Expectations and Bubbles in an Experimental Asset Pricing Model

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Abstract

We present results on expectation formation in a controlled experimental environment. In each period subjects are asked to predict the next price in a standard asset pricing model. In most experiments bubbles emerge endogenously. These bubbles are inconsistent with rational expectations and seem to be driven by trend chasing behavior or *positive feedback expectations* of the participants. We also analyse individual predictions of participants and find that participants within a group tend to coordinate on a common prediction strategy.

Keywords: experimental economics, expectations, asset pricing, speculative bubbles

JEL classification code: C91, C92, D84, G12, G14

1 Introduction

The exuberant rise and fall in stock prices in recent years has drawn renewed attention to the possible existence of so-called *speculative price bubbles*. Such a bubble, where a stock is traded at prices significantly higher than (and seemingly unrelated to) the fundamental value of the stock, is

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closely related to traders' (optimistic) expectations about the future price of the stock. Traders buy an asset that is already 'overpriced' because they expect the price of this asset to increase even more and they want to benefit from the perceived capital gains of this further price increase.

There have been many empirical studies on the question whether part of the fluctuations in stock prices can be attributed to speculative price bubbles or not (see for example Flood and Garber (1980), West (1987) and Froot and Obstfeld (1991)). Garber (1990), for example, argues that even the widely acknowledged "classical" bubbles known as the Dutch Tulipmania (1634-1637), the Mississipi Bubble (1719-1720) and the South Sea Bubble (1720) can be explained, to a large extent, by changes in market fundamentals. There are also some theoretical papers on the possibility of *rational bubbles*, i.e. speculative price bubbles consistent with rational expectations. Tirole (1982) claims that in a model with a finite number of infinitely lived traders, common knowledge of rationality inhibits the possibility of trade against prices different from the market fundamental. Trade against nonfundamental prices can occur if traders do not have a common prior about the distribution of private signals about the fundamental value. Tirole (1985) shows that rational bubbles are possible in an overlapping generations model with finitely lived traders, provided that the growth rate of the economy is larger than the return on the stock. Diba and Grossman (1988) use the nonnegativity of stock prices to rule out the existence of rational bubbles.

That price bubbles can occur in experimental asset markets is less controversial. The possibility of experimental bubbles was for the first time recognized in an intriguing paper by Smith, Suchanek and Williams (1988). They investigate an experimental asset market where an asset is traded that pays (uncertain) dividends for 15 consecutive periods. Participants differ only in their endowments of the number of stocks and the amount of money, but there is no asymmetric information. Bubbles, where the asset is traded for prices above the fundamental value, emerge in most of the experiments. This remarkable finding has been corroborated in many other asset market experiments, with varying designs (e.g. King, Smith, Williams and van Boening (1993), Porter and Smith (1995), Noussair, Robin and Ruffieux (1998) and Smith, van Boening and Wellford (2000)).

Many of these experimenters believe that expectations play an important role. Referring to the theoretical result by Tirole (1982), Smith, Suchanek and Williams (1988) conjecture that it is a lack of common expectations (i.e. a lack of a common prior) that drives the emergence of bubbles. That is, although every participant has the same information, a participant engages in trade at a price higher than the intrinsic value of the stock, because he or she speculates to be able to sell it to somebody later on. However, in a recent experimental paper Lei, Noussair and Plott (2001) show that, even if speculation is prohibited (that is, a subject can only buy or only sell the asset, but subjects are not able to do both in order to reap the capital gains), bubbles occur. They claim that this points at irrationality of participants instead of at a lack of common expectations.

Although their main interest lies with the trading decisions of participants, Smith, Suchanek and Williams (1988) also try to obtain explicit information on the expectations of the participants of the experiment. In some of their experiments each participant is asked to give a forecast for the mean trading price. The participant with the lowest mean forecast error over the course of the experiment earns an additional $1.00. Williams (1988) uses the same method to study expectation formation in an experimental double auction market. However, in both kinds of experiments observations on expectation formation follow as a by-product of the experiment and might therefore not be very accurate.[1]

In the present paper we present an experiment which focusses explicitly on expectation formation of participants. We consider a standard asset pricing model, where the only task for the participants is to predict the asset price for the next period. They do not have knowledge of the underlying market equilibrium equation, but they know all past realized prices and, of course, their own predictions. Their earnings are inversely related to the average prediction error they make. Given the price forecast of a participant, a computer program computes the associated optimal trading decision and subsequently the market equilibrium price. Clearly, the realized price is a function of the individual forecasts. This expectations feedback is an important feature of economic dynamic systems in general and financial markets in particular. Our experiment is designed such that we obtain explicit information about expectations of participants in such a controlled expectations feedback environment.

Our main result is that, even in this simple setup, price bubbles emerge. We conjecture that this is due to so-called *positive feedback expectations*, that is, participants seem to extrapolate trends in realised asset prices into the future. If the asset price increases (decreases), participants expect a further increase (decrease). This expected price increase (decrease) is selffulfilling and leads to a further price increase (decrease). We also analyze individual predictions and find that they are very similar for participants in the same group. We therefore have coordination on a common prediction strategy,

[1] This is also argued in Hey (1994) who points out that (p.230): "In these studies, the question of expectations formation has tended to be of rather peripheral concern, with the data on expectations elicited in a somewhat unsatisfactory and only partial motivated manner."

which contrasts with the conjecture of lack of common expectations by Smith, Suchanek and Williams (1988).

There is substantial evidence that many people, much like the participants to our experiment, try to extrapolate trends when forecasting the price of a stock. This implies that these people will buy (sell) the stock if its price has increased (decreased) in anticipation of a further price increase (decrease). De Long, Shleifer, Summers and Waldmann (1990) call such traders *positive feedback traders*. Many trading strategies used by professional investors search for trends in the data and give buy or sell signals on the basis of an extrapolation of such trends. There is also experimental and empirical evidence on extrapolative expectations and positive feedback trading. In Andreassen and Kraus (1990) several experimental studies are described where participants are confronted with a historical stock price series and are asked to trade stocks at these prices in order to maximize their wealth. After they have made a trading decision the next price, which is independent of their trading decision, is revealed. Apparently participants tend to buy when prices are low and sell when prices are high, which is consistent with conventional economic wisdom. However, when the *saliency* of trends in the prices is high, that is, when price changes occur often, their variance is low or their mean absolute value is large, participants tend to use price changes instead of price levels, for making a trading decision. In that case they are more likely to buy (sell) stock when the price has been rising (falling). De Bondt (1993) presents further evidence from experiments and surveys that people tend to extrapolate trends when predicting stock prices. Finally, Frankel and Froot (1988) investigate survey data on exchange rates and find that, in the short run, traders expect the exchange rate to depreciate further after a depreciation.

An important motivation for our research has been to obtain information about how agents form expectations in expectations feedback systems such as financial markets. The experimental approach seems very suitable for studying these issues, since it provides explicit observations on expectations in a controlled environment, which is an advantage over using survey data about expectations (as is done, for example, by Frankel and Froot (1987, 1988) and Shiller (1990)). There have been a number of other experiments designed to study expectation formation in a time series context, in particular Schmalensee (1976), Dwyer, Williams, Battalio and Mason (1993) and Hey (1994). The drawback of these experiments is that they disregard the expectations feedback, which is so relevant for dynamic economic models and which we want to account for explicitly. In Hommes, Sonnemans, Tuinstra and van de Velden (1999) we used the experimental approach for investigating expectation formation in a simple commodity market with a cobweb structure. There it was shown that, for an unstable cobweb model, the heterogeneity of expectations leads to excess volatility of realized prices. Marimon, Spear and Sunder (1993) employ a similar method, where predictions of participants are sollicited in an overlapping generations framework and the computer program then computes the associated optimal demand.

The paper is organized as follows. In Section 2 we discuss the asset pricing model we use in the experiment. Section 3 describes the design of the experiment. Section 4 presents an analysis of the experimental results. Concluding remarks are given in Section 5. The appendix contains some auxiliary information.

2 Asset Prices and Expectations

2.1 The asset pricing model

Consider an asset market with H traders, indexed by h. A trader can invest his money in a risk free asset (e.g. a savings deposit) with a risk free gross rate of return $R = 1 + r$, where r is the real interest rate, or he can invest his money in shares of an infinitely lived risky asset. The price of this risky asset in period t is p_t. Furthermore, for each share dividends y_t are paid out in period t. We assume these dividends to be independently and identically distributed with mean $\overline{y}$ and variance σ_y^2. Denote by z_{ht} the number of shares of the risky asset purchased by trader h in period t. The trader's realized wealth in period $t + 1$ then is

$$W_{h,t+1} = RW_{h,t} + (p_{t+1} + y_{t+1} - Rp_t)\, z_{ht}.$$

Traders subjective beliefs about the evolution of wealth are characterized by their subjective conditional mean E_{ht} and their subjective conditional variance V_{ht}. Traders are mean-variance optimizers, that is, their demand for shares corresponds to the solution to

$$\begin{aligned}
&\max_{z_{ht}} \left\{ E_{ht}\left(W_{t+1}\right) - \frac{1}{2} a V_{ht}\left(W_{t+1}\right) \right\} \\
&= \max_{z_{ht}} \left\{ z_{ht} E_{ht}\left(p_{t+1} + y_{t+1} - Rp_t\right) - \frac{1}{2} a z_{ht}^2 V_{ht}\left(p_{t+1} + y_{t+1} - Rp_t\right) \right\},
\end{aligned}$$

where a measures the degree of risk aversion (assumed to be the same for all traders). We assume $V_{ht}\left(p_{t+1} + y_{t+1} - Rp_t\right) = \sigma^2$, for all h, that is, traders believe that the conditional variance of *excess returns* is constant (and the same for all traders). There is no harm in this assumption since the present paper deals only with point predictions of traders and not with traders beliefs about the distribution of returns. The solution is given by

$$z_{ht} = \frac{E_{ht}\left(p_{t+1} + y_{t+1} - Rp_t\right)}{a\sigma^2}. \tag{1}$$

Notice that trader h will supply the asset if he\she expects a (large) decrease in its price. Assuming that there is no outside supply of shares, the market equilibrium condition becomes

$$\sum_{h=1}^{H} z_{ht} = \frac{1}{a\sigma^2}\sum_{h=1}^{H} E_{ht}\left(p_{t+1} + y_{t+1} - Rp_t\right) = 0,$$

which can be written as

$$Rp_t = \frac{1}{H}\sum_{h=1}^{H} E_{ht}\left(p_{t+1} + y_{t+1}\right). \tag{2}$$

Condition (2) says that today's asset price is determined by beliefs about tomorrow's asset price and dividend. Hence, when traders have to make a prediction for the price in period $t+1$ they do not know the price in period t yet, and they can only use information up till time $t-1$.

An important feature of the asset pricing model is its *self-confirming* nature: if all traders have a high (low) prediction the realized price will also be high (low). This important feature is characteristic for a speculative asset market: if traders expect a high price, the demand for the risky asset will be high, and as a consequence the realized market price will be high, assuming that the supply is fixed.

2.2 The fundamental solution and rational bubbles

The basic equation of the asset pricing model is equation (2). The development of the asset price depends upon the (subjective) expectations of the traders. We will now briefly consider the dynamics of the asset pricing model under rational expectations (RE). In the next section we will discuss the dynamics of the asset pricing model under boundedly rational prediction strategies.

Under rational expectations the subjective expectation E_{ht} of trader h is equal to the objective mathematical conditional expectation E_t, for all h. Equation (2) then reduces to

$$Rp_t = E_t\left(p_{t+1} + y_{t+1}\right).$$

After K steps of repeated substitution we find

$$p_t = \frac{E_t\left(p_{t+K}\right)}{R^K} + \sum_{k=1}^{K} \frac{E_t\left(y_{t+k}\right)}{R^k},$$

where we have used $E_t E_{t+k}(.) = E_t(.)$ for $k > 0$. There are two types of solutions. Sometimes the solution paths are required to satisfy the *no-bubbles condition* $\lim_{K\to\infty} \frac{E_t(p_{t+K})}{R^K} = 0$. Given this condition we have

$$p_t = \sum_{k=1}^{\infty} \frac{E_t\left(y_{t+k}\right)}{R^k},$$

which equals the present discounted value of the expected future dividends. This solution will be denoted the *fundamental* price p^f. For the IID dividend process that we have specified, this fundamental price is

$$p^f = \frac{\overline{y}}{R-1} = \frac{\overline{y}}{r}.$$

According to the *efficient market hypothesis* the price should be equal to $p_t = p^f$. However, there is a priori no convincing reason why the *no-bubbles* condition should hold. In fact, it can easily be checked that under rational expectations any solution of the form

$$p_t^b = R^t c + p^f = R^t c + \frac{\overline{y}}{r}, \qquad c \geq 0$$

is an RE solution satisfying (2). These solutions are called *rational bubbles.* They grow with a rate R and a solution exists for each $c \geq 0$. Hence, under rational expectations there is a continuum of (exploding) solution orbits. These bubble solutions are often ignored and attention is given primarily to the fundamental solution p^f, but for no other reason than convenience.

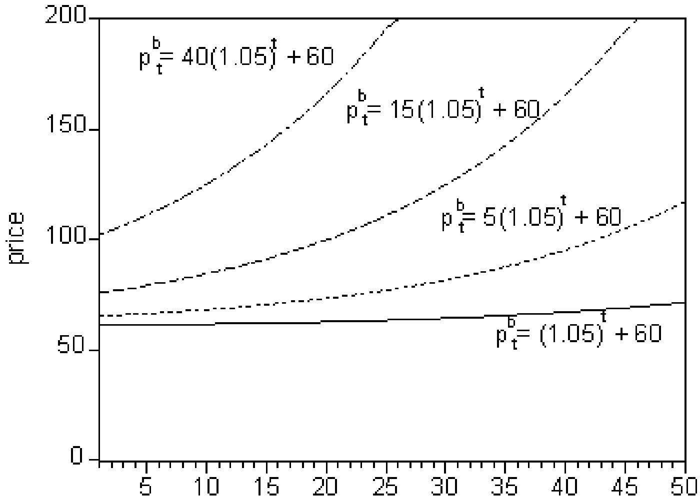

Figure 1: rational bubbles in the asset pricing model.

Figure 1 shows four possible bubble solutions. The values of the parameters $\overline{y}$ and r correspond to the parameter values in our experimental design. An important question we try to answer in this paper is whether the participants in the experimental asset market will coordinate on the fundamental solution, or on one of the rational bubbles solutions.

2.3 Boundedly rational prediction strategies

The rational expectations hypothesis is quite demanding. It requires that traders know the underlying asset pricing model and use this to compute the conditional expectation for the future price and that they do not make structural forecast errors. In particular, in a heterogeneous world RE requires knowledge about the beliefs of all other traders. A RE solution will only prevail when traders are able to coordinate on one of the possible rational expectations equilibria. In this section we investigate the price behavior when the agents in the model use simple forecasting rules. They do not have (exact) knowledge of the underlying model, but have their own beliefs about the development of asset prices and use this belief and the available time series observations to predict the price. The beliefs of the traders are sometimes called the *perceived laws of motion*. Given those perceived laws of motion the underlying model (2) is then referred to as the *implied actual law of motion*. An important objective of this paper is to get some insights into the nature of the perceived laws of motion people actually use. We assume that, when traders have to predict a price for time $t+1$, they know the interest rate r (which is constant over time), the realized prices up to time

$t-1$ and their own price predictions up to time t. We assume that the IID dividend process $y_t = \overline{y} + \delta_t$ is common knowledge and $E_{ht} y_t = \overline{y}$ for all h. The market equilibrium price in (2) then simplifies to

$$p_t = \frac{1}{RH} \sum_{h=1}^{H} E_{ht}(p_{t+1}) + \frac{\overline{y}}{R},$$

A general form of a trader's forecasting rule or prediction strategy is

$$E_{ht}(p_{t+1}) = p^e_{h,t+1} = f_h\left(p_{t-1}, p_{t-2}, \ldots, p_1, p^e_{ht}, p^e_{h,t-1}, \ldots, p^e_{h1}, \overline{y}, r\right), \qquad (3)$$

where f_h can be any (possibly time-varying) function. There are no restrictions on the specification f_h and the possibilities are therefore unbounded.[2] Given traders forecasting rules (3), the implied actual law of motion becomes

$$p_t = \frac{1}{RH} \sum_{h=1}^{H} f_h\left(p_{t-1}, p_{t-2}, \ldots, p_1, p^e_{ht}, p^e_{h,t-1}, \ldots, p^e_{h1}, \overline{y}, r\right) + \frac{\overline{y}}{R}. \qquad (4)$$

The actual dynamics of prices is to a great extent characterized by the prediction strategies used by the traders. Depending on the prediction strategies used by the agents (which may, for example, be nonlinear or discontinuous) almost any type of price behavior can occur under boundedly rational prediction strategies. Nothing much can be said about these prediction strategies a priori, but in this paper we will try to find out what prediction strategies people typically use in such an dynamic economic environment with expectations feedback.

There are two other important points we want to address here. First, let us briefly consider those prediction strategies that give the correct expectations. It is easy to see that there are two types of these perfect foresight solutions. The first arises when all traders predict the fundamental price

$$p^e_{t+1} = p^f. \qquad (5)$$

Given the fundamental forecast (5) the realized market price (4) becomes

$$p_t = p^f = \frac{\overline{y}}{r}.$$

The second perfect foresight solution occurs when all traders believe that the price deviation from the fundamental grows by the gross rate of return each period, i.e.

$$p^e_{t+1} = p^f + (1+r)^2\left(p_{t-1} - p^f\right). \qquad (6)$$

[2]Notice that traders have all necessary information (the risk free rate of return r and the mean dividend $\overline{y}$) to calculate the fundamental price $p^f = \frac{\overline{y}}{r}$ and use this as their forecast.

If agents believe in exploding prices, (6), the implied actual law of motion (4) becomes

$$p_t - p^f = (1+r)\left(p_{t-1} - p^f\right).$$

That is, if agents expect the price deviation from the fundamental to grow each period with the gross rate of return, the price will grow with the gross rate of return and this belief is self-fulfilling. Hence, both these perfect foresight solutions are self-fulfilling in the sense that what they expect will be realized.

The second important feature of our asset pricing model is that it is stable in the sense that if traders (on average) do not expect prices to diverge too fast the asset price will converge to a steady state. Consider, for example, the case where traders have *naive* or *static expectations*, where

$$p^e_{h,t+1} = p_{t-1},$$

that is, their prediction for the next price corresponds to the last observed asset price. Under the assumption that all traders have naive expectations the price dynamics reduces to a linear difference equation with steady state p^f and slope $\frac{1}{1+r}$,

$$p_t = \frac{1}{1+r}\left(p_{t-1} + rp^f\right).$$

Since the slope lies between 0 and 1 prices converge monotonically to the steady state. The asset pricing model is stable under naive expectations and there is (slow and monotonic) convergence to the steady state because the slope is close to 1. That this stability property is a more general characteristic of the model can be seen by rewriting (2) as

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

where $\overline{p}^e_{t+1} = \frac{1}{H}\sum_{h=1}^{H} p^e_{h,t+1}$ is the average prediction for period $t+1$. It follows that the realized price will always lie between the average price prediction $\overline{p}^e_{t+1}$ and the fundamental price $p^f = \frac{\overline{y}}{r}$. Now suppose that traders use forecast errors to update their prediction, that is, their current prediction is their previous prediction adapted in the direction of the last observation. An example of such a prediction strategy is *adaptive expectations*, where $p^e_{h,t+1} = p^e_{ht} + w\left(p_{t-1} - p^e_{ht}\right)$ with $0 < w \leq 1$ (notice that $w = 1$ corresponds to naive expectations). If the price lies above (below) the fundamental value, the predictions are above (below) the price and on average the agents will adjust their predictions downward (upward). For this type of prediction strategy the price will monotonically converge to the fundamental price. Intuitively, prediction strategies where people try to learn the equilibrium price, for example by some kind of recursive least squares learning process, will also converge monotonically to the fundamental price.

It should therefore be clear that bubbles can only occur in this framework if traders expect them to occur. For example, if traders believe that

$$p^e_{h,t+1} = \beta p_{t-1}, \qquad \beta > R$$

prices grow with rate $\frac{\beta}{R} > 1$ and a *speculative* bubble emerges. As noted before, the asset pricing model has a *self-confirming* nature: if traders expect prices to explode, it is likely that prices will indeed explode.

Another important class of prediction strategies are those with 2 lags, that is

$$p^e_{h,t+1} = \alpha_h + \beta_{h1} p_{t-1} + \beta_{h2} p_{t-2}. \tag{8}$$

If all traders use such a prediction strategy, the implied actual law of motion (2) becomes

$$p_t = \frac{1}{R} \left(\alpha + \beta_1 p_{t-1} + \beta_2 p_{t-2} \right) + \frac{\overline{y}}{R}$$

where $\alpha = \frac{1}{H} \sum_{h=1}^{H} \alpha_h$ and $\beta_l = \frac{1}{H} \sum_{h=1}^{H} \beta_{hl}$. Depending on the values of β_1 and β_2 one can have different types of dynamics. In particular, for $\beta_1 + \beta_2 > R$, a speculative bubble occurs. Prediction strategy (8) can be rewritten as

$$p^e_{h,t+1} = \alpha + \beta p_{t-1} + \delta \left(p_{t-1} - p_{t-2} \right),$$

where $\beta \equiv \beta_1 + \beta_2$ and $\delta \equiv -\beta_2$. Expressed in this way it provides a nice intuition. Participants believe that the price will be determined by the last observation (the first two terms on the right-hand side) but they also try to follow the *trend* in the prices (expressed in the third term): if $\delta > 0$ they believe that an upward movement in prices will continue the next period, whereas if $\delta < 0$ they believe an upward movement in the prices will be (partially) offset by a downward movement in prices in the next period. The former correspond to positive feedback traders, whereas the latter correspond to so-called *contrarians*.

3 Experimental design

We consider an experimental asset pricing model consisting of 6 participants and lasting for 50 periods. In total 36 subjects (6 groups) participated in this experiment. Subjects (mostly undergraduates in economics, chemistry and psychology) were recruited by means of announcements on information boards in university buildings. The computerized experiment was conducted in the CREED laboratory. It lasted for approximately 1.5 hours and average earnings are 21.63 Dutch guilders ($\approx$ 9.81 EURO).

In financial markets traders are involved in two related activities: *prediction* and *trade*. They make a prediction concerning the future price of the stock, and given this prediction, they make a trading decision. The experiment is aimed at investigating the way subjects form predictions. Given the predictions made by subjects the computer derives individual demand from mean-variance maximization as given by the optimal demand function (1). Each subject therefore acts as an advisor or a professional forecaster and is paired with one trader, which may be thought of as a large pension fund. The subject has to make the most accurate prediction for this trader and then the trader (i.e. the computer) decides how much to trade. The earnings of the subjects in the experiment are determined by their prediction accuracy.

The experiment is presented to the participants as follows. The participants are told that they are an advisor to a pension fund and that this pension fund can invest its money in a risky asset (the stock market) or in a risk free asset (a bank account). The task of the advisor (i.e. the participant) is to predict the price of the risky asset. Participants know that the price of the asset is determined by market equilibrium between demand and supply of the asset. Although they do *not* know the exact underlying market equilibrium equation they are informed that the higher their forecast is, the larger will be the fraction of money invested in the risky asset and the larger will be the demand for stocks. They do not know the investment strategy of the pension fund they are advising and the investment strategies of the other pension funds but they do know how many pension funds are in this market. The participants are not explicitly informed about the fact that the price of the asset depends on their prediction and the prediction of the other participants. They also do not know the identity of the other members of the group.

The information for the participants is given in computerized instructions. Comprehension of the instructions is checked by two control questions. At the beginning of the experiment the participants are given two sheets of paper with a summary of all necessary information, general information, information about the stock market, information about the investment strategies of the pension funds, forecasting task of the financial advisor and information about the earnings. The information on the handout summarizes the computerized instructions. The handout also contains information about the financial parameters (mean dividend and risk free rate of return) with which an accurate prediction of the fundamental price can be made. Finally they are given a table from which they can read, for a given forecast error, their earnings (see Appendix B). Appendix A contains an English translation of the information given to the participants.

In every period t in the experiment the task of the participants is to predict the price of the risky asset in period $t+1$, given the available information. This information consists of past prices of the risky asset $p_{t-1}, p_{t-2}, \dots, p_1$ and past individual predictions $p^e_{ht}, p^e_{h,t-1}, \dots, p^e_{h1}$. Participants also know the interest rate r and the mean $\overline{y}$ of the IID dividend process. In periods 1 and 2 no information about past prices is available but the subjects are told that their price forecast has to be between 0 and 100. Furthermore, the program does not accept predictions above 1000 in any period, but the participants are not informed about this in advance. If, in a certain period, a participant predicts a price higher than 1000, the computer screen will notify him that predictions above 1000 are not accepted and that the participant has to submit a new and lower prediction. At the end of period t, when all predictions for period $t+1$ have been submitted, the participants are informed about the realized market price in period t and earnings for that period are revealed. Figure 2 shows an English translation of the computer screen the participants are facing during the experiment. On the screen the subjects are informed about their earnings in the previous period, total earnings, a table of the last twenty prices and the corresponding predictions and a time series of the prices and the predictions.

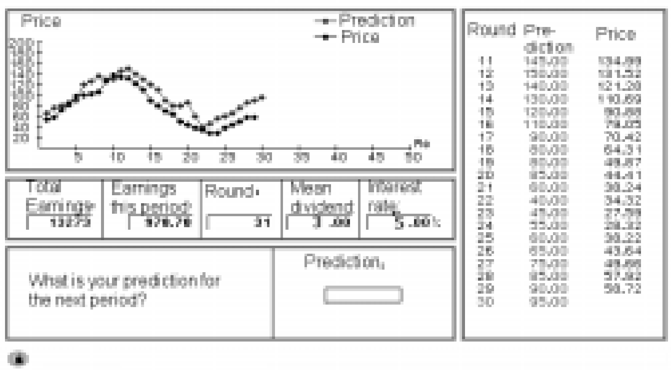

Figure 2: Computerscreen as seen by the participants.

Recall that the market equilibrium price is given by

$$p_t = \frac{1}{1+r}\left[\frac{1}{6}\sum_{h=1}^{6} p^e_{h,t+1} + \overline{y}\right], \qquad (9)$$

where $H = 6$ is the number of participants. The risk free rate of return, r, is equal to 0.05 and $\overline{y}$ is equal to 3 so that $p^f = \frac{\overline{y}}{r} = 60$. The earnings of the participants consist of a "show-up" fee of 10 Dutch guilders (1 Dutch guilder is approximately 0.45 EURO) and of the earnings from the experiment which depended upon their forecasting errors. The number of points earned in period t by participant h is given by the quadratic scoring rule $e_{ht} = \max\left\{1300 - \frac{1300}{49}\left(p_t - p^e_{ht}\right)^2, 0\right\}$, where 1300 points is equivalent to 1 Dutch guilder. Notice that earnings are zero in period t when $|p_t - p^e_{ht}| > 7$.

4 The results

In this section we discuss the experimental results. Notice that *in theory* rational bubbles are excluded if it is public information that asset prices cannot exceed 1000. Notice also that the upper bound of 1000 is approximately 16 times the RE fundamental price $p^f = 60$. In Section 4.1 the behavior of the realized asset prices is discussed, and in Section 4.2 the individual prediction strategies of the participants are analyzed.

4.1 Behavior of the asset prices

Figure 3 gives the realized prices for the six different sessions. The most striking feature is that in 5 of the 6 groups the realized price approaches 1000 and subsequently drops, and hence a bubble seems to occur in these groups. In 4 of these 5 groups the bubble seems to "burst" because price forecasts are restricted to be below 1000. In group 6, however, the bubble bursts earlier (the maximum value of the asset price in that group is 749.62 in period 29) which can, most likely, not be attributed to the existence of the upper limit.[3] In group 1 the upper bound is not reached, but the maximum realized asset price is still a factor 3 or 4 larger than the fundamental price.

[3]In each of the groups 2 to 5 there are at least 4 participants with a highest prediction of 999 or 1000, whereas the highest prediction in group 6 is 906.

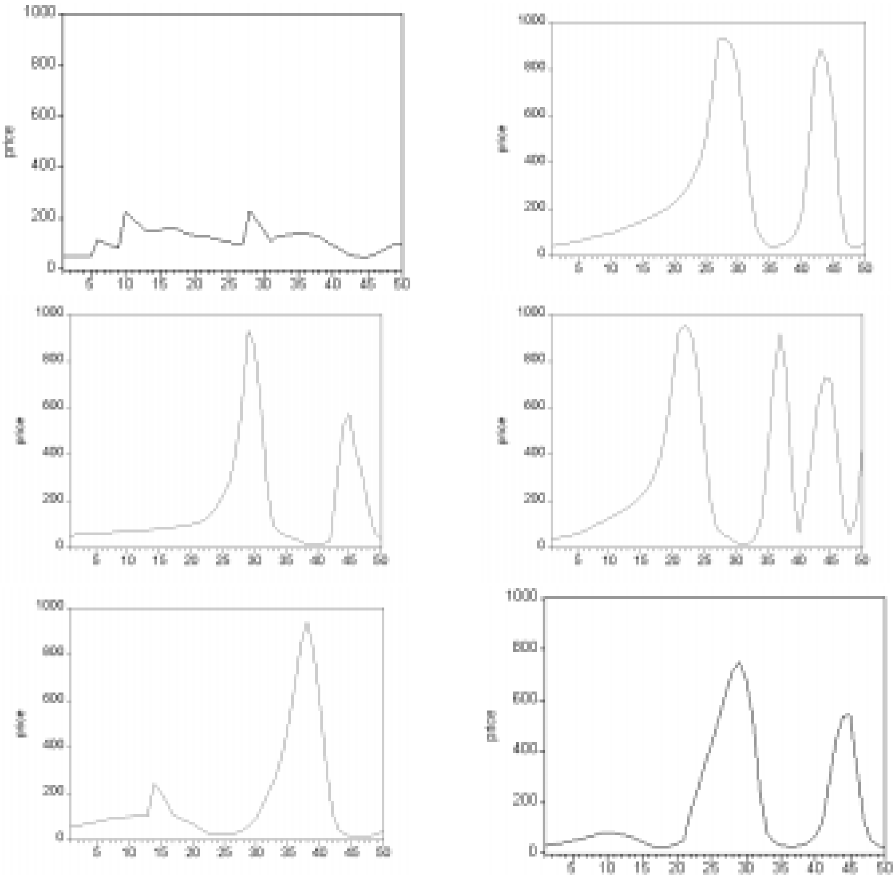

Figure 3: realized prices in the experiment

Let us now describe some other general features of the evolution of asset prices. First consider the 'atypical' group 1, where no bubble occurs. In this group there are some sudden jumps in the asset price. These jumps are due to very high predictions of individual participants.[4] Apart from these jumps, the time series of the realized prices moves towards the fundamental price of 60 in an oscillatory fashion. Also for groups 5 and 6 prices seem to settle down in the first 20 periods, after which the emergence of the bubble is "triggered". Now let us turn to groups 2 to 6 and consider what happens when prices approach 1000. Since there is an upper bound on predictions, the realized price will eventually stop increasing.[5] Predictions will decrease,

[4] For period 7 participant 6 predicts a price of 448.70, for period 11 participant 1 predicts a price of 1000 and for period 29 participant 6 predicts a price of 908.80. A similar sudden jump occurs in period 14 in group 5, where participant 3 predicts a price of 1000 for period 15.

[5] Actually, the maximum value of the realized price is $p_{\max} = \frac{20}{21}(1000 + 3) = 955\frac{5}{21}$. In groups 2, 3, 4 and 5 the price actually comes close to this maximum price (934.54, 931.11,

which will be followed by a decrease in realized prices. For all groups (except group 6) the price subsequently falls to the lowest value since the start of the experiment.[6] After this minimum the price increases again and reaches another peak (except for group 5), which is typically rather high but not as high as the first peak. Subsequently the price decreases again (followed by yet another peak in group 4). This suggest that the dynamics in most of the groups is driven by the interaction between participants trying to extrapolate trends and the restrictions on the price predictions of 0 and 1000. Also, since the height of the respective “booms” decreases over time and the frequency with which these booms occur increases one might conjecture that the realized prices will eventually converge to the neighborhood of the fundamental price.

We analyze the behavior of the asset prices further by considering the following two questions: *i)* do the observed bubbles correspond to *rational* bubbles? *ii)* is the experimental asset market *efficient*?

4.1.1 The nature of the experimental bubbles

Along a rational bubble we have $p_t = p^f + R^t c$, i.e. prices grow with a constant rate, the risk free gross rate of return $R = 1 + r$. Now consider the series $q_t = \ln\left(p_t - p^f\right)$. If prices evolve according to a rational bubble we have $q_t = \ln c + t \ln R$ and $q_{t+1} - q_t = \ln R$. Figure 4 plots $q_{t+1} - q_t$ against t for groups $2 - 6$. A few remarks on the data we use are in order. Since the upper bound on price predictions flattens the last part of the bubble, the last observation we take into account is the last one that satisfies $p_t - p_{t-1} > p_{t-1} - p_{t-2}$. On the other hand, q_t only exists when the price is above the fundamental value and since in all experiments the price starts out below the fundamental value we discard the first observations. We also want to allow for some coordination and learning. Therefore we use observations starting at period $t = 7$, except for groups 5 and 6 where a bubble sets in after quite some time. The number of observations for the last two groups is pretty small.

954.75, 940.16, with implied averages predictions of 978.27, 974.67, 999.49 and 984.17, respectively) and in group 6 the highest realized price is 749.62, (with an implied average price of 784.1) which is also more than 12 times the fundamental price.

[6] The subsequent minimum prices for groups $2 - 6$ are given by 36.95, 9.68, 9.21, 12.56 and 27.29, respectively.

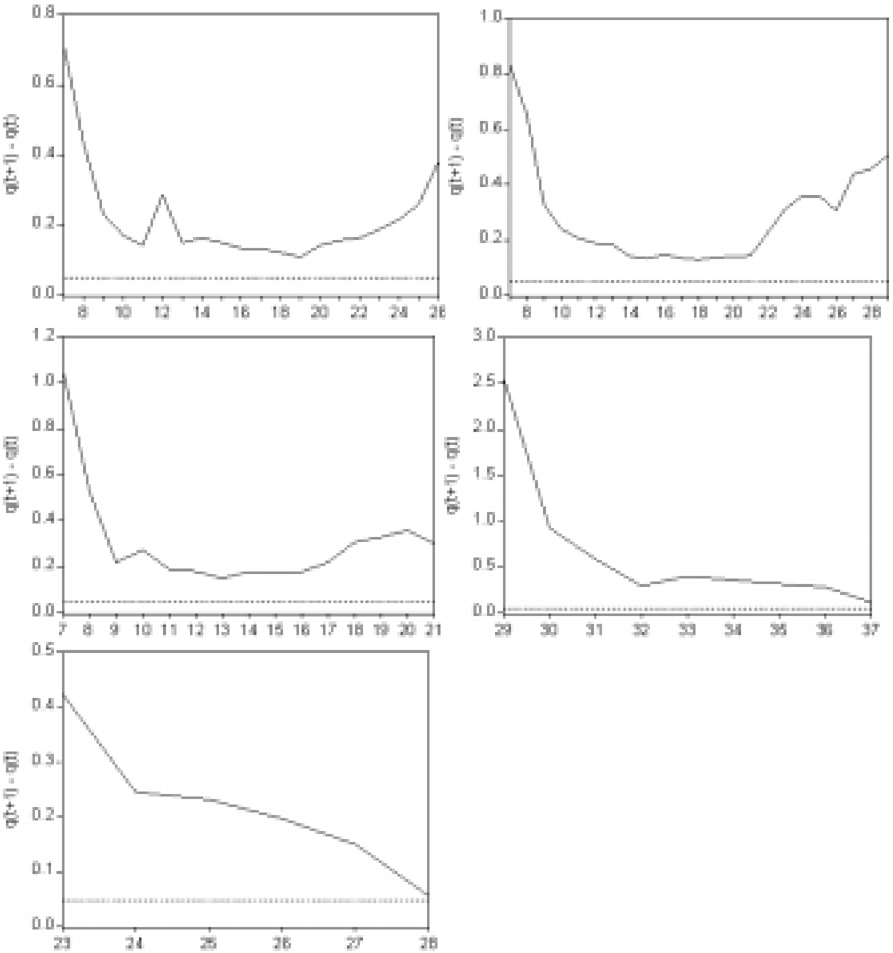

Figure 4: Plots of $q_{t+1} - q_t$ against t for groups $2 - 6$.

From Figure 4 it follows that, although over some intervals $q_{t+1} - q_t$ seems to be approximately constant, its value is much higher than $\ln R \approx 0.0488$. From this we conclude that the bubbles observed in the experiment do *not* correspond to rational bubbles, but seem to be *speculative* bubbles driven by the (boundedly rational) prediction strategies of the participants.[7] Table 1 shows, for each group, the average value of $q_{t+1} - q_t$ along the bubble, the implied growth rate $\widehat{R}$ and the theoretical growth rate R of a rational bubble. In all groups, except for group 5, the mean value of $q_{t+1} - q_t$ is significantly different from $\ln R \approx 0.0488$ at the 5% significance level.

Let us conclude this discussion about the bubbles with two observations. First, since there is no exogenous uncertainty in the model rational agents

[7] The use of the word "speculative" does not mean that participants can enter into speculative trades by buying and selling the asset, but refers to the speculative or extrapolative expectations participants entertain.

group	$\overline{q_{t+1} - q_t}$	$\widehat{R}$	R	sample
2	0.222	1.248	1.050	7-26
3	0.292	1.339	1.050	7-29
4	0.310	1.363	1.050	7-21
5	0.227	1.255	1.050	29-42
6	0.271	1.311	1.050	23-29

Table 1: Test of the rational bubbles hypothesis

would make no forecast errors along the bubble and hence have high earnings. Since the average earnings (see Appendix C) are fairly low this is not the case in the experiment. Secondly, given that the first price is below 100 and for a rational bubble the growth rate equals R, along a rational bubble the price approaches 1000 not sooner than at $t = 48$ (since $100 \times 1.05^{47} \approx 991$).

From this analysis we conclude that our laboratory asset pricing experiments exhibit endogenous *speculative* bubbles. An explanation for this is that participants try to extrapolate trends. If, by accident, prices increase a little and agents pick this up, they tend to extrapolate this trend. This is also consistent with the results in groups 5 and 6. There it seems that the asset price is relatively stable for quite some time until it starts to increase a little. This increase in the price is perceived by the participants as an upward trend, which they subsequently extrapolate, leading to the explosion of prices. Following the literature on *positive feedback trading* (see for example De Long, Shleifer, Summers and Waldmann (1990)) we refer to this trend chasing behavior as *positive feedback expectations*. Unfortunately, this type of behavior fails to explain why the bubbles in groups 5 and 6 do not occur earlier and why the bubble in group 6 bursts prematurely.

4.1.2 Efficiency and predictability

A celebrated result from the theory on financial markets is the so-called *efficient market hypothesis*. This hypothesis claims that all information on an asset is incorporated in its price and it implies that one cannot obtain above "normal" profits by trading on a financial market. A testable implication of this hypothesis is that the *excess returns* $x_t = \ln p_t - \ln p_{t-1}$ are uncorrelated with past information. In particular, the excess returns should not show serial correlation, otherwise traders can improve their prediction of the excess return by using its past values. Figure 5 shows the excess returns for the prices in the six different groups.

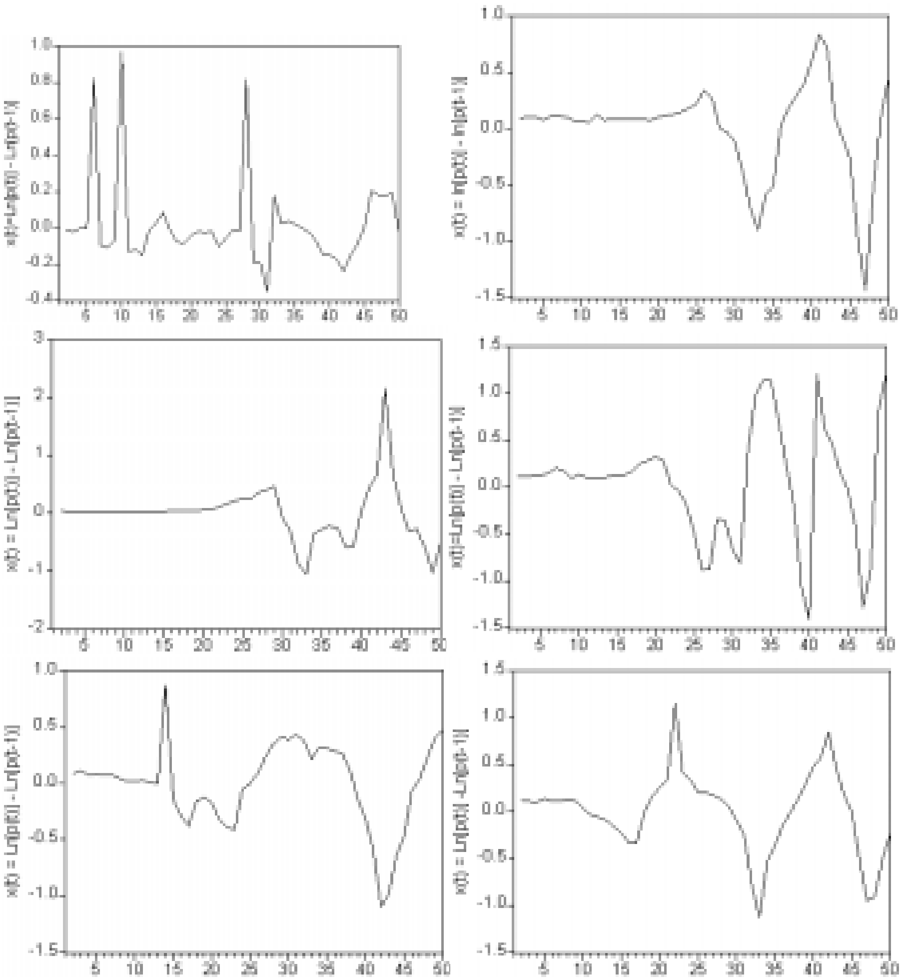

Figure 5: excess returns of realized asset prices

For groups 2 to 6, there appears to be serial correlation in the excess returns over the full sample of 50 periods. However, this serial correlation in returns is mainly due to the large amplitude fluctuations in the last part of the return series, after the price series reaches its upper bound. Since the upper bound 1000 is in fact an artifact of our experimental setup to stop an exploding asset price, it is more interesting to investigate informational (in)efficiency before the bubble reaches its upper bound. Furthermore, if we only consider the first 23, 26, 18, 27 and 28 observations in groups 2, 3, 4, 5 and 6 respectively, we find almost no significant autocorrelation. Figure 6 shows the first 10 lags of the autocorrelation function where only observations along the first bubble are used. During the first part of the bubble the market seems to be apporximately efficient, according to our autocorrelation test.

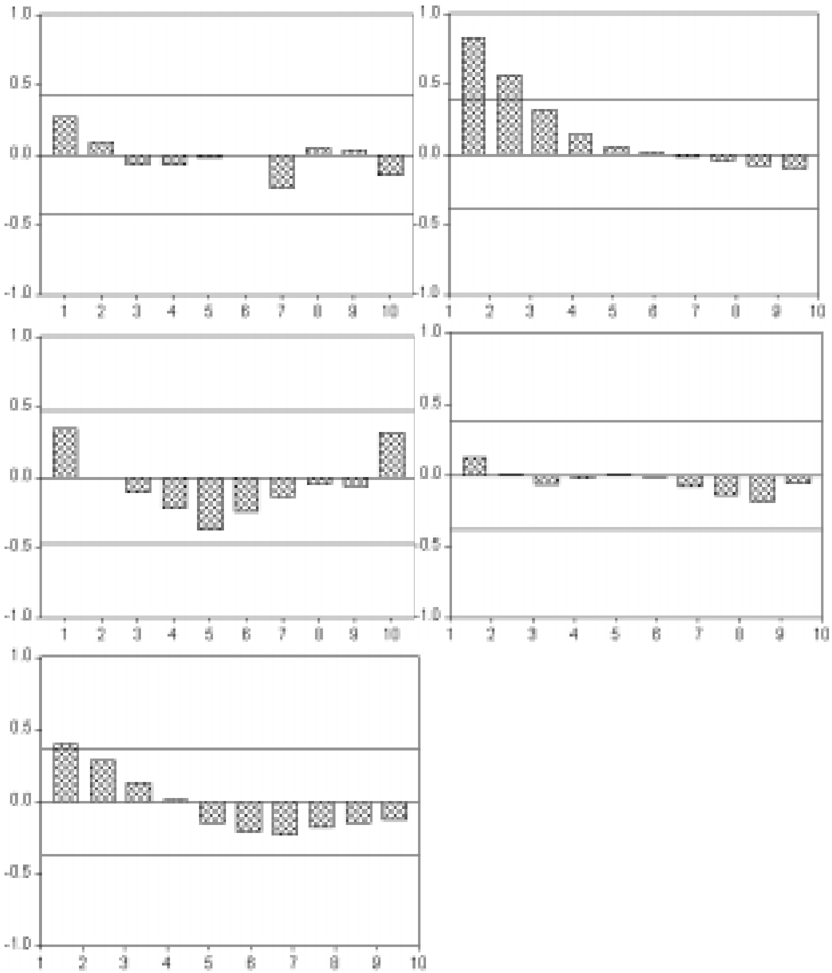

Figure 6: Autocorrelation of excess returns for groups $2-6$.

Notice that when forecasting the price or return at date t, only past prices or returns up to date $t-2$ are in the information set, so that a significant first order autocorrelation coefficient can **not** be exploited. Hence group 6, where all autocorrelation coefficients of lags $2-10$ are not significant is also informationally efficient. Only group 3 is not fully informationally efficient, since it has a significant second order autocorrelation coefficient. Moreover, the markets seem close to being informational efficient until the first bubble, after this bubble the market is not informationally efficient anymore. Market efficiency is sometimes also defined in terms of whether prices reflect economic fundamentals. Since in 5 out of the 6 groups prices show large deviations from the RE fundamental price, our asset pricing experiments are not efficient in this sense.

4.2 Individual prediction strategies

We now turn to the individual prediction strategies of the participants in our asset pricing experiment. Figure 7 shows, per group, the predictions of all participants. Typically, the differences between prediction strategies within groups are small. This suggests that the different participants in a group *coordinate* on some common prediction strategy.

Moreover, the individual predictions of most of the participants *lead* the realized price, i.e. $p^e_{h,t+1}$ is close to p_t. These two features (coordination on a common prediction strategy and predictions leading realized prices) are obtained in all groups. Table 2 shows values of some measures that quantify these features.

group	"forecast error"	"lead"	"coordination"
1	32.26	24.76	24.63
2	92.11	33.80	28.61
3	91.57	49.57	47.45
4	151.11	73.79	68.88
5	68.38	41.39	39.69
6	79.97	43.14	41.97

Table 2: Different measures for the individual prediction strategies

Here

$$\text{"forecast error"} = d\left(p^e_{ht}, p_t\right) = \frac{1}{H\left(T - t_0\right)} \sum_{h=1}^{H} \sum_{t=t_0+1}^{T} \left|p^e_{ht} - p_t\right|,$$

$$\text{"lead"} = d\left(p^e_{h,t+1}, p_t\right) = \frac{1}{H\left(T - t_0\right)} \sum_{h=1}^{H} \sum_{t=t_0+1}^{T} \left|p^e_{h,t+1} - p_t\right|$$

and

$$\text{"coordination"} = d\left(p^e_{ht}, \overline{p}^e_t\right) = \frac{1}{H\left(T - t_0\right)} \sum_{h=1}^{H} \sum_{t=t_0+1}^{T} \left|p^e_{ht} - \overline{p}^e_t\right|$$

are measures of the (average) distance between p^e_{ht} and p_t and $\overline{p}^e_t$, where $\overline{p}^e_t = \frac{1}{H} \sum_{h=1}^{H} p^e_{ht}$. Notice that these averages are computed with $t_0 = 10$, in order to abstract from variations in predictions and prices in the beginning of the experiment that are due to participants trying to learn how to predict prices accurately. The first measure, $d\left(p^e_{ht}, p_t\right)$, gives, for each group, the absolute value of the forecast error, averaged over time and participants. The second measure, $d\left(p^e_{h,t+1}, p_t\right)$, gives, for each group, the distance (averaged over time and over participants) between the individual prediction for time $t+1$, $p^e_{h,t+1}$ and the realized price at time t, p_t. This "lead" distance is a measure for the degree in which predictions lead the realized prices. The third measure, $d\left(p^e_{ht}, \overline{p}^e_t\right)$, gives, for each group, the distance between the individual prediction and the average prediction $\overline{p}^e_t$ within the group, averaged over time and participants. This distance measures dispersion between individual predictions: $d\left(p^e_{ht}, \overline{p}^e_t\right)$ equals 0 if and only if all participants use exactly the same prediction strategy. Hence, this distance measures coordination on a common prediction strategy.

From inspection of the table it is clear that, for all groups, the three measures are decreasing in magnitude. Several features stand out. First, for all groups we have

$$\text{"forecast error"} >> \text{"coordination"},$$

that is, the dispersion of prediction strategies is much smaller than the average forecast error participants make. Recall that they have an incentive to minimize the forecast error. Hence participants coordinate on a common prediction strategy. *All participants make significant forecasting errors, but they are alike in the way that they make these forecasting errors.*

The other relationship that stands out is

$$\text{"forecast error"} >> \text{"lead"}.$$

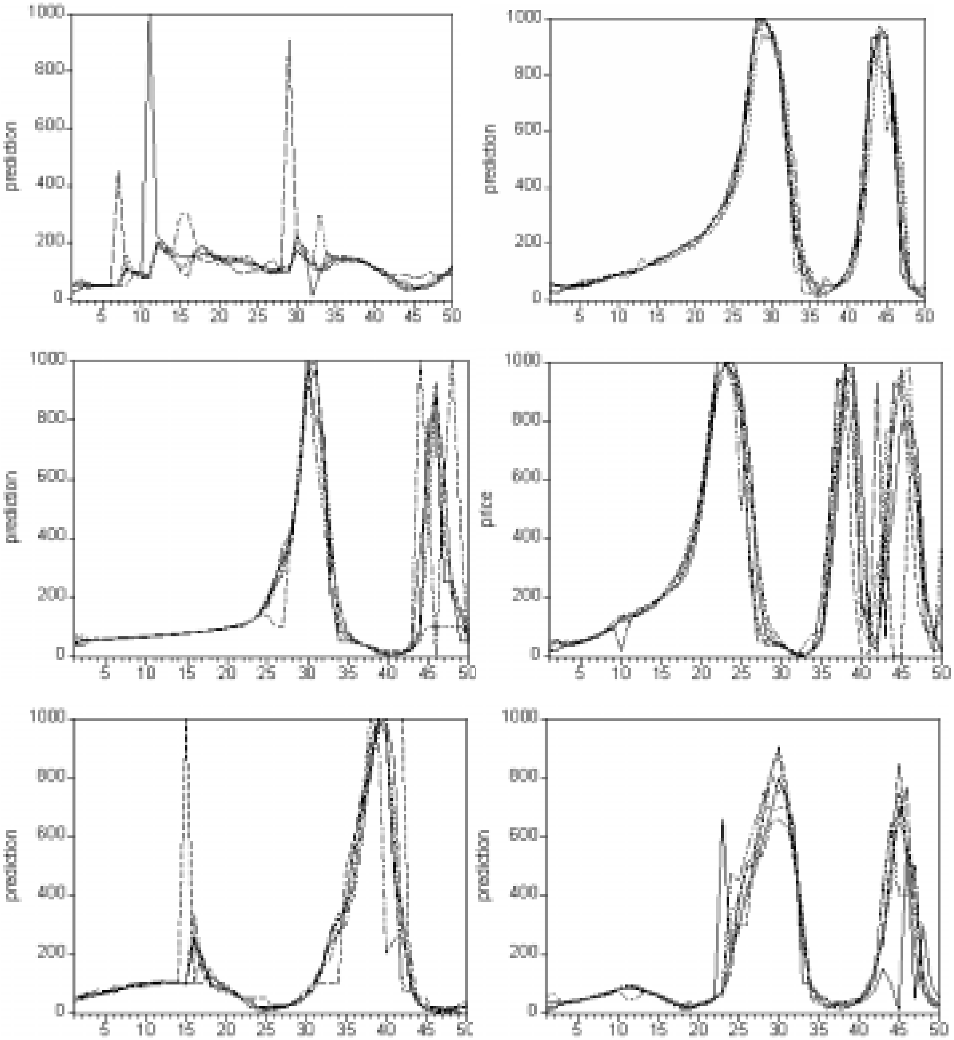

Figure 7: Participants' individual predictions

The "lead" distance is small because the individual predictions for time $t+1$ determine the realized price at time t. Moreover, the only determinant of p_t (outside exogenous variables such as r and $\overline{y}$) is the average prediction for the next period, $\overline{p}^e_{t+1}$, and indeed the distance between $\overline{p}^e_{t+1}$ and p_t is very small for all groups. The inequality above says that the individual predictions for time $t+1$ give much more accurate predictions for time t than for time $t+1$. That is, in trying to predict p_{t+1}, participants are very succesfull in predicting p_t. However, they do not seem to use this relationship to improve their predictions.

The analysis of Table 2 suggests that participants make structural forecast errors. However, if participants are rational their forecast error should be uncorrelated with available information. To test whether participants are rational in this sense, we computed, for each participant, the first 10 lags of the autocorrelation function of the time series of forecast errors $p_t - p^e_{ht}$, where we only used the last 40 observations. The significant lags are presented in Table 3.

	group 1	group 2	group 3	group 4	group 5	group 6
part. 1	–	1-4-5	–	1-3-4-10	1	–
part. 2	–	1-5-6	1	1-3-4-10	1	1-9-10
part. 3	–	1-4	1	1	1	1-2
part. 4	1	1-4-5	–	1-3-4	–	1-2-9
part. 5	–	1-4	1-2	1-3-4-10	1	1-9-10
part. 6	–	1-2-5-9	1	4	1	1-9-10

Table 3: Autocorrelation structure of individual forecast errors

Notice that the autocorrelation function of the forecast errors is significant at the first lag for many participants. However, participants do *not* have p_t in their information set, when predicting p_{t+1}. Hence, they are not able to exploit the first order autocorrelation structure in the forecast errors to improve their predictions. Therefore we should focus on higher order lags of the autocorrelation function. We thus find that for about half of the participants there is no exploitable structure in the forecast errors. Notice that the differences between autocorrelation patterns of participants within groups is much smaller than the differences of the autocorrelation patterns between groups. Participants in group 1 have almost no structure in their forecast errors, whereas most participants in groups 3 and 5 only have significant autocorrelation at the first lag, which is innocuous. There is much more structure in the forecast errors of the participants from the other groups. Half of the participants do not exploit all structure in the forecast errors. For these participants it might be the case that they are still in the process of exploiting this structure by adapting their prediction strategies. The analysis of the individual prediction strategies leads us to the conclusion that participants make structural forecasting errors and deviate from rationality, but they tend to deviate from rationality in a common way. However, it is more interesting to to only consider the observations along the first bubbles (the first 23, 26, 18, 27 and 28 observations for groups 2, 3, 4, 5 and 6). We now find significant lags of the autocorrelation function of the forecast errors for only 8 participants. That is, a vast majority of the participants do not make structural forecast errors until the price has reached its upper bound.

5 Concluding Remarks

In this paper we investigated expectation formation in an experimental asset pricing model. In 5 of the 6 experiments a bubble emerges endogenously. The growth rates of these experimental bubbles are inconsistent with rational expectations. Moreover, due to the restriction of an upper bound of 1000 recurring bubbles and crashes appear in most of the experiments. Apparently, participants are not able to coordinate on the fundamental price even if they know that prices cannot keep on growing forever and have to crash eventually. These recurring bubbles and crashes are similar to the periodically collapsing bubbles studied by Evans (1991). These (rational) bubbles collapse with a certain probability each period, and restart again when they do. When they do not collapse they have to grow faster than a 'regular' rational bubble. The bubbles observed in our experiment seem to be triggered by the trend chasing behavior of participants: when observing a small price increase, they predict the price to increase even further, after which this price increase becomes self-fulfilling. These *positive feedback expectations* seem to drive much of the dynamics. Although the experimental bubbles do not correspond to rational bubbles the excess returns of the asset along this first bubble does, in general, not exhibit a significant autocorrelation structure. In this sense the market is informationally efficient. At an individual level, the analysis in Section 4.2 has revealed that participants seem to coordinate on a common prediction strategy and that their predictions tend to lead the realized price.

In a related paper (Hommes, Sonnemans, Tuinstra and van de Velden (2002)) we present results on an experiment with an asset pricing model, which is adapted such that speculative bubbles are impossible. In these experiments we observe oscillating asset prices in some groups and convergence to the fundamental price in others. The oscillations in these experiments are reminiscent of the oscillations in the atypical group 1 in the experiment described in this paper. With respect to the individual prediction strategies we find similar results as in the present study. Participants within one group tend to coordinate on a common prediction strategy that leads the realized price. In fact, prediction strategies can be estimated pretty accurately. It is found that many participants coordinate on using simple linear predictions strategies. The coordination on a common and simple prediction strategy seems to be a robust feature in this type of experiment.

References

[1] Andreassen, P.B. and S.J. Kraus (1990): "Judgemental Extrapolation and the Salience of Change," *Journal of Forecasting*, **9**, 347-372.

[2] De Bondt, W.F.M. (1993): "Betting on Trends: Intuitive Forecasts of Financial Risk and Return," *International Journal of Forecasting*, **9**, 355-371.

[3] De Long, J.B., A. Shleifer, L.H. Summers and R.J. Waldmann (1990): "Positive Feedback Investment Strategies and Destabilizing Rational Speculation," *Journal of Finance*, **45**, 379-396.

[4] Diba, B.T. and H.I. Grossman (1988): "The Theory of Rational Bubbles in Stock Prices," *Economic Journal*, **98**, 746-754.

[5] Dwyer, G.P., A.W. Williams, R.C. Battalio and T.I. Mason (1993): "Tests of Rational Expectations in a Stark Setting," *Economic Journal*, **103**, 586-601.

[6] Evans, G.W. (1991): "Pitfalls in Testing for Explosive Bubbles in Asset Prices," *American Economic Review*, **81**, 922-930.

[7] Flood, R.P. and P.M. Garber (1980): "Market Fundamentals versus Price Bubbles: The First Tests," *Journal of Political Economy*, **88**, 745-770.

[8] Frankel, J.A. and K.A. Froot (1987): "Using Survey Data to Test Standard Propositions Regarding Exchange Rate Expectations," *American Economic Review*, **77**, 133-153.

[9] Frankel, J.A. and K.A. Froot (1988): "Chartists, Fundamentalists and the Demand for Dollars," *Greek Economic Review*, **10**, 49–102.

[10] Froot, K.A. and M. Obstfeld (1991): "Intrinsic Bubbles: The Case of Stock Prices," *American Economic Review*, **81**, 1189-1214.

[11] Garber, P.M. (1990): "Famous First Bubbles," *Journal of Economic Perspectives*, **4**, 35-54.

[12] Hommes, C.H., J. Sonnemans, J. Tuinstra and H. van de Velden (1999): "Expectations Driven Prive Volatility in an Experimental Cobweb Economy," CeNDEF Working Paper 99-07.

[13] Hommes, C.H., J. Sonnemans, J. Tuinstra and H. van de Velden (2002): "Coordination of Expectations in an Experimental Asset Pricing Model," CeNDEF Working Paper.

[14] King, R.R., V.L. Smith, A.W. Williams and M. van Boening (1993): "The Robustness of Bubbles and Crashes in Experimental Stock Markets," in *Nonlinear Dynamics and Evolutionary Economics*, ed. by I. Prigogine, R. Day and P. Chen. Oxford: Oxford University Press.

[15] Lei, V., C.N. Noussair and C.R. Plott (2001): "Nonspeculative Bubbles in Experimental Asset Markets: Lack of Common Knowledge of Rationality vs. Actual Irrationality," *Econometrica*, **69**, 831-859.

[16] Marimon, R., S.E. Spear and S. Sunder (1993): "Expectationally Driven Market Volatility: An Experimental Study," *Journal of Economic Theory*, **81**, 74–103.

[17] Noussair, C.N., S. Robin and B. Ruffieux (2000): "Price Bubbles in Laboratory Asset Markets with Constant Fundamental Values," Mimeo.

[18] Porter, D.P, V.L Smith (1995): "Futures Contracting and Dividend Uncertainty in Experimental Asset Markets," *Journal of Business*, **68**, 509-541.

[19] Schmalensee, R. (1976): "An Experimental Study of Expectation Formation," *Econometrica*, **44**, 17–41.

[20] Shiller, R.J. (1990): "Speculative Prices and Popular Models," *Journal of Economic Perspectives*, **4**, 55–65.

[21] Smith, V.L., G.L. Suchanek and A.W. Williams (1988): "Bubbles, Crashes and Endogenous Expectations in Experimental Spot Asset Markets," *Econometrica*, **56**, 1119-1151.

[22] Smith, V.L., M. van Boening and C.P. Wellford (2000): "Dividend Timing and Behavior in Laboratory Asset Markets," *Economic Theory*, **16**, 567-583.

[23] Tirole, J. (1982): "On the Possibility of Speculation under Rational Expectations," *Econometrica*, **50**, 1163-1181.

[24] TIROLE, J. (1985): "Asset Bubbles and Overlapping Generations," *Econometrica*, **53**, 1499-1528.

[25] WEST, K.D. (1985): "A Specification Test for Speculative Bubbles," *Quarterly Journal of Economics*, **102**, 553-580.

[26] WILLIAMS, A.W. (1987): "The Formation of Price Forecasts in Experimental Markets," *Journal; of Money, Credit and Banking*, **19**, 1-18.

A Information for Participants

General information
You are a **financial advisor** to a pension fund that wants to optimally invest a large amount of money. The pension fund has two investment options: a risk free investment and a risky investment. The risk free investment is putting all money on a bank account paying a fixed interest rate. The alternative risky investment is an investment in the stock market. In each time period the pension fund has to decide which fraction of their money to put on the bank account and which fraction of the money to spend on buying stocks. In order to make an optimal investment decision the pension fund needs an accurate prediction of the price p_t of stocks. As their financial advisor, you have to predict the stock market price p_t (in guilder) during 51 subsequent time periods. Your earnings during the experiment depend upon your forecasting accuracy. The smaller your forecasting errors in each period, the higher your total earnings.

Information about the stock market
The stock market price p_t is determined by equilibrium between demand and supply of stocks. The supply of stocks is fixed during the experiment. The demand for stocks is mainly determined by the aggregate demand of 6 different pension funds active in the stock market. The price p_t of the stocks is determined by market equilibrium, that is, the stock market price p_t in period t will be the price for which aggregate demand equals supply.

Information about the investment strategies of the pension funds
The precise investment strategy of the pension fund that you are advising and the investment strategies of the other pension funds are unknown. The bank account of the risk free investment pays a fixed interest rate of 5% per time period. The holder of the stocks receives an uncertain dividend payment in each time period. These dividend payments are uncertain however and vary over time. Economic experts of the pension funds have computed that the average dividend payments are 3 guilder per time period. The return of the stock market per time period is uncertain and depends upon (unknown)

dividend payments as well as upon price changes of the stock. As the financial advisor of a pension fund you are **not** asked to forecast dividends, but you are only asked to forecast the price of the stock in each time period. Based upon your stock market price forecast, your pension fund will make an optimal investment decision. The higher your price forecast the larger will be the fraction of money invested by your pension fund in the stock market, so the larger will be their demand for stocks.

Forecasting task of the financial advisor

The only task of the financial advisors in this experiment is to forecast the stock market index p_t in each time period as accurate as possible. The price p_t of the stock will always be between 0 and 100 guilder. The stock price has to be predicted **two** time periods ahead. At the beginning of the experiment begins, you have to predict the stock price in the first **two** periods, that is, you have to give predictions p_1^e and p_2^e for time periods 1 and 2. After all participants have given their predictions for the first two periods, the stock market price p_1 in the first period will be revealed and based upon your forecasting error $p_1 - p_1^e$ your earnings for period 1 will be given. After that you have to give your prediction p_3^e for the stock market index in the third period. After all participants have given their predictions for period 3, the stock market index p_2 in the second period will be revealed and, based upon your forecasting error $p_2 - p_2^e$ your earnings for period 2 will be given. This process continues for 51 time periods.

To forecast the stock price p_t in period t, the available information thus consists of

Summary of information

- past prices up to period $t-2$ $\{p_{t-2}, p_{t-2}, \cdots, p_1\}$
- past predictions up to period $t-1$ $\{p_{t-1}^e, p_{t-2}^e, \cdots, p_1^e\}$
- past earnings up to period $t-2$

Earnings

Earnings will depend upon forecasting accuracy only. The better you predict the stock market price in each period, the higher your aggregate earnings.

Earnings will be according to the following earnings table.

B Earnings Table

Insert Payoff Table

Payoff table 1300 points equal 1 guilder									
error	points	error	points	error	points	error	points	error	points
0.1	1300	1.5	1240	3	1061	4.4	786	5.8	408
0.15	1299	1.55	1236	3.05	1053	4.45	775	5.85	392
0.2	1299	1.6	1232	3.1	1045	4.5	763	5.9	376
0.25	1298	1.65	1228	3.15	1037	4.55	751	5.95	361
0.3	1298	1.7	1223	3.2	1028	4.6	739	6	345
0.35	1297	1.75	1219	3.25	1020	4.65	726	6.05	329
0.4	1296	1.8	1214	3.3	1011	4.7	714	6.1	313
0.45	1295	1.85	1209	3.35	1002	4.75	701	6.15	297
0.5	1293	1.9	1204	3.4	993	4.8	689	6.2	280
0.55	1292	1.95	1199	3.45	984	4.85	676	6.25	264
0.6	1290	2	1194	3.5	975	4.9	663	6.3	247
0.65	1289	2.05	1189	3.55	966	4.95	650	6.35	230
0.7	1287	2.1	1183	3.6	956	5	637	6.4	213
0.75	1285	2.15	1177	3.65	947	5.05	623	6.45	196
0.8	1283	2.2	1172	3.7	937	5.1	610	6.5	179
0.85	1281	2.25	1166	3.75	927	5.15	596	6.55	162
0.9	1279	2.3	1160	3.8	917	5.2	583	6.6	144
0.95	1276	2.35	1153	3.85	907	5.25	569	6.65	127
1	1273	2.4	1147	3.9	896	5.3	555	6.7	109
1.05	1271	2.45	1141	3.95	886	5.35	541	6.75	91
1.1	1268	2.6	1121	4	876	5.4	526	6.8	73
1.15	1265	2.65	1114	4.05	865	5.45	512	6.85	55
1.2	1262	2.7	1107	4.1	854	5.5	497	6.9	37
1.25	1259	2.75	1099	4.15	843	5.55	483	6.95	19
1.3	1255	2.8	1092	4.2	832	5.6	468	error ≥ 7	0
1.35	1252	2.85	1085	4.25	821	5.65	453		
1.4	1248	2.9	1077	4.3	809	5.7	438		
1.45	1244	2.95	1069	4.35	798	5.75	423		

C Earnings

The experiment was conducted in the CREED laboratory of the University of Amsterdam in Februari 2001 and consisted of 6 groups of 6 participants.

Table 4 gives averages and variances of the earnings in points for the two different treatments. The table also splits the whole time interval in two subintervals (periods $1-25$ and periods $26-50\,(51)$), to see if it there is a learning or coordination effect over time.

Table 5 gives individual earnings of participants in the different groups.

Earnings	average	st.dev.
1-50 (51)	13815	7067
1-25	9448	6585
26-50 (51)	4367	2336

Table 4: Aggregate earnings

Individual Earnings								
in Dutch guilders								
group	part. 1	part. 2	part. 3	part. 4	part. 5	part. 6	sample average	sample variance
group 1	9.83	11.54	14.74	12.45	13.66	7.04	11.54	2.54
group 2	8.55	8.91	8.46	9.64	8.90	9.77	9.04	0.50
group 3	22.17	19.73	20.52	25.96	18.48	20.09	21.16	2.41
group 4	3.91	4.61	9.27	4.72	5.00	5.00	5.42	1.76
group 5	11.59	14.88	8.57	14.80	16.85	15.72	13.73	2.81
group 6	4.94	9.79	11.98	9.55	6.53	10.42	8.87	2.40

Table 5: Individual earnings