by Stöckl et al. (2010), and can even be negative, despite high RAD.

3.3 Earnings

We compare subjects' earnings in the experiment to the hypothetical case where all subjects play according to the REE in all 50 periods. Subjects can earn 1300 points per period for the forecasting task when they play according to REE because they make no prediction errors, and 800 points for the trading task when they play according to the REE because the asset return is 0 and they should not buy or sell. We use the ratio of actual to hypothetical REE payoffs as a measure of payoff efficiency. This measure can be larger than 100% in treatments with the trading decision, because the subjects can profit if they buy and the price increases and vice versa. These earnings efficiency ratios, as reported in Table 3, are generally high (more than 75%).

The earnings efficiency for the forecasting task is higher in the LtF treatment than in the Mixed treatment (difference is significant at 5% level according to Mann-Whitney-Wilcoxon test), which suggests the high cognitive load in the Mixed treatment makes it difficult for the subjects to give an accurate forecast. At the same time, the earnings efficiency for the trading task is very similar in the LtO treatment and the Mixed treatment. This may be because in our experiment the trading task is easier than the forecasting task, and moreover, the high profit from speculative transaction in some markets in the Mixed treatment (such as Market 8) drives the average efficiency ratio up. Indeed, in several markets the trading efficiency is higher than 100%. Moreover, in the Mixed market 8 with the super bubble (price goes above 200), the subjects earn the most (with earnings efficiency more than 130%).

3.4 Conditional optimality of forecast and quantity decision in mixed treatment

Under the Mixed treatment of our experiment, each subject makes both a forecast and a quantity decision. It is therefore possible to investigate whether these two are consistent, namely, whether the subjects' quantity choices are close the optimal demand conditional on the price forecast (8), which is 1/6 of the corresponding expected asset return. Figure 4 shows the scatter plot of the quantity decision against the implied predicted return, which we constructed based on the price predictions of each subject, for each period separately.[8] If all individuals made consistent decisions, these points should lie on the (blue) line with slope 1/6.

Figure 4 brings two interesting observations. First, subjects focus on 'round levels', in the sense of trading quantities with typically no or only one digit after the decimal. Second, the quantity choices are far from being consistent with the price expectations. In fact, the subjects sometimes sold (bought) the asset even though they believed its return will be substantially positive (negative).

To further evaluate this finding, we run a series of Maximum Likelihood (ML) regressions based on

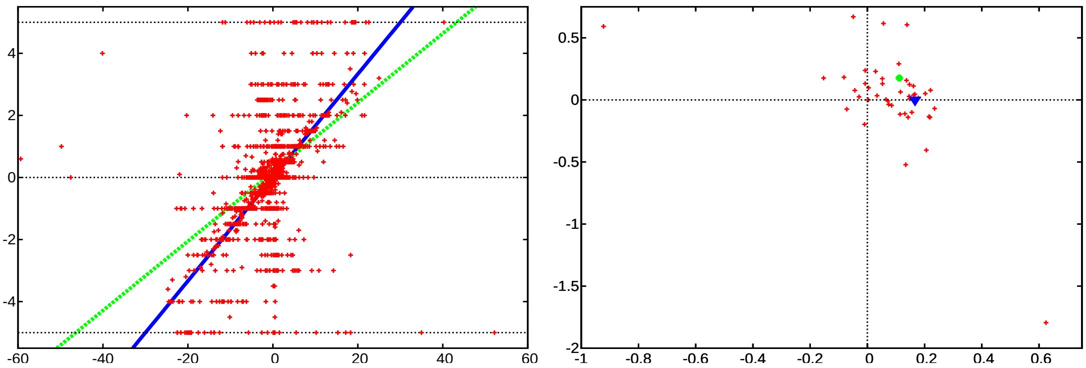
$$q_{i,t} = c_i + \phi_i \rho^e_{i,t} + \eta_{i,t}, \tag{14}$$

[8] Sometimes the subjects would pass extremely high price predictions, which in many cases seem to be typos. We exclude from our analysis outliers, which we define as predicted returns on the asset greater than 60 in absolute terms.

Treatment	Payoff	Payoff REE	Earnings efficiency
		LtF	
Market 1	25.69	26.67	96.35%
Market 2	25.19	26.67	94.47%
Market 3	25.61	26.67	96.03%
Market 4	25.65	26.67	96.18%
Average	25.54	26.67	95.76%
		LtO	
Market 1	18.80	18.33	102.54%
Market 2	17.46	18.33	95.25%
Market 3	18.00	18.33	98.21%
Market 4	18.41	18.33	100.43%
Market 5	17.85	18.33	97.39%
Market 6	18.27	18.33	99.64%
Average	18.13	18.33	98.91%
		Mixed Forecasting	
Market 1	23.36	26.67	87.62%
Market 2	17.94	26.67	67.27%
Market 3	20.17	26.67	75.63%
Market 4	20.64	26.67	77.41%
Market 5	23.22	26.67	87.07%
Market 6	24.52	26.67	91.94%
Market 7	21.65	26.67	81.20%
Market 8	16.21	26.67	60.80%
Average	20.96	26.67	78.62%
		Mixed Trading	
Market 1	18.50	18.33	100.89%
Market 2	16.01	18.33	87.33%
Market 3	14.60	18.33	79.61%
Market 4	21.02	18.33	114.63%
Market 5	18.15	18.33	99.03%
Market 6	17.83	18.33	97.24%
Market 7	17.33	18.33	94.55%
Market 8	24.20	18.33	132.01%
Average	18.45	18.33	100.66%

Table 3: Average earnings (in Euro) and earnings efficiency for each market.

with $\eta_{i,t} \sim NID(0, \sigma^2_{\eta,i})$. This model has a straightforward interpretation: it takes the quantity choice of subject i in period t as a linear function of the implied (by the price forecast) return on the asset. It has two important special cases: homogeneity and optimality (nested in homogeneity). To be specific, subject homogeneity (heterogeneity) corresponds to an insignificant (significant) variation in the slope $\phi_i = \phi_j$ ($\phi_i \neq \phi_j$) for any two subjects i and j. Optimality of individual quantity decisions implies homogeneity with an additional restriction that $\phi_i = \phi_j = 1/6$. The constant c_i shows subject's i 'irrational' optimism/pessimism bias. Optimality thus correspond to homogeneity such that $c_i = c_j = 0$ (no



(a) Expected return vs trade **(b)** Trade rule (14): slope vs constant

Figure 4: ML estimation for trading rule (14) in the Mixed treatment. Panel (a) is scatter plot of the traded quantity (vertical axis) against the implied expected return (horizontal axis). Each point represents one decision of one subject in one period from one group. Panel (b) is scatter plot of trading rule (14) slope (reaction to expected return; horizontal axis) against constant (trading bias; vertical axis). Each point represents one subject from one group. Solid line (left panel)/triangle (right panel) denotes optimal trade rule ($q_{i,t} = 1/6\rho^e_{i,t}$). Dashed line (left panel)/circle (right panel) denotes the estimated rule under restriction of homogeneity ($q_{i,t} = c + \phi\rho^e_{i,t}$). Expected returns greater than 60 excluded from the sample.

agent has a decision bias). Notice that under optimality, other factors should be irrelevant, which motivates our choice for (14).

We can directly test the assumptions that the subjects are (1) homogeneous and (2) perfect optimisers by estimating (14) with the above mentioned restrictions on the homogeneity of parameters c_i and ϕ_i.[9] These regressions can be compared with an unrestricted regression (with $\phi_i \neq \phi_j$ and $c_i \neq c_j$) *via* a Likelihood Ratio test (LR).[10] The detailed results can be found in Table 8 in Appendix C, but they boil down to one observation: any model that imposes homogeneity, including self-consistent trading strategies, is strongly rejected by the data.

This is a surprising result. The RE hypothesis is built on model consistent expectations, which the agents in turn use to optimise their decisions. Many

[9]We use ML since the optimality constraint does not exclude heterogeneity of the idiosyncratic shocks $\eta_{i,t}$ and so the model is non-linear. We exclude outliers defined as observations when a subject would predict the asset to have its return higher than 60 in absolute terms. To account for the initial learning, we exclude first ten periods from the sample. We also drop subjects 4 and 5 from group 6, since they would always pass $q_{i,t} = 0$ for $t > 10$. Interestingly, these two subjects had non-constant price predictions, which suggests that they were not optimisers.

[10]In our estimations we use F-test to check significance of a set of linear restrictions on a model. For the sake of simplicity, we use LR test if the restrictions are non-linear or require data transformation.

economists find the first element of RE unrealistic: agents have problems in understanding the structure of the economy, in coordinating or predicting each others behaviour. But the second part of RE is often taken as a good approximation: agents should make an optimal decision *conditional* on what they think about the economy, *even* if their forecast is wrong. Our subjects were endowed with as much information as possible, including an asset return calculator, a table for profits based on the predicted asset return and chosen quantity and the explicit formula for profits; and yet many failed to behave optimally in a consistent fashion. The design of the payoff excludes risk hedging as a potential reason. The simplest explanation is that individuals, simply, are not perfect optimisers.

3.5 Estimation of individual behavioural rules

Prior experimental work (Heemeijer et al., 2009) suggests that in LtF experiments, subjects use simple forecasting heuristics. Two that are often identified in positive feedback markets are adaptive expectations

$$p^e_{i,t} = \alpha p_{t-1} + (1-\alpha)p^e_{i,t-1}, \tag{15}$$

with $\alpha \in [0,1]$; and trend extrapolation rule

$$p^e_{i,t} = p_{t-1} + \gamma(p_{t-1} - p_{t-2}). \tag{16}$$

We estimate these two types of rules for each individual subject in LtF treatment, for the full sample of subjects and the last 40 periods. We call an estimation successful if it generates coefficient estimates that are statistically significant at the 5% level, and if there is no serial correlation in the errors.[11] If both types of estimation are successful for the same individual, we characterise her or him as following the one with the higher R^2 value. It turns out about 50% of the subjects (11 out of 24) can be categorised in this way for the LtF treatment. For the successful estimations, the average of coefficient α is 0.8736 and the average of coefficient γ is 0.3833, which suggests the subjects were following a (weak) trend extrapolation type of rules. This result is consistent with Heemeijer et al. (2009).

To explain the behaviour of the subjects from the LtO treatment, we look at two simple quantity rules. First, a persistent demand is a simple AR process. We focus on

$$q_{i,t} = \chi_i q_{i,t-1}, \tag{17}$$

[11]For all the discussed estimations we use Durbin-Watson test to determine the appropriate number of lags of the regressand in the unconstrained model, and use them in any (un-) constrained regression. We do not report their coefficients, as we think of them only as auxiliary variables without any economic interpretation.

where χ_i is an AR(1) memory coefficient. Second rule is a simple asset return extrapolation in the form of

$$q_{i,t} = \phi_i \rho_{t-1} = \phi_i \left(p_{t-1} + 3.3 - 1.05 p_{t-2} \right). \tag{18}$$

Notice that if the agents believe $\rho_t \approx \rho_{t-1}$, they should rely on $\phi_i = 1/6$.

We test the importance of these two rules for our subjects by estimating individual quantity decisions in the general form of

$$q_{i,t} = constant_i + \chi_i q_{i,t-1} + \phi_i \rho_{t-1}. \tag{19}$$

We will refer to the rule (19) as a mixed rule, since it is a combination of AR(1) and return extrapolation rules (17) and (18). Also, a subject is generally an optimist/pessimist if $constant_i$ is larger/smaller than 0. If χ_i memory and ϕ_i return extrapolation coefficients are both zero (statistically insignificant), (19) becomes a pure random rule with quantity decisions centred around the optimism coefficient $constant_i$ (notice that by definition this rule is always stationary).

We estimate the mixed rule (19) separately for every individual in the LtO treatment, for the last 40 periods. In the estimation procedure, we start with full (19), but re-estimate it by dropping χ_i memory or ϕ_i return extrapolation coefficients if either parameter is insignificant. The results are reported in Table 7 in Appendix C. We were able to identify a non-random rule for 26 (72%) of the LtO treatment subjects, usually with a high R^2. Around half of the subjects (19) used the return extrapolation rule (18), 4 can be described by the full mixed rule (19) and 3 by the AR(1) (17) rule. Only 3 subjects seem to have been pessimists (with significant negative $constant_i$) and none was an optimist.

Out of the 26 subjects with a non-random rule, 23 focused on the past asset return, with the average coefficient ϕ equal to 0.135 (and all the estimated coefficients positive). Demand of seven subjects was persistent, and here the average coefficient of the previous quantity was 0.283 (despite two negative estimates). One can show that using the rules AR1 (17) with χ and asset extrapolation (18) with ϕ coefficients in the LtO treatment effectively gives a behaviour as if using the price trend rule (16) under the LtF treatment, with $\beta \approx \chi$ and $\beta \approx 6\phi$ coefficients respectively. This means that more than a half of the subjects from the LtO treatment implicitly followed (or behaved as if following) the price trend, with the average coefficient roughly equal to 0.683,[12] a number almost twice as high as in the case of LtF treatment, and the direct reason for the LtO markets to generate stronger oscillations.

[12]Which is the appropriate weighted average of the average χ and 6 times the average ϕ.

As established previously, under the mixed treatment the subjects would often choose suboptimal quantities conditional on their price predictions. It makes therefore sense to estimate these two variables as a joint two-dimensional system. We take the price expectations to follow the price First-Order rule, a mixture of the adaptive (15) and trend extrapolation (16) rules in the form of

$$p^e_{i,t} = \alpha p_{t-1} + (1-\alpha)p^e_{i,t-1} + \gamma(p_{t-1} - p_{t-2}) \tag{20}$$

with $\alpha \in [0, 1]$ constraint. For the quantity choices we focus on a modified quantity First-Order rule, which includes the observed expected return

$$q_{i,t} = constant_i + \chi_i q_{i,t-1} + \phi_i \rho_{t-1} + \zeta \rho^e_{i,t}. \tag{21}$$

The estimation results are presented in Table 9 in Appendix B.[13] For the price expectations equation, we first estimate the full rule and check with LR test whether either trend extrapolation or adaptive expectation constrained rule cannot be rejected.[14] In this case, only 3 out of 48 subjects use adaptive expectations, 12 use simple trend extrapolation, while the rest uses a full mixed rule.

Only 4 subjects exhibited a persistent optimism or pessimism in their trading behaviour. We explicitly tested whether the subjects used a quantity rule that cannot be statistically distinguished from the self-consistent rule $q_{i,t} = \rho^e_{i,t}/6$. That is the case only for 11 subjects (around 23%). They appear in all groups with the exception of group 8, and at most constitute half of the group (group 4). Interestingly, many other subjects would still use the expected return to decide upon the quantity, but with suboptimal coefficients. Few others would rely on the past return and only 13 would use neither.

In total 26 out of 48 subjects followed the price trend in price forecasting, with the average coefficient of 0.772. This is around 0.087 in absolute terms (or 12.7%) higher coefficient then the one implied by the quantity rules in the LtO treatment, without considering further effects of quantity rules (suboptimal use of the expected asset, further extrapolation of asset return or persistence in demand). It means that out of the three treatments the subjects under the mixed treatments

[13]The subjects have to report their price expectation and hence the quantity choice sequentially. However, it is unclear whether they also *decided* sequentially on these two variables, which means that the contemporary idiosyncratic errors in (20) and (21) are potentially correlated. This results in potential endogeneity for the heuristic (21), as the quantity choice depends on the contemporary predicted price. To rule out this problem, we use a simple instrumental variable approach. First we estimate the exogenous price expectations equation, which gives us the fitted price expectations of the subjects. We use these as instruments for the reported price expectations whenever the Hausman test indicates to do so.

[14]We use LR, since we impose $\alpha \in [0, 1]$, which makes the estimation non-linear.

were the most likely to extrapolate the price trend, which reinforced it and caused the super-bubbles.

This result shows that the subjects are able to identify the variables that are relevant to their economic problem, and are not a subject to a systematic bias (like optimism/pessimism). Nevertheless, they miss the mathematically optimal solution, despite the instructions and the asset return calculator. We speculate that instead of optimizing in the mathematical sense, the subjects follows simple rules of thumb, in which a good solution has only to be 'good enough'.

4 Rational strategic behaviour

Our experimental results are clearly different from the predictions of the rational expectation equilibrium (REE). In the previous section we discussed some evidence that non-fundamental prices and oscillations are caused by bounded rationality and simple individual heuristics of our subjects. However, we also found that they would typically earn high payoffs, implying some sort of profit seeking behaviour.

In this section, we discuss whether rational strategic behaviour can explain our experimental results. It turns out that different types of rational equilibria may exist depending on subjects' perception of the game structure. By rational we mean that the subjects maximise their expected profit given their beliefs about the economy. First, we evaluate more carefully the competitive equilibrium, in which agents are price takers. Secondly, we discuss the collusive outcome, where the agents coordinate on monopolistic behaviour. Thirdly, we examine the case where agents behave strategically, but cooperation is not possible. We show that in the price-taking case, LtF and LtO treatments are equivalent, with the same rational fundamental solution. Next we show that, if the subjects behave strategically or try to collude, the economy can have alternative rational equilibria, where the subjects can collectively 'ride a bubble', or jump around the fundamental price. Nevertheless, these equilibria predict different outcomes than the individual and aggregate behaviour observed in the experiment.

Without loss of generality, we focus on the one-shot game version of the experimental market to derive our results. More precisely, we look at the optimal decisions that the agents in period t (knowing prices and individual traded quantity until and including period t) have to formulate *only* for the next period $t+1$. This follows two observations. First, by definition agents are myopic and their payoff in $t+1$ depends only on the realised profit from that period, and not on the stream of future profits from period $t+2$ onward. Second, the experiment is a repeated game with finitely many repetitions, and subjects knew it would end after 50 periods. Using the standard backward induction reasoning, one can easily show that a sequence of one-period game equilibria forms a rational equilibrium of the finitely repeated game as well.

4.1 Price takers

The realised utility of investors in the LtO treatment is given by (3) and is equivalent to the following form:

$$U_{i,t}(z_{i,t}) = z_{i,t}\left(p_{t+1} + y - Rp_t\right) - \frac{a\sigma_z^2}{2} z_{i,t}^2, \tag{22}$$

where $z_{i,t}$ is the traded quantity and $U_{i,t}$ is a quadratic function of the traded quantity. In Section 2 we already discussed that, assuming the agent is a price taker, the optimal traded quantity conditional on the expected price $p^e_{i,t+1}$ is given by

$$z_{i,t}^{PT} = \arg\max_{z_{i,t}} U_{i,t} = \frac{p^e_{i,t+1} + y - Rp_t}{a\sigma_z^2}. \tag{23}$$

Note that this result relies on the assumption that the subjects do not know the price determination function. We argue that the subjects also have an incentive to minimise their forecasting error. To see that, suppose that the realised market price in the next period is p_{t+1}, and the subject makes a prediction error of ϵ, *i.e.* her prediction is $p^e_{i,t+1} = p_{t+1} + \epsilon$. The payoff function can be rewritten as:

$$\begin{aligned}
U_{i,t}(z_{i,t}) &= z_{i,t}\left(p_{t+1} + y - Rp_t\right) - \frac{a\sigma_z^2}{2} z_{i,t}^2 \\
&= \frac{(p_{t+1} + \epsilon + y - Rp_t)(p_{t+1} + y - Rp_t)}{a\sigma_z^2} - \frac{(p_{t+1} + \epsilon + y - Rp_t)^2}{2a\sigma_z^2} \\
&= \frac{(p_{t+1} + y - Rp_t)^2}{2a\sigma_z^2} - \frac{\epsilon^2}{2a\sigma_z^2}.
\end{aligned} \tag{24}$$

We can see that the utility is maximised when $\epsilon = 0$. This means that, assuming perfect rationality and price taking behaviour (perfect competition), the task of finding the optimal trade *coincides* with the task of minimizing the forecast error. Thus when all the agents have rational expectations and are price takers, the market converges to the REE defined in Section 2 regardless of the task.[15] One could express that by saying that in a one-shot game, REE is the only Nash Equilibrium. It follows that REE is also the unique NE for the finitely repeated game. We summarise this finding below.

[15] The uniqueness of REE is straightforward and we prove it in the Appendix E. It also implies that there are no so called 'rational bubbles' in this set-up.

Finding 1. *When the subjects act as price takers, the utility function in the Learning to Optimize treatment is a quadratic function of the prediction error, the same (up to a monotonic transformation) as in the Learning to Forecast treatment. In this situation, the Rational Expectation Equilibrium, i.e. the fundamental price, is the only Nash Equilibrium throughout the* 50 *experimental periods,* regardless *of the design: when subjects are price takers, LtF and LtO are equivalent under rational expectations.*

4.2 Collusive outcome

Consider now the case when the agents realise how their predictions/trading quantities influence the price and are able to coordinate on a common strategy. This resembles a collusive (oligopoly) market, *e.g.* in a cobweb economy in which the sellers can coordinate their production.

We assume that in the collusive solution, all agents behave as a monopoly that maximises joint (unweighed) utility; thus the solution is symmetric, that is for each agent i, $z_{i,t} = z_t$. In our experiment the price determination function is:

$$p_{t+1} = p_t + 6\lambda z_t, \tag{25}$$

and so the monopoly maximises

$$\begin{aligned} U_t = \sum_{i=1}^{6} U_{i,t}(z_t) &= 6\left[z_t(p_{t+1} + y - Rp_t) - \frac{a\sigma_z^2}{2} z_t^2\right] \\ &= 6\left[z_t^2\left(6\lambda - \frac{a\sigma_z^2}{2}\right) + z_t(y - rp_t)\right]. \end{aligned} \tag{26}$$

Here we assume that the rational agent has perfect knowledge about the pricing function (25). Notice that when $\lambda = 20/21, a\sigma_z^2 = 6$, as in the experiment, the coefficient before z_t^2 is positive, $6\lambda - \frac{a\sigma_z^2}{2} = \frac{19}{7} > 0$, and thus the profit function is U shaped, instead of inversely U shaped.[16] This means that a finite global maximum does not exist (utility goes to $+\infty$ when z_t goes to either $+\infty$ or $-\infty$). The global *minimum* is obtained when $z_{i,t} = \frac{7}{38}(rp_t - y) = \frac{7r}{38}(p_t - p^f)$.

In our experiment, the subjects are restricted to choose a quantity from $[-5, +5]$ and the price is bound to the interval $[0, 300]$. Collusive equilibrium in the one-shot game implies that the subjects coordinate on $z_{i,t} = 5$ or $z_{i,t} = -5$, depending

[16] If $6\lambda - \frac{a\sigma_z^2}{2} < 0$, this objective function is inversely U shaped. The maximum point is achieved when $z_{i,t} = \frac{rp_t - y}{12\lambda - a\sigma_z^2}$. This means when $p_t = y/r$, namely when the price is at the REE, the optimal quantity under collusive equilibrium is still 0. When the price is higher or lower than the REE, the optimal quantity increases with the difference between the price and the REE. This means there is a continuum of equilibrium when the economy does not start at the REE.

on which is further away from $\frac{7(rp_t-y)}{38}$ (as (26) is a symmetric parabola). Since $\frac{7(rp_t-y)}{38} > 0$ when the price is above the fundamental ($p^f = y/r$), we can see that the agents coordinate on -5 if the price is higher than the REE ($p_t > y/r$). Similarly, rational agents coordinate on $+5$ if the price is lower than the REE ($p_t < y/r$). If the price is exactly at the fundamental, rational agents are indifferent between -5 and 5. Notice that in such a case trading the REE quantity ($z_{i,t} = 0$) gives the global *minimum* for the monopoly.

As a consequence, the collusive outcome predicts that the subjects will 'jump up and down' around the fundamental. When the price is just below the fundamental, rational agents will buy the asset, which brings the price above the fundamental, and hence the agents in the next period will sell the asset, and so forth. Notice that if the initial price is far below (over) from the fundamental, the monopoly will buy (sell) the asset until the price overshoots (undershoots) the fundamental. Then the subjects start to 'jump up and down' as described before.

Finding 2. *When the subjects know the price determination function and can coordinate their behaviour, the collusive profit function in the LtO treatment is U shaped. Subjects would buy under-priced and sell an over-priced asset. In the long run rational collusive subjects will alternate their trading quantities between* -5 *and* 5 *and so the price will alternate around the equilibrium.*

Such alternating dynamics would resemble coordination on contrarian type of behaviour, but has not been observed in any of the experimental groups. Instead, our subjects coordinated on trend-following trading rules, which resulted in smooth, gradual price oscillations.

Notice also that the demand at the edge of the liquidity constraint ($z_{i,t} = \pm 5$) would generate rapid price changes, namely $p_{t+1} = p_t \pm (20/21)/(6*5) \approx p_t \pm 28.57$, that is the price would change *in every period* by around 28.57 in absolute terms. This has not been observed even in the super-bubble group 8 from the Mixed treatment. Indeed, quantity decisions equal to 5 or -5 happened only 7 times in the LtO and 44 times in the Mixed treatment (*i.e.* 0.39% and 1.83% respectively). Typical subject behaviour was much more conservative: 97% and 91% traded quantities in the LtO and Mixed treatments respectively were confined in the interval $[-2.5, 2.5]$. A good example is group 4 from the Mixed treatment, in which the price reached 150, but the individual trades were rarely outside the interval $[-3, 3]$ (see Fig. 3).

4.3 Perfect information non-cooperative game

Consider a scenario, in which the subjects realise the experimental price determination mechanism, but cannot coordinate their actions and play a symmetric Nash equilibrium (NE) instead of the collusive one. There is a positive externality of the subjects' decisions: when one subject buys the asset, it pushes up the price and also the benefits of all the other subjects. The collusive equilibrium internalises this externality, but could the same happen if the subjects in the experiment could not coordinate? In other words, would they have an incentive to 'free-ride' on the demand of others, and would that push the price back to the REE?

In the case of a non-cooperative one-shot game, we again focus on a symmetric solution. Consider agent i, who optimises her quantity choice believing that all other agents will choose z^o_t. This means that the price at $t+1$ becomes

$$p_{t+1} = p_t + 5\lambda z^o_t + \lambda z_{i,t}. \tag{27}$$

Agent i maximises therefore

$$\begin{aligned} U_{i,t} &= z_{i,t}\left(\lambda z_{i,t} + 5\lambda z^o_t + y - rp_t\right) - \frac{a\sigma^2_z}{2} z^2_{i,t} \\ &= z^2_{it}\frac{2\lambda - a\sigma^2_z}{2} + z_{i,t}(5\lambda z^o_t + y - rp_t). \end{aligned} \tag{28}$$

Notice that $2\lambda - a\sigma^2_z = -86/21 < 0$. This is an inversely U shaped parabola with the unique maximum given by the reaction function

$$z^*_{i,t}(z^o_t) = \frac{5\lambda z^o_t + y - rp_t}{a\sigma^2_z - 2\lambda}. \tag{29}$$

A symmetric solution requires $z^*_{i,t}(z^o_t) = z^o_t$, which implies

$$z^*_t = \frac{rp_t - y}{7\lambda - a\sigma^2_z} = \frac{3}{2}(rp_t - y). \tag{30}$$

Furthermore the reaction function $z^*_{i,t}(z^o_t)$ is linear with respect to z^o_t, with a slope $\frac{5\lambda}{a\sigma^2_z - 2\lambda} = \frac{100}{86} > 1$. Thus, $z^o_t > z^*_t$ ($<$ and $=$) implies $z^*_{i,t} > z^o_t$ ($<$ and $=$), or in words, if agent i believes that the other players will buy (sell) the asset, she has an incentive to buy (sell) *even more*. Then as a best response, the other agents should further increase/decrease their demand, and this is limited only by the liquidity constraints. The strategy (30) thus defines the threshold point between the two corner strategies, *i.e.* the full NE strategy is defined as

$$z^{NE}_{i,t} = \begin{cases} 5 & \text{if } z^o_t > z^*_t \\ z^*_t & \text{if } z^o_t = z^*_t \\ -5 & \text{if } z^o_t < z^*_t. \end{cases} \tag{31}$$

The boundary strategies can be infeasible if the previous price is too close to zero or 300.[17] To sum up, as long as the price p_t is sufficiently far from the edges of the allowed interval $[0, 300]$, there are *three* NE of the one-shot non-cooperative game, which are defined by all players playing $z_{i,t} = -5$, $z_{i,t} = z_t^*$ and $z_{i,t} = +5$ for all $i \in \{1, \ldots, 6\}$.

If the agents coordinate on the strategy $z_{i,t} = z_t^*$, the price evolves according to the following law of motion:

$$p_{t+1} = \frac{10p_t - 60y}{7}. \tag{32}$$

In contrast to the collusive game, in the non-cooperative game the fundamental price is therefore a possible steady state, but *only* if it is an outcome in the initial period. Additional equilibrium refinements may further exclude it as a rational outcome, since it is the least profitable one. Recall that the subjects earn 0 when they play z_t^* with price at the fundamental (because there is no trade). On the other hand, they may earn a positive profit by coordinating on -5 or 5. For example, when all of them buy 5 units of asset, the utility for each of them will be $(p_{t-1} + y + 6\lambda z_{i,t} - (1 + r)p_{t-1})z_{i,t} - \frac{\alpha\sigma_z^2}{2} z_{i,t}^2 = (33.3 - 0.05p_{t-1}) * 5 - 75$. This equals 76.5 when $p_{t-1} = 60$, 16.5 when $p_{t-1} = 300$ and 75 when the previous price is equal to the fundamental, $p_{t-1} = 66$. This explains why the payoff efficiency (average experimental payoff divided by payoff under REE) is larger than 100% in some markets in the LtO or Mixed treatments where prices have large oscillations.

Notice that the linear equation (32) is unstable, so the NE of the one-shot game leads to unstable price dynamics in the repeated game even if the agents coordinate on $z_{i,t} = z_t^*$, as long as the initial price is different from the fundamental price. Indeed, if the initial price is 67 or 65 (fundamental price plus or minus one), the price hits the upper cap of 300 or the lower cap of 0 in 16 and 12 periods respectively, and rational non-cooperative agents would be forced to use appropriate corner strategies (-5 and 5 respectively). Furthermore the agents can switch *at any moment* between the three one-shot game NE defined by (31). This implies that in the repeated non-cooperative game, many price paths are possible. This includes many price paths where agents will often coordinate on 5 or -5 strategies. Furthermore, notice that the up and down alternating price behaviour around the fundamental, which was the solution for the collusive equilibrium, is a NE as well, and hence this is the Pareto efficient equilibrium for this game.

[17] Notice that we can interpret z_t^o as the average quantity traded by all other agents, besides agent i, and the reasoning for NE strategy (31) remains intact. This implies that NE has to be symmetric.

Finding 3. *In the non-cooperative game with perfect information, there are two possible types of NE. The fundamental outcome is a possible outcome only if the initial price is equal to the fundamental price. Otherwise, the agents will coordinate on unstable, possibly oscillatory price dynamics, with traded quantities of* -5 *or* 5*. When they coordinate on a non-zero quantity, their payoff can be higher than their payoff under the REE under price-taking beliefs.*

Altogether, the perfectly rational agents can coordinate on price bubbles. However, this would require even stronger assumptions than the fundamental equilibrium, namely that the agents perfectly understand the underlying price determination mechanism. Furthermore, the cycle of bubbles and crashes is suboptimal in comparison with the 'jumping up and down around the fundamental' equilibrium. If the agents were rational enough to coordinate, then it remains a mystery why they would coordinate on the less efficient path of bubbles and crashes.

Furthermore, such rational equilibria with price oscillations predict the subjects to coordinate on *homogeneous* trades at the edge of the liquidity constraints (traded quantities should often, or even always, be either 5 or -5). The subjects from the LtO and Mixed treatments behaved differently. Their traded quantities were highly heterogeneous (which implied the observed heterogeneity of the estimated trading and forecasting rules), and rarely reached the liquidity constraints, as discussed above.

We argue therefore that rational solutions, in particular the ones from the perfect information, non-cooperative games provide some useful insights on why subjects "ride the bubbles" in the LtO and Mixed treatment. However, since the rational solution cannot explain the heterogeneity of the individual decisions and the fact that the subjects shy away from the boundary solutions, the bubbles and crashes we see from the data is probably a result of the joint forces of rational (profit seeking) and boundedly rational behaviour with some coordination on trend-following buy and hold and short sell strategies.

5 Conclusion

The origins of asset price bubbles is an important topic for both researchers and policy makers. This paper investigates the price dynamics and bubble formation in an experimental asset pricing market with a price adjustment rule. A fundamental question about the origins of bubbles we address is: do bubbles arise because agents fail to learn to forecast accurately or because they fail to optimize their trading? We investigate the occurrence, the magnitude and the recurrence of bubbles in three treatments based on the tasks of the subjects: price forecasting, quantity trading and both. Under perfect rationality and perfect competition, these three tasks are equivalent and should lead the subjects to an equilibrium with a constant fundamental price. In contrast, we find none of the experimental markets to show a reliable convergence to the fundamental outcome, and recurring bubbles and crashes occur with the highest frequency and magnitude when the subjects submit both a price forecast and a trading quantity decision.

This result shows that the asset bubbles in former learning to forecast experiments (Hommes et al, 2005) are a robust phenomenon. Moreover when the subjects act in a learning to optimise environment or submit both a forecast and a quantity, the bubbles become more severe. In contrast to the learning to forecast experiments, the coordination of individual decisions is lower in the trading treatment, which suggests that coordination of beliefs is not a necessary condition for bubbles to occur in financial markets. In particular, we observe that our subjects follow heterogeneous forecasting and trading rules: to our best knowledge, our experiment is the first to explicitly test this result statistically. In the mixed treatment, in which we directly observe both the trading decisions and price expectations, we also show that only a quarter of the subjects trade consistently with their price forecasts, despite the design that encourages them to do so. This heterogeneity fits the stylised features of real financial markets, in which different traders may disagree substantially about the future price dynamics and trading strategy, and often resort to simple 'rules of thumb' — especially during a built-up of a bubble, of which further sustainability is uncertain.

The earnings efficiency (in comparison to rational expectations payoff) is high in all of our treatments. Notably, we find that the payoff efficiency for the forecasting task is much lower in the Mixed treatment than in the learning to forecasts treatment due to poorer forecasting accuracy, and the payoff for the trading task is about the same as the learning to optimize treatment, and particularly high in some markets in the Mixed treatment with super bubbles. By coordinating on a strong trend following strategy (buy/sell a lot when the price is increasing/decreasing), the subjects earn much from the capital gain. This can provide some evidence of subjects "riding the bubble" during the boom periods, even if they know that the boom is not sustainable in the long run.

Financial bubbles can cause serious market inefficiencies, and if left unmitigated, become a threat to the overall economic stability, as shown by the 2007 financial and economic crisis. It is therefore crucial to study the origins of assets' mispricing, before we devise policies regulating the financial sector. Proponents of the rational expectations would often claim that the serious asset pricing bubbles cannot arise, because rational economic agents would efficiently arbitrage against it and quickly push the 'irrational' (non-fundamental) investors away from the market. Thus asset prices changes follow shocks to fundamentals more than anything else. Our experiment suggests otherwise: people exhibit heterogeneous and not necessarily optimal behaviour, but because they are trend-followers, their 'irrational' (non-fundamental) beliefs are correlated. This is reinforced by the *positive feedback* between expectations and realised prices on the asset pricing markets, as stressed e.g. in Hommes (2013). Therefore, price oscillations cannot be mitigated by more rational market investors, and trading heterogeneity persists. As a result, waves of optimism and pessimism can arise despite the fundamentals being relatively stable. A strong policy implication is that the financial authorities should remain sceptical about the moods of the investors: fast increase of asset prices should be considered as a warning signal, instead of a reassuring signal of growth of the economic fundamentals only.

The design of our experiment can be extended to study other topics related to financial bubbles, such as markets with financial derivatives and the housing market. The advantage of our framework is that we can define a constant fundamental with positive dividend process, and the price is easy to calculate, and the same for all participants in the market.[18] However, the subjects in our experiment can short-sell the asset as much as they want in order to profit from the fall of asset price during the market crash, which may not be feasible in real markets. An interesting topic for future reasearch are experimental markets where agents face short selling constraints (Anufriev and Tuinstra, 2013) or the role of financial derivatives in (de)stabilising markets.

Another possible extension is to impose a network structure among the traders, i.e. one trader can only trade with some, but not all the other traders; or traders need to pay a cost in order to be connected to other traders. This design can help us to examine the mechanism of bubble formation in financial networks (Gale and Kariv, 2007), and network games (Galeotti et al., 2010) in general. There has been a pioneering experimental literature by Gale and Kariv (2009) and Choi et al. (2013) that study how network structure influence market efficiency when subjects act as intermediaries between sellers and buyers. Our experimental setup can be extended to study how network structure influences market efficiency and stability when subjects act as traders of financial assets in the over the counter (OTC) market.

[18]The asset price is usually defined for each transaction in a typical Smith et al. (1988) experiment, but it can also be the same for the whole market if the trading mechanism is a call market system, e.g. Akiyama et al. (2012)).

References

Akiyama, E., Hanaki, N., and Ishikawa, R. (2012). Effect of uncertainty about others' rationality in experimental asset markets: An experimental analysis. *Available at SSRN 2178291*.

Anufriev, M. and Tuinstra, J. (2013). The impact of short-selling constraints on financial market stability in a heterogeneous agents model. *Journal of Economic Dynamics and Control*, 31:1523–1543.

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

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

Beja, A. and Goldman, M. B. (1980). On the dynamic behavior of prices in disequilibrium. *The Journal of Finance*, 35(2):235–248.

Bondt, W. and Thaler, R. (2012). Further evidence on investor overreaction and stock market seasonality. *The Journal of Finance*, 42(3):557–581.

Bostian, A. A. and Holt, C. A. (2009). Price bubbles with discounting: A web-based classroom experiment. *The Journal of Economic Education*, 40(1):27–37.

Campbell, J. and Shiller, R. (1989). Stock prices, earnings and expected dividends. NBER working paper.

Campbell, J. Y., Lo, A. W., and MacKinlay, A. C. (1997). *The Econometrics of Financial Markets*. Princeton University Press.

Chiarella, C., Dieci, R., and He, X.-Z. (2009). Heterogeneity, market mechanisms, and asset price dynamics. *Handbook of financial markets: Dynamics and evolution*, pages 277–344.

Choi, S., Galeotti, A., and Goyal, S. (2013). Trading in networks: Theory and experiment.

Duffy, J. (2008). Macroeconomics: a survey of laboratory research. *Handbook of Experimental Economics*, 2.

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

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work*. *The Journal of Finance*, 25(2):383–417.

Farmer, J. and Lo, A. (1999). Frontiers of finance: Evolution and efficient markets. *Proceedings of the National Academy of Sciences*, 96(18):9991–9992.

Gale, D. M. and Kariv, S. (2007). Financial networks. *The American economic review*, pages 99–103.

Gale, D. M. and Kariv, S. (2009). Trading in networks: A normal form game experiment. *American Economic Journal: Microeconomics*, pages 114–132.

Galeotti, A., Goyal, S., Jackson, M. O., Vega-Redondo, F., and Yariv, L. (2010). Network games. *The review of economic studies*, 77(1):218–244.

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

Haruvy, E., Noussair, C., and Powell, O. (2013). The impact of asset repurchases and issues in an experimental market. *Review of Finance*, pages 1–33.

Heemeijer, P., Hommes, C., Sonnemans, J., and Tuinstra, J. (2009). Price stability and volatility in markets with positive and negative expectations feedback: An experimental investigation. *Journal of Economic Dynamics and Control*, 33(5):1052–1072.

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

Hommes, C. (2013). *Behavioral Rationality and Heterogeneous Expectations in Complex Economic Systems*. Cambridge University Press.

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

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.

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

LeBaron, B. (2006). Agent-based computational finance. *Handbook of computational economics*, 2:1187–1233.

Lei, V., Noussair, C. N., and Plott, C. R. (2001). Nonspeculative bubbles in experimental asset markets: Lack of common knowledge of rationality vs. actual irrationality. *Econometrica*, 69(4):831–859.

Lucas Jr, R. E. (1972). Expectations and the neutrality of money. *Journal of economic theory*, 4(2):103–124.

Marimon, R., Spear, S. E., and Sunder, S. (1993). Expectationally driven market volatility: an experimental study. *Journal of Economic Theory*, 61(1):74–103.

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica*, 29(3):315–335.

Noussair, C., Robin, S., and Ruffieux, B. (2001). Price bubbles in laboratory asset markets with constant fundamental values. *Experimental Economics*, 4(1):87–105.

Noussair, C. N. and Tucker, S. (2013). Experimental research on asset pricing. *Journal of Economic Surveys*.

Rubinstein, A. (2007). Instinctive and cognitive reasoning: A study of response times*. *The Economic Journal*, 117(523):1243–1259.

Shiller, R. (2003). From efficient markets theory to behavioral finance. *The Journal of Economic Perspectives*, 17(1):83–104.

Smith, V., Suchanek, G., and Williams, A. (1988). Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica: Journal of the Econometric Society*, pages 1119–1151.

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

Sunder, S. (1995). Experimental asset markets: A survey. In Kage, J. and Roth, A., editors, *Handbook of Experimental Economics*, pages 445–500. NJ: Princeton University Press, Princeton.

A Instructions and computer screen (not for publication)

A.1 LtF treatment

General information
In this experiment you participate in a market. Your role in the market is a professional **Forecaster** for a large firm, and the firm is a major trading company of an asset in the market. In each period the firm asks you to make a prediction of the market price of the asset. The price should be predicted one period ahead. Based on your prediction, your firm makes a decision about the quantity of the asset the firm should buy or sell in this market. Your forecast is the only information the firm has on the future market price. The more accurate your prediction is, the better the quality of your firm's decision will be. You will get a payoff based on the accuracy of your prediction. You are going to advise the firm for 50 successive time periods.

About the price determination
The price is determined by the following price adjustment rule: when there is more demand (firm's willingness to buy) of the asset, the price goes up; when there is more supply (firm's willingness to sell), the price will go down.
There are several large trading companies on this market and each of them is advised by a forecaster like you. Usually, higher price predictions make a firm to buy more or sell less, which increases the demand and vice versa. Total demand and supply is largely determined by the sum of the individual demand of these firms.
About your job
Your only task in this experiment is to predict the market price in each time period as accurately as possible. **Your prediction in period** 1 **should lie between** 0 **and** 100**.** At the beginning of the experiment you are asked to give a prediction for the price in period 1. When all forecasters have submitted their predictions for the first period, the firms will determine the quantity to demand, and the market price for period 1 will be determined and made public to all forecasters. Based on the accuracy of your prediction in period 1, your earnings will be calculated.
Subsequently, you are asked to enter your prediction for period 2. When all participants have submitted their prediction and demand decisions for the second period, the market price for that period, will be made public and your earnings will be calculated, and so on, for all 50 consecutive periods. The information you can refer to at period t consists of all past prices, your predictions and earnings.

Please note that due to liquidity constraint, your firm can only buy and sell up to a maximum amount of assets in each period. This means although you can submit any prediction for period 2 and all periods after period 2, if the price in last period is p_{t-1}, and you prediction is p_t^e: the firm's trading decision is constrained by $p_t^e \in [p_{t-1} - 30, p_{t-1} + 30]$. More precisely, **the firm will trade as if** $p_t^e = p_{t-1} + 30$ if $p_t^e > p_{t-1} + 30$, **and trade as if** $p_t^e = p_{t-1} - 30$ if $p_t^e < p_{t-1} - 30$.

About your payoff

Your earnings depend only on the accuracy of your predictions. The earnings shown on the computer screen will be in terms of points. If your prediction is p_t^e and the price turns out to be p_t in period t, your earnings is determined by the following equation:

$$Payoff = \max\left[1300 - \frac{1300}{49}\left(p_t^e - p_t\right)^2, 0\right].$$

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 can make. You will earn 0 points if your prediction error is larger than 7. There is a **Payoff Table** on your table, which shows the points you can earn for different prediction errors.

We will pay you in cash at the end of the experiment based on the points you earned. You earn 1 euro for each 2600 points you make.

A.2 LtO treatment

General information

In this experiment you participate in a market. Your role in the market is a Trader of a large firm, and the firm is a major trading company of an asset. In each period the firm asks you to make a trading decision on the quantity D_t your firm will BUY to the market. (You can also decide to sell, in that case you just submit a negative quantity.) You are going to play this role for 50 successive time periods. The better the quality of your decision is, the better your firm can achieve her target. The target of your firm is to maximize the expected asset value minus the variance of the asset value, which is also the measure by the firm concerning your performance:

$$(1) \quad \pi_t = W_t - \frac{1}{2} Var\left(W_t\right)^2$$

The total asset value W_t equals the return of the per unit asset multiplied by the number of unit you buy D_t. **The return of the asset** is $p_t + y - Rp_{t-1}$, where

R is the gross interest rate which equals 1.05, p_t is the asset price at period t, therefore $p_t - Rp_{t-1}$ is the capital gain of the asset, and $y = 3.3$ is the dividend paid by the asset. We assume the variance of the price of a unit of the asset is $\sigma^2 = 6$, therefore the expected variance of the asset value is $6D_t^2$. Therefore we can rewrite the performance measure in the following way

$$(2) \quad \pi_t = (p_t + y - Rp_{t-1})D_t - 3D_t^2$$

The asset price in the next period p_{t+1} is not observable in the current period. You can make a forecast p_t^e on it. **There is an asset return calculator in the experimental interface** that gives the asset return for each price forecast p_t^e you make. Your own payoff is a function of the value of target function of the firm:

$$(3) \quad Payoff_t = 800 + 40 * \pi_t$$

This function means you get 800 points (experimental currency) as basic salary, and 40 points for each 1 unit of performance (target function of the firm) you make. If your trades will be unsuccessful, you may lose points and earn less than your basic salary, down to 0. Based on the asset return, you can look up your payoff for each quantity decision you make in the **payoff table**.

You can of course also calculate your payoff for each given forecast and quantity using equation (2) and (3) directly. In that situation you can ask us for a calculator.

About the price determination

The price is determined by the following price adjustment rule: when there is more demand than supply of the asset (namely, more traders want to buy), the price will go up; and when there is more supply than demand of the asset (namely, more people want to sell), the price will go down.

About your job

Your only task in this experiment is to decide the quantity the firm will buy/sell. At the beginning of period 1 you determine the quantity to buy or sell (submitting a positive number means you want to buy, and negative number means you want to sell) for period 1. After all traders submit their quantity decisions, the market price for period 1 will be determined and made public to all traders. Based on the value of the target function of your firm in period 1, your earnings in the first period will be calculated.

Subsequently, you make trading decisions for the second period, the market price for that period will be made public and your earnings will be calculated, and so on, for all 50 consecutive periods. The information you can refer to at period t

consists of all previous prices, your quantity decisions and earnings.
Please notice that due to the liquidity constraint of the firm, the amount of asset you buy or sell cannot be more than 5 units. Which means you quantity decision should be between -5 and 5. The numbers on the payoff table are just examples. You can use any other number such as 0.01, -1.3, 2.15 etc., as long as they are within $[-5, 5]$. if When you want to submit numbers with a decimal point, please write a ".", NOT a ",".

About your payoff
In each period you are paid according to equation (3). The earnings shown on the computer screen will be in terms of points. We will pay you in cash at the end of the experiment based on the points you earned. You earn 1 euro for each 2600 points you make.

A.3 Mixed treatment

General information
In this experiment you participate in a market. Your role in the market is a Trader of a large firm, and the firm is a major trading company of an asset. In each period the firm asks you to make a trading decision on the quantity D_t your firm will BUY to the market. (You can also decide to sell, in that case you just submit a negative quantity.) You are going to play this role for 50 successive time periods. The better the quality of your decision is, the better your firm can achieve her target. The target of your firm is to maximize the expected asset value minus the variance of the asset value, which is also the measure by the firm concerning your performance:

$$(1) \quad \pi_t = W_t - \frac{1}{2}Var\left(W_t\right)^2$$

The total asset value W_t equals the return of the per unit asset multiplied by the number of unit you buy D_t. **The return of the asset** is $p_t + y - Rp_{t-1}$, where R is the gross interest rate which equals 1.05, p_t is the asset price at period t, therefore $p_t - Rp_{t-1}$ is the capital gain of the asset, and $y = 3.3$ is the dividend paid by the asset. We assume the variance of the price of a unit of the asset is $\sigma^2 = 6$, therefore the expected variance of the asset value is $6D_t^2$. Therefore we can rewrite the performance measure in the following way

$$(2) \quad \pi_t = (p_t + y - Rp_{t-1})D_t - 3D_t^2$$

The asset price in the next period p_{t+1} is not observable in the current period. You can make a forecast p_t^e on it. **There is an asset return calculator in the**

experimental interface that gives the asset return for each price forecast p_t^e you make. Your own payoff is a function of the value of target function of the firm:

$$(3) \quad Payoff_t = 800 + 40 * \pi_t$$

This function means you get 800 points (experimental currency) as basic salary, and 40 points for each 1 unit of performance (target function of the firm) you make. If your trades will be unsuccessful, you may lose points and earn less than your basic salary, down to 0. Based on the asset return, you can look up your payoff for each quantity decision you make in the **payoff table**.
You can of course also calculate your payoff for each given forecast and quantity using equation (2) and (3) directly. In that situation you can ask us for a calculator.
The payoff for the forecasting task is simply a decreasing function of your forecasting error (the distance between your forecast and the realized price). When your forecasting error is larger than 7, you earn 0 points.

$$(4) \quad Payoff_{forecasting} = \max\left[1300 - \frac{1300}{49}\left(p_t^e - p_t\right)^2, 0\right]$$

About the price determination
The price is determined by the following price adjustment rule: when there is more demand than supply of the asset (namely, more traders want to buy), the price will go up; and when there is more supply than demand of the asset (namely, more people want to sell), the price will go down.

About your job
Your task in this experiment consists of two parts: (1) to make a price forecast; (2) to decide the quantity the firm will buy/sell. At the **beginning of period** 1 **you submit your price forecast between** 0 **and** 100, and then determine the quantity to buy or sell (submitting a positive number means you want to buy, and negative number means you want to sell) for period 1, and the market price for period 1 will be determined and made public to all traders. Based on your forecasting error and performance measure for the trading task, in period 1, your earnings in the first period will be calculated.
Subsequently, you make forecasting and trading decisions for the second period, the market price for that period will be made public and your earnings will be calculated, and so on, for all 50 consecutive periods. The information you can refer to at period t consists of all previous prices, your past forecasts, quantity decisions and earnings.

Please notice that due to the liquidity constraint of the firm, the amount of asset you buy or sell cannot be more than 5 units. Which means you quantity decision should always be **between** -5 **and 5**. The numbers on the payoff table are just examples. You can use **any other numbers** such as 0.01, -1.3, 2.15 etc. as long as they are within $[-5, 5]$.

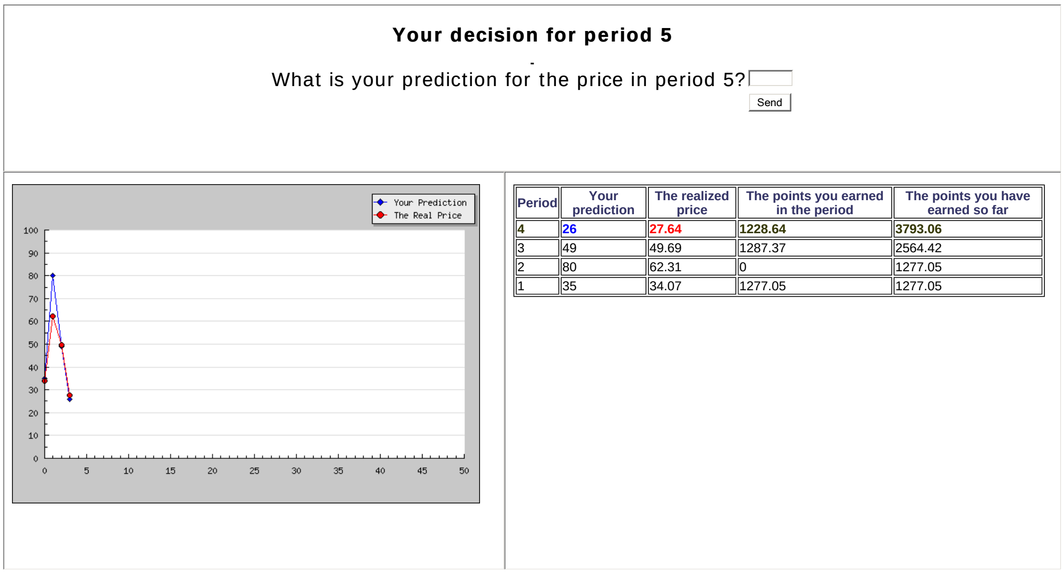
About your payoff

In each period you are paid for the forecasting task according to equation (4) and trading task according to equation (3). The earnings shown on the computer screen will be in terms of points. We will pay you in cash at the end of the experiment based on the points you earned for **either** the forecasting task or the trading task. Which task will be paid will be determined randomly (we will invite one of the participants to toss a coin). **That is, depending on the coin toss, your earnings will be calculated either based on equation (3) or equation (4)**. You earn 1 euro for each 2600 points you make.

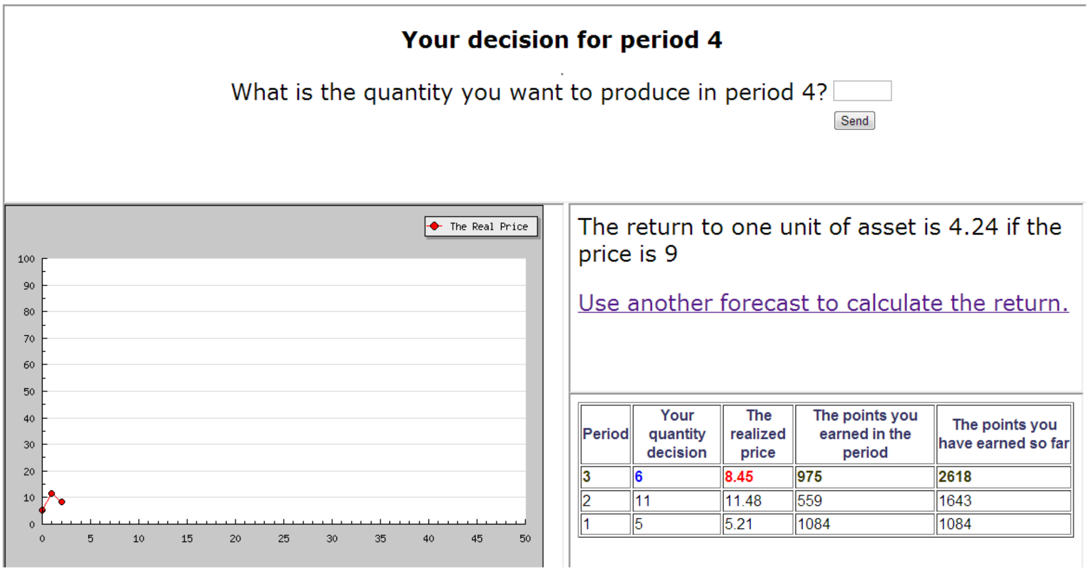
A.4 Computer screen

An illustration of the computer screens seen by the subjects is shown on Figure 5. The screen was divided into 3 mini pages. In the top mini page, subjects were prompted to submit their decisions, *i.e.*, their price forecast or the amount they want to trade. After submitting their decisions, they go to a waiting page until all the subjects have made their decisions for this period, and then the price and payoff of this period is calculated, the program goes to next period and the screen is reloaded to show the updated information. In the bottom left mini page there was a graph plotting past market prices (the "Real Price") and, if they were a forecaster, they also saw their own past price forecast history ("Your Prediction"). Finally, in the bottom right mini page they saw a table reporting the history of realized prices, as well as their own prior decisions and cumulative payoffs. If the subject was a quantity decision maker, he/she was also helped by an imbedded calculator. In each period, the subjects could type in their price forecast and press "calculate", and the calculator will tell them the asset return for this forecast in this period.

Subjects in LtF/LtO treatment seen the screen for a forecaster/trader only. In a Mixed treatment, the subjects first see the screen of the forecast, and then go to the trading page.



(a) Screen for a forecaster.



(b) Screen for a quantity decision maker.

Figure 5: Computer screen for subjects in LtF treatment (upper panel) and LtO panel (lower panel).

B Payoff tables (not for publication)

Payoff Table for Forecasting Task							
Your Payoff=max[1300 − $\frac{1300}{49}$(Your Prediction Error)^2, 0]							
3000 points equal 1 euro							
error	points	error	points	error	points	error	points
0	1300	1.85	1209	3.7	937	5.55	483
0.05	1300	1.9	1204	3.75	927	5.6	468
0.1	1300	1.95	1199	3.8	917	5.65	453
0.15	1299	2	1194	3.85	907	5.7	438
0.2	1299	2.05	1189	3.9	896	5.75	423
0.25	1298	2.1	1183	3.95	886	5.8	408
0.3	1298	2.15	1177	4	876	5.85	392
0.35	1297	2.2	1172	4.05	865	5.9	376
0.4	1296	2.25	1166	4.1	854	5.95	361
0.45	1295	2.3	1160	4.15	843	6	345
0.5	1293	2.35	1153	4.2	832	6.05	329
0.55	1292	2.4	1147	4.25	821	6.1	313
0.6	1290	2.45	1141	4.3	809	6.15	297
0.65	1289	2.5	1134	4.35	798	6.2	280
0.7	1287	2.55	1127	4.4	786	6.25	264
0.75	1285	2.6	1121	4.45	775	6.3	247
0.8	1283	2.65	1114	4.5	763	6.35	230
0.85	1281	2.7	1107	4.55	751	6.4	213
0.9	1279	2.75	1099	4.6	739	6.45	196
0.95	1276	2.8	1092	4.65	726	6.5	179
1	1273	2.85	1085	4.7	714	6.55	162
1.05	1271	2.9	1077	4.75	701	6.6	144
1.1	1268	2.95	1069	4.8	689	6.65	127
1.15	1265	3	1061	4.85	676	6.7	109
1.2	1262	3.05	1053	4.9	663	6.75	91
1.25	1259	3.1	1045	4.95	650	6.8	73
1.3	1255	3.15	1037	5	637	6.85	55
1.35	1252	3.2	1028	5.05	623	6.9	37
1.4	1248	3.25	1020	5.1	610	6.95	19
1.45	1244	3.3	1011	5.15	596	$error \geq 0$	
1.5	1240	3.35	1002	5.2	583		
1.55	1236	3.4	993	5.25	569		
1.6	1232	3.45	984	5.3	555		
1.65	1228	3.5	975	5.35	541		
1.7	1223	3.55	966	5.4	526		
1.75	1219	3.6	956	5.45	512		
1.8	1214	3.65	947	5.5	497		

Table 4: Payoff table for forecasters.

Your profit																						
		Asset quantity: positive number means to buy, negative to sell																				
		−5	**−4.5**	**−4**	**−3.5**	**−3**	**−2.5**	**−2**	**−1.5**	**−1**	**−0.5**	**0**	**0.5**	**1**	**1.5**	**2**	**2.5**	**3**	**3.5**	**4**	**4.5**	**5**
Asset return	**−15**	800	1070	1280	1430	1520	1550	1520	1430	1280	1070	800	470	80	0	0	0	0	0	0	0	0
	−14	600	890	1120	1290	1400	1450	1440	1370	1240	1050	800	490	120	0	0	0	0	0	0	0	0
	−13	400	710	960	1150	1280	1350	1360	1310	1200	1030	800	510	160	0	0	0	0	0	0	0	0
	−12	200	530	800	1010	1160	1250	1280	1250	1160	1010	800	530	200	0	0	0	0	0	0	0	0
	−11	0	350	640	870	1040	1150	1200	1190	1120	990	800	550	240	0	0	0	0	0	0	0	0
	−10	0	170	480	730	920	1050	1120	1130	1080	970	800	570	280	0	0	0	0	0	0	0	0
	−9	0	0	320	590	800	950	1040	1070	1040	950	800	590	320	0	0	0	0	0	0	0	0
	−8	0	0	160	450	680	850	960	1010	1000	930	800	610	360	50	0	0	0	0	0	0	0
	−7	0	0	0	310	560	750	880	950	960	910	800	630	400	110	0	0	0	0	0	0	0
	−6	0	0	0	170	440	650	800	890	920	890	800	650	440	170	0	0	0	0	0	0	0
	−5	0	0	0	30	320	550	720	830	880	870	800	670	480	230	0	0	0	0	0	0	0
	−4	0	0	0	0	200	450	640	770	840	850	800	690	520	290	0	0	0	0	0	0	0
	−3	0	0	0	0	80	350	560	710	800	830	800	710	560	350	80	0	0	0	0	0	0
	−2	0	0	0	0	0	250	480	650	760	810	800	730	600	410	160	0	0	0	0	0	0
	−1	0	0	0	0	0	150	400	590	720	790	800	750	640	470	240	0	0	0	0	0	0
	0	0	0	0	0	0	50	320	530	680	770	800	770	680	530	320	50	0	0	0	0	0
	1	0	0	0	0	0	0	240	470	640	750	800	790	720	590	400	150	0	0	0	0	0
	2	0	0	0	0	0	0	160	410	600	730	800	810	760	650	480	250	0	0	0	0	0
	3	0	0	0	0	0	0	80	350	560	710	800	830	800	710	560	350	80	0	0	0	0
	4	0	0	0	0	0	0	0	290	520	690	800	850	840	770	640	450	200	0	0	0	0
	5	0	0	0	0	0	0	0	230	480	670	800	870	880	830	720	550	320	30	0	0	0
	6	0	0	0	0	0	0	0	170	440	650	800	890	920	890	800	650	440	170	0	0	0
	7	0	0	0	0	0	0	0	110	400	630	800	910	960	950	880	750	560	310	0	0	0
	8	0	0	0	0	0	0	0	50	360	610	800	930	1000	1010	960	850	680	450	160	0	0
	9	0	0	0	0	0	0	0	0	320	590	800	950	1040	1070	1040	950	800	590	320	0	0
	10	0	0	0	0	0	0	0	0	280	570	800	970	1080	1130	1120	1050	920	730	480	170	0
	11	0	0	0	0	0	0	0	0	240	550	800	990	1120	1190	1200	1150	1040	870	640	350	0
	12	0	0	0	0	0	0	0	0	200	530	800	1010	1160	1250	1280	1250	1160	1010	800	530	200
	13	0	0	0	0	0	0	0	0	160	510	800	1030	1200	1310	1360	1350	1280	1150	960	710	400
	14	0	0	0	0	0	0	0	0	120	490	800	1050	1240	1370	1440	1450	1400	1290	1120	890	600
	15	0	0	0	0	0	0	0	0	80	470	800	1070	1280	1430	1520	1550	1520	1430	1280	1070	800

Note that 3000 points of your profit corresponds to €1.

Table 5: Payoff table for traders.

C Estimation of individual forecasting rules (not for publication)

Adaptive Rule				
Subject	**Coefficient**	**p – value**	$\mathbf{R^2}$	**MSE**
sub23	0.4723	0.0000	0.9937	0.7060
sub24	0.9196	0.0000	0.9910	0.7981
sub25	1.1253	0.0000	0.9960	0.3592
sub43	1.0770	0.0000	0.9910	0.3224
sub44	0.7736	0.0000	0.9898	0.3650
Trend Following Rule				
Subject	**Coefficient**	**p – value**	$\mathbf{R^2}$	**MSE**
sub14	0.3807	0.0000	0.9964	0.2207
sub34	0.3053	0.0000	0.9955	0.1815
sub35	0.3482	0.0000	0.9931	0.2672
sub42	0.6733	0.0000	0.9578	1.2695
sub45	0.2451	0.0000	0.9949	0.1601
sub46	0.3472	0.0000	0.9938	0.1985

Table 6: Estimation results for subjects in treatment 1 who could be successfully categorized by one of the two forecasting rules.

	Rule coefficients			R^2	rule	stability
Subject	**cons.**	**AR(1)**	**past return**			
			Group 1			
1		−0.447	0.203	0.904	mixed	S
2			0.175	0.819	return	U
3			0.167	0.804	return	U
4			0.111	0.856	return	S
5	−0.125		0.168	0.833	return	U
6			0.159	0.854	return	S
			Group 2			
1				0.0451	random	S
2				0.168	random	S
3				0.00997	random	S
4				0.106	random	S
5		0.478	−0.0473	0.24	mixed	U
6				0.0473	random	S
			Group 3			
1	−0.188	−0.291	0.221	0.836	mixed	U
2			0.16	0.272	return	S
3	−0.26		0.16	0.645	return	S
4			0.0781	0.124	return	S
5		0.283	0.105	0.676	mixed	S
6			0.152	0.879	return	S
			Group 4			
1		0.811		0.677	AR(1)	N
2			0.174	0.549	return	U
3			0.113	0.69	return	S
4			0.14	0.824	return	S
5			0.174	0.798	return	U
6			0.119	0.346	return	S

Table 7: Estimated individual rules for the LtO treatment. S, N and U denote respectively stable, neutrally stable and unstable rule if all six subjects would use this rule.

Subject	Rule coefficients			R^2	rule	stability
	cons.	AR(1)	past return			
			Group 5			
1				0.0975	random	S
2				0.0695	random	S
3		0.579		0.333	AR(1)	N
4				0.00356	random	S
5				0.0238	random	S
6			0.0487	0.183	return	S
			Group 6			
1				0.0496	random	S
2			0.135	0.588	return	S
3			0.125	0.854	return	S
4		0.566		0.663	AR(1)	N
5			0.108	0.468	return	S
6			0.148	0.595	return	S

Table 7: (continued) Estimated individual rules for the LtO treatment.

		Sample restriction		
		None	$\rho^{e}_{i,t} \leqslant 60$	$\rho^{e}_{i,t} \leqslant 30$
Type of bias	**Parameters**	**LogLikelihood**		
		Heterogeneous return		
Heterogeneous	138	−2843.05	−2787.24	−2737.28
(*unrestricted*)		—	—	—
Common	93	−2926.99	−2872.52	−2825.44
$(c_i = c)$		(0.00000)	(0.00000)	(0.00000)
No	92	−2927.43	−2873.08	−2825.99
$(c_i = 0)$		(0.00000)	(0.00000)	(0.00000)
		Common return		
Heterogeneous	93	−3460.58	−3169.44	−3075.8
$(\phi_i = \phi)$		(0.00000)	(0.00000)	(0.00000)
Common	48	−3496.66	−3262.95	−3177.11
$(\phi_i = \phi,\ c_i = c)$		(0.00000)	(0.00000)	(0.00000)
No	47	−3497.7	−3265.54	−3179.06
$(\phi_i = \phi,\ c_i = 0)$		(0.00000)	(0.00000)	(0.00000)
		Perfect return		
Heterogeneous	92	−3666.97	−3242.27	−3129.37
$(\phi_i = 1/6)$		(0.00000)	(0.00000)	(0.00000)
Common	47	−3795.54	−3371.24	−3259.28
$(\phi_i = 1/6,\ c_i = c)$		(0.00000)	(0.00000)	(0.00000)
No	46	−3796.43	−3371.48	−3259.48
$(\phi_i = 1/6,\ c_i = 0)$		(0.00000)	(0.00000)	(0.00000)
		No return		
Heterogeneous	92	−3461	−3443.13	−3415.29
$(\phi_i = 0)$		(0.00000)	(0.00000)	(0.00000)
Common	47	−3496.99	−3479.39	−3451.83
$(\phi_i = 0,\ c_i = c)$		(0.00000)	(0.00000)	(0.00000)
No	46	−3498.1	−3480.5	−3452.93
$(\phi_i = 0,\ c_i = 0)$		(0.00000)	(0.00000)	(0.00000)
Observations		1840	1840	1840

Table 8: Mixed treatment: quantities chosen by individuals explained by their contemporary expected asset returns. Log-likelihhod measures for models with various restrictions on the parameters and parameter heterogeneity. In parenthesis, likelihood ratio test p-values for the restrictions imposed in the estimation on the unrestricted model (reported in first row). Estimation for 46 individuals, unrestricted sample and sample restricted for observations with expected asset return above 60 and 30.

	Quantity rule coefficients				Price prediction rule coefficients					
Subject	**cons.**	**AR(1)**	**Exp. return**	**Past return**	**cons.**	**AR(1)**	**Past price**	**Past trend**	**Type**	**Stability**
					Group 1					
1	0.112		0.161		−2.344		1.214	0.694		U
2†			0.167			0.347	0.650	0.946		S
3		−0.485		0.373	5.654		0.936	1.210		U
4†			0.167		6.335		0.929	0.842		S
5	0.092	0.714					1.000	0.884	*TRE*	N
6				0.129			1.000	1.089	*TRE*	S
					Group 2					
1			0.037		48.425		0.216			S
2		0.580			14.590		0.759	−0.285		N
3†			0.167		22.056		0.649			S
4†			0.167		17.683		0.712	−0.649		S
5						0.251	0.749		*ADA*	N
6		0.327								N
					Group 3					
1			−0.807			0.212	0.788		*ADA*	U
2					−13.408	0.535	0.661			N
3					9.092		0.867			N
4				−0.319			1.004			U
5†			0.167		−12.399	0.302	0.878			U
6		0.635				0.402	0.598		*ADA*	N

Table 9: Estimated individual rules for the mixed treatment (system of quantity and predicted price rules). S, N and U denote respectively stable, neutrally stable and unstable system of rules if all six subjects would use this system. ADA and TRE denore a price prediction rule of a subject that could by classified as adaptive or trend extrapolation expectations respectively.

	Quantity rule coefficients				Price prediction rule coefficients					
Subject	**cons.**	**AR(1)**	**Exp. return**	**Past return**	**cons.**	**AR(1)**	**Past price**	**Past trend**	**Type**	**Stability**
					Group 4					
1†			0.167				0.931			S
2		0.256	0.115		9.748		0.887			S
3†			0.167		3.696	−0.421	1.381	0.994		S
4†			0.167				1.000	0.669	*TRE*	S
5		0.870	0.112				1.000	1.022	*TRE*	U
6		0.916					1.000	0.996	*TRE*	N
					Group 5					
1						−0.831	1.795			N
2†			0.167		6.572		1.257	0.814		U
3				0.081			1.000	0.860	*TRE*	S
4	0.093		0.065	0.096			1.000	1.158	*TRE*	U
5			0.149		7.634		0.886	1.231		U
6		0.564	0.220		6.024		1.103			U
					Group 6					
1	−0.129		0.216		23.173		0.539			S
2				0.005			1.119			S
3		0.657		−0.447						U
4*					15.897	0.685		0.618		N
5*					28.577		0.431			N
6							1.044			N

Table 9: Estimated individual rules for the mixed treatment (system of quantity and predicted price rules). S, N and U denote respectively stable, neutrally stable and unstable system of rules if all six subjects would use this system. ADA and TRE denore a price prediction rule of a subject that could by classified as adaptive or trend extrapolation expectations respectively.

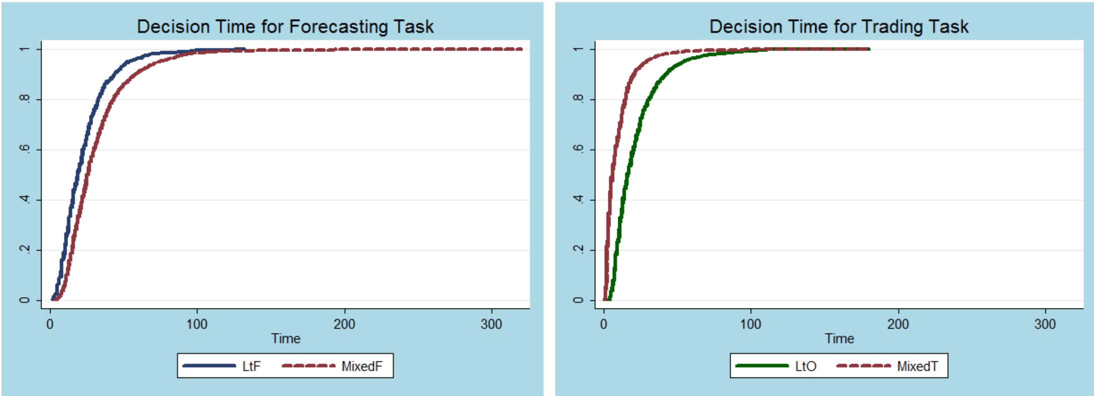
	Quantity rule coefficients				Price prediction rule coefficients					
Subject	**cons.**	**AR(1)**	**Exp. return**	**Past return**	**cons.**	**AR(1)**	**Past price**	**Past trend**	**Type**	**Stability**
					Group 7					
1			0.048				1.000			S
2†			0.167				1.000	0.543	*TRE*	S
3				0.085			0.926			S
4							1.054			N
5†			0.167				1.000	0.471	*TRE*	S
6			−0.202	0.203		0.585	0.424	0.599		U
					Group 8					
1				0.135			1.014			S
2			0.131		5.329	0.953		1.057		S
3			0.195				1.000	0.898	*TRE*	U
4		0.816			2.947		0.983	0.902		N
5		−0.572		0.281			1.000	0.801	*TRE*	U
6		0.815					1.000	0.944	*TRE*	N

Table 9: Estimated individual rules for the mixed treatment (system of quantity and predicted price rules). S, N and U denote respectively stable, neutrally stable and unstable system of rules if all six subjects would use this system. ADA and TRE denore a price prediction rule of a subject that could by classified as adaptive or trend extrapolation expectations respectively.

D Decision time (not for publication)

Rubinstein (2007) provides evidence that choices requiring greater cognitive activity are associated with longer decision times. While there was no decision time limit in our experiment, the computer program takes record of the time taken for each decision (in the Mixed treatment, we take separate record for the forecasting and the trading tasks) in unit of seconds. Figure 6 plots the empirical CDF of decision time for the forecasting task in the LtF and Mixed treatment, as well as the trading task for the LtO and the Mixed treatment. Recall that under the Mixed treatments, subjects first submitted forecast and only then the trading decision. It can be seen that it takes longer time for a subject to make a forecast in the Mixed treatment than in the LtF treatment, and shorter time for a subject to make a trading decision only in the Mixed treatment than in the LtO treatment. The difference in the time taken for a forecasting task suggests that the subjects have higher cognitive load in the Mixed treatment than in the other treatments. The difference in the time taken for a trading decision implies that making a quantity decision for a given forecast is very fast, and the subjects in the LtO treatment take longer time probably because they also make an implicit price forecast. Nevertheless, the subjects in the Mixed treatment take more time in total than in the LtO treatment, which could also mean that they pay more attention to the price forecast itself.

Indeed, the average decision time is 22.92 seconds in the LtF treatment, 21.48 in the LtO treatment, 31.40 seconds for making a price forecast in the Mixed treatment, and 9.54 seconds for making a trading decision in the Mixed treatment. The difference between the time taken for the forecasting/trading tasks across treatments is significant at 5% level according to Mann-Whitney-Wilcoxon test. There is no significant difference between the time taken in the LtF and the LtO treatment, and the total time taken for completing the forecasting and trading task in the Mixed treatment is significantly longer than the decision time in the LtF and LtO treatments.



(a) Forecasting decisions

(b) Trade decisions

Figure 6: The empirical cumulative distribution functions of the time taken to complete decision tasks. The unit of time is seconds, as measured on the horizontal axis.

E Uniqueness of the equilibrium for price takers (not for publication)

As explained in the Section 2, if the agents are price-takers, their optimal demand is given by

$$z_{i,t}^{PT} = \frac{p_{i,t+1}^e + y - Rp_t}{a\sigma_z^2}, \tag{33}$$

whereas the price adjustment equation is

$$p_{t+1} = p_t + \lambda \sum_{i=1}^{6} z_{i,t} + \varepsilon_t. \tag{34}$$

Recall the following assumptions of the model: $R\lambda = 1$ and $a\sigma_z^2 = 6$ and $\varepsilon_t \sim NID(0,1)$ and $r = R - 1 = \frac{1}{20}$. Notice that the demand function is perfectly symmetric between the agents in respect to all the variables with the exception of the price prediction $p_{i,t+1}^e$.

Proposition 1. *Price-taking economy defined by* (33) *and* (34) *has a unique Rational Expectations (RE) solution* $p^{RE} = \frac{y}{r}$ *in terms of prices for period* $t + 1$*, regardless of the price* p_t*.*

Proof. The equations (33) and (34), together with the assumptions about the parameters, give

$$(35)\qquad \begin{aligned} p_{t+1} &= p_t + \lambda \frac{\sum_{i=1}^{6} p^e_{i,t+1}}{a\sigma_z^2} + 6\lambda \frac{y - Rp_t}{a\sigma_z^2} + \varepsilon_t \\ &= p_t + \lambda \frac{\sum_{i=1}^{6} p^e_{i,t+1}}{a\sigma_z^2} + \lambda y - p_t + \varepsilon_t \\ &= \lambda \frac{\sum_{i=1}^{6} p^e_{i,t+1}}{a\sigma_z^2} + \lambda y + \varepsilon_t. \end{aligned}$$

Notice that the equation (35) shows already the second part of the proposition. Rational agents will optimize their demand to the form (33), which depends on p_t. However, the parametrization of the economy implies that this p_t cancels out in the price adjustment equation (34).

The symmetry of the agents and the definition of RE imply that for any two agents $i \neq j$, their price predictions $p^e_{i,t+1}$ and $p^e_{j,t+1}$ are equal and fulfill the necessary condition

$$(36)\qquad E_t\{p_{t+1}\} = p^e_{i,t+1}, \quad \forall i \in \{1, \ldots, 6\}.$$

Denote $p^e_{i,t+1} = p^e_{j,t+1} \equiv p^e_{t+1}$. Substituting this into (35) gives

$$(37)\qquad p_{t+1} = \lambda(p^e_{t+1} + y) + \varepsilon_t.$$

RE condition (36) implies therefore that $p^e_{t+1} = \lambda(p^e_{t+1} + y)$. Because $\lambda \neq 0$, this equation has *exactly* one solution such that $p^{RE} = p^e_{t+1} = \frac{\lambda}{1-\lambda} y = \frac{y}{r}$, where the last follows from $(1+r)\lambda = 1$. □

Proposition 2. *Under the economy as in Proposition 1 and RE, in period t and given p_t the agents trade in such a way that the next price p_{t+1} in expectation equals to the fundamental price, regardless of p_t. Moreover, if $p_t = p^{RE}$ then $z_{i,t} = 0$.*

Proof. The first part of the proposition follows directly from Proposition 1. Notice that one can also prove it indirectly. Assume that all the agents expect p_{t+1} to be equal to the fundamental price $p^{RE} = \frac{y}{r}$. Then their demand $z^{PT}_{i,t}$ is given by

$$(38)\qquad z^{PT}_{i,t} = \frac{\frac{y}{r} + y - Rp_t}{a\sigma_z^2} = \frac{\frac{y(1+r)}{r} - Rp_t}{a\sigma_z^2} = R\frac{\frac{y}{r} - p_t}{a\sigma_z^2}, \quad \forall i \in \{1, \ldots, 6\}.$$

Substituting in the price adjustment mechanism (34) and taking its expected value yields

$$(39)\qquad \begin{aligned} E\{p_{t+1}\} &= p_t + 6\lambda R \frac{\frac{y}{r} - p_t}{a\sigma_z^2} \\ &= p_t + \frac{y}{r} - p_t \\ &= p^{RE}, \end{aligned}$$

where the equalities follow since $a\sigma_z^2 = 6$ and $R\lambda = 1$. Equation (39) shows that predicting the fundamental price p^{RE} is *always* self-consistent, regardless of the initial price p_t which only determines the necessary trading with which the agents move to the fundamental equilibrium. Moreover, substituting $p_t = p^{RE}$ into the optimal demand (38) yields

$$\begin{aligned} z_{i,t}^{PT} &= R\frac{\frac{y}{r} - p^{RE}}{a\sigma_z^2} \\ &= 0, \end{aligned} \tag{40}$$

which is trivial since $p^{RE} = \frac{y}{r}$. □