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Managing Bubbles in Experimental Asset Markets with Monetary Policy

We study the effect of a “leaning against the wind” monetary policy on asset price bubbles in a learning-to-forecast experiment, where prices are driven by the expectations of market participants. We find that a strong interest rate response is successful in preventing or deflating large price bubbles, while a weak response is not. Giving information about the interest rate changes and communicating the goal of the policy increases coordination of expectations and has a stabilizing effect. When the steady-state fundamental price is unknown and the interest rate rule is based on a proxy instead, the policy is less effective.

JEL codes: C92, D84, E52, G12, G41

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Since the burst of the U.S. housing bubble in 2007 and the following financial crisis, the consensus view that monetary policy should not

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respond to asset price bubbles no longer holds. Prominent policymakers, such as Trichet (2005) and Bernanke (2010), have called to carefully monitor asset prices and remain open to using monetary policy as a supplementary tool to address bubbles, while keeping in mind the difficulties and dangers of that approach.¹ But aside from the difficulty of identifying a bubble and the danger of harming other parts of the economy, the relationship between monetary policy and asset price bubbles is not yet clear.

In this paper, we examine this relationship in a learning-to-forecast experiment (LtFE) where the only task of participants is to submit asset price forecasts. Previous laboratory experiments of this type have shown that large price bubbles frequently occur in these asset markets, caused by coordination on trend-following expectations (Hommes et al. 2005, Bao et al. 2020, Hommes et al. 2008, Hommes, Kopányi-Peucker, and Sonnemans 2021).² By introducing monetary policy in this controlled environment, we can study the interaction between individual expectations, asset price bubbles, and interest rate policy.

The appropriate monetary policy response to asset price bubbles is heavily disputed in the theoretical literature. A brief overview of this debate is given in the next section. Although theoretical models give insight in the possible effects of monetary policy, the policy conclusions are conflicting and depend crucially on the modeling assumptions. Both rational and behavioral models make assumptions about the behavior of economic agents that might not be realistic. Identifying the causal effect of monetary policy using field data is difficult as well, since policy is endogenous to the state of the economy. The key advantage of a lab experiment is that it provides full control over the economic setting and the information and incentives for participants, making it an ideal environment to study causal relationships without imposing assumptions on behavior. Our experiment is particularly designed to study the interaction of monetary policy with individual expectations and market outcomes. Moreover, it is practically impossible to experiment with different monetary policies in the real world. A lab experiment makes it easy to try out various policies and directly observe their effects. Our experimental study, therefore, complements the theoretical and empirical literature on monetary policy and bubbles.

A “leaning against the wind” policy reacts to asset price bubbles by increasing the interest rate. Theoretically, this policy can mitigate bubbles by reducing asset prices via the discount rate effect.³ However, asset prices are not only determined by funda-

1. A recent study by Cieslak and Vissing-Jorgensen (2021) suggests that the Federal Reserve already reacts to stock market declines with interest rate cuts, but they do not find a response to stock market rises.

2. Trend extrapolation by investors is widely documented in the empirical literature (see, e.g., Shleifer and Summers 1990, Hirshleifer 2001, Shiller 2002, Barberis and Thaler 2003, Greenwood and Shleifer 2014, Barberis et al. 2018), suggesting that this is an important factor in real-world asset markets as well.

3. Several empirical studies find that asset prices indeed fall after an increase in the interest rate (see, e.g., Rigobon and Sack 2004, Bernanke and Kuttner 2005, Gürkaynak, Sack, and Swanson 2005, Ioannidis and Kontonikas 2008). Both the discount rate effect and the effect on expectations seem to play a role. However, Galí and Gambetti (2015) challenge the view that a “leaning against the wind” policy can reduce bubbles and provide empirical evidence that the opposite effect could also occur.

mentals, but also by return expectations. The way in which expectations are formed is, therefore, crucial for the transmission of monetary policy. For example, if the asset market is having a “rational bubble,” the price grows at a rate proportional to the interest rate, so increasing the interest rate leads to faster price growth and has a destabilizing effect. Alternatively, boundedly rational agents might display trend-following behavior that is too strong for monetary policy to be effective, despite the downward pressure of the interest rate on the price. Yet, it could also be that interest rate policy is able to prevent or manage coordination on expectations that cause bubbles.⁴

The goal of our experimental study is to shed light on the ambiguous effect of a “leaning against the wind” policy in a simple setting. By focusing on a single dimension, namely, expectations in a simple asset market, we can clearly identify the effect of monetary policy on individual expectations and aggregate outcomes. Our experimental results can validate and improve theoretical models by pointing toward realistic assumptions to model expectation formation and revealing potential reactions to certain policies. Furthermore, our study is informative for future experiments using more complex settings, where our results can serve as a baseline. A caveat of our simple design is that we omit important economic factors, such as inflation and output. Therefore, we are unable to draw conclusions about the best monetary policy response to bubbles in a wider economic context. Since part of the debate is about potential side effects of monetary policy on other parts of the economy, this is clearly an important topic for further research. Nevertheless, we see our simple setting as an advantage and as a necessary first step before studying more complex environments.

Our experiment builds on the design of Hommes et al. (2008), to which we add a “leaning against the wind” policy rule.⁵ The Taylor-type rule in our experiment sets the interest rate in response to relative deviations from the steady-state fundamental price. We compare a weak and a strong interest rate rule to study the effect of the policy on market stability. To find out how subjects respond to information about interest rate changes, we consider two additional treatments with a strong interest rate rule. First, we take away the information about current and past interest rates and only tell participants that the target rate is 5%. Second, we give participants extra information by including the goal of the interest rate policy in the instructions. Finally, we conduct a treatment where we account for the possibility that the central bank does not know the steady-state price and uses the sample average price as a proxy to set the interest rate.

4. Experiments in a New Keynesian framework show that monetary policy rules that react aggressively to inflation can avoid coordination on destabilizing trend-following expectations by reducing the degree of positive feedback in the system (Assenza et al. 2021, Pfajfar and Žakelj 2018). Experimental asset markets with a lower degree of feedback throughout the whole experiment are also more stable and show faster convergence (Sonnemans and Tuinstra 2010, Bao and Hommes 2019).

5. A related experiment of Hommes et al. (2005) includes a stabilizing force in the form of fundamental robot traders whose share increases when the price deviates more from the fundamental, but the implementation is ad hoc and cannot be interpreted as a policy rule.

Our results indicate that a weak interest rate response is not able to prevent the formation of large bubbles. By contrast, bubbles are absent or remain smaller in markets with a strong interest rate response. When participants do not get any information about the interest rate changes, the price patterns are more irregular and coordination is less strong than when they know the current and past interest rates. Communicating the goal of the policy further enhances price stabilization. When the interest rate rule is based on the sample average price instead of the steady-state price, the policy is less effective.

This paper is organized as follows. Section 1 places our study in the context of related theoretical and experimental literature. Section 2 explains the design of our experiment in detail. Next, the experimental results are discussed: Section 3 focuses on market prices, Section 4 on interest rates, and Section 5 on individual expectations. Finally, Section 6 concludes.

1. RELATED THEORETICAL AND EXPERIMENTAL LITERATURE

Our paper relates to the theoretical and experimental literature on monetary policy and asset price bubbles. In the theoretical literature, there is wide disagreement about the appropriate interest rate response to bubbles. Most prominently, Bernanke and Gertler (1999, 2001) show that inflation targeting can achieve both general macroeconomic stability and financial stability in their New Keynesian model with a financial accelerator. In their model, the bubble process is exogenous and agents have forward-looking (rational) expectations, with the exception of inflation expectations which are modeled as a combination of forward- and backward-looking behavior. Bernanke and Gertler recommend against a systematic response of interest rates to asset price bubbles since it could do more harm than good to the economy. Their results have been challenged by Cecchetti et al. (2000) and Cecchetti, Genberg, and Wadhvani (2002), who use the same model but reach the opposite conclusion. The disagreement seems largely due to different assumptions about whether a central bank can identify asset price bubbles and distinguish them from other shocks.

Recent models that depart from assuming rationality on asset markets and make bubble formation endogenous also lead to opposing views. Winkler (2020) constructs a business cycle model in which agents learn about asset prices and finds that a monetary policy response to asset prices stabilizes the economy by dampening fluctuations in expectations and preventing investor optimism from building up. Boehl (2020) introduces trend extrapolating asset traders in a New Keynesian model and concludes that a “leaning against the wind” policy decreases volatility in asset prices, but increases volatility of inflation and output.

Yet another modeling approach is taken by Galí (2014, 2021), who assumes that bubbles are rational so that raising the interest rate increases the volatility of asset prices and the size of bubbles. In such a scenario, a “leaning against the wind” policy is counterproductive.

Our experimental results point toward the importance of allowing for nonrational expectations and endogenous bubbles in macroeconomic models, in contrast with the modeling approach of Bernanke and Gertler (1999, 2001), Cecchetti et al. (2000), and Cecchetti, Genberg, and Wadhvani (2002). In relation to their different views, our treatment where the central bank uses a proxy for the steady-state fundamental price suggests that interest rate policy may still help to prevent large bubbles even if bubbles cannot be perfectly identified, although the policy could be less effective. The assumptions and conclusions of Galí (2014, 2021) are also opposed by our findings, since our experiment clearly shows that bubbles are nonrational and that “leaning against the wind” can mitigate bubbles. We find that asset markets are stabilized via the expectations channel just as in the model of Winkler (2020), thereby lending support to his findings. Our results also validate the presence of trend-following traders and the ability of monetary policy to decrease asset price volatility as in Boehl (2020).

So far, there is little experimental work on monetary policy and asset price bubbles, with three notable exceptions.⁶ Simultaneously but independently, Bao and Zong (2019) investigate the impact of an interest rate change on asset price bubbles in a learning-to-forecast experiment. They use a simple policy rule that substantially raises or cuts the interest rate when the asset price reaches a certain threshold, and find that this policy effectively stabilizes prices. Instead of having sudden shocks in the interest rate, our Taylor-type policy rule smoothly responds to asset price movements. In addition, we consider three scenarios with different information about the policy, and a scenario in which the central bank uses a proxy for the steady-state fundamental price.

Fenig, Mileva, and Petersen (2018) combine a production economy with an asset market. Participants submit labor supply, output demand, and asset trading decisions. A “leaning against the wind” policy unintendedly gives rise to bubbles at first, but rapidly increasing interest rates are successful at quickly deflating bubbles and stabilizing asset prices. The policy has minimal negative effects on production and generally enhances welfare. While the general equilibrium framework of Fenig, Mileva, and Petersen may be closer to a real-world economy, it also makes analysis and causal inference more difficult—the authors only examine aggregate effects, not individual behavior. Although expectations were not elicited in the experiment, they provide a model with heterogeneous expectations of the asset price to explain their findings. Our simple experimental design allows us to study this key element of expectation formation and cleanly identify the effects of monetary policy.

Fischbacher, Hens, and Zeisberger (2013) study a partial equilibrium economy that extends the classical design of Smith, Suchanek, and Williams (1988). Participants can trade in both a risky stock and an interest bearing bond. They find that increasing the interest rate in response to stock price bubbles has only a limited effect in

6. Most experiments with monetary policy use a New Keynesian framework and do not include asset markets, such as Arifovic and Petersen (2017), Assenza et al. (2021), Cornand and M'baye (2018), Hommes, Massaro, and Salle (2019), Hommes, Massaro, and Weber (2019), Kryvtsov and Petersen (2021), Petersen (2015), Pfajfar and Žakelj (2018), Noussair, Pfajfar, and Zsiros (2021).

reducing bubbles. Furthermore, explaining the purpose of the interest rate policy in the instructions does not increase policy effectiveness. An issue with the design of Fischbacher, Hens, and Zeisberger is that the fundamental price is declining even without increasing the interest rate. Asset markets with declining fundamentals have been associated with larger bubble formation (Noussair, Robin, and Ruffieux 2001, Kirchler, Huber, and Stöckl 2012, Giusti, Jiang, and Xu 2016). In our setting, the fundamental price is constant in absence of interest rate policy, and the steady-state price always remains constant. Another main advantage of our asset pricing LtFE is that we separate expectation formation from trading decisions. This provides clean data on expectations, since it does not involve a joint test on rational expectations and optimal decision making. While an asset trading experiment à la Smith, Suchanek, and Williams might be closer to real-world asset trading, a learning-to-forecast experiment is more suitable to study expectations formation and learning in a setting where there is limited information about the market, as is often the case in real financial markets.

2. EXPERIMENTAL DESIGN

2.1 Asset Pricing Framework with Interest Rate Rule

Our experimental design is based on Hommes et al. (2008). The novel aspect is that we let the risk-free interest rate be variable instead of fixed, so that we can implement an interest rate rule. A detailed description of the asset pricing framework is given in Online Appendix A. In short, the framework is as follows. Consider an asset market with I traders with heterogeneous price expectations. At the beginning of each period, traders can choose to invest in a risk-free asset paying an interest rate r_t , or a risky asset paying an i.i.d. dividend with mean $\bar{y} = 3$. The interest rate r_t is variable, but it is known at the time of the investment decision and, therefore, risk-free. Traders use myopic mean-variance optimization to calculate their demand for shares based on their expectations for the next period. Outside supply is assumed to be zero, implying that traders buy and sell shares among themselves. Equilibrium between demand and supply then gives the market price of the risky asset (for the derivation, see Online Appendix A):

$$p_t = \frac{1}{1 + r_t} \left[\frac{1}{I} \sum_{i=1}^I p_{i,t+1}^e + \bar{y} \right], \quad (1)$$

where $E_{ii}(p_{t+1}) = p_{i,t+1}^e$ denotes the prediction by trader i in period t for the price in period $t + 1$. The price of the risky asset depends on the average price forecast of all traders in the market, so there is positive expectations feedback. When the interest rate is low, expectations are almost self-fulfilling. Increasing the interest rate makes the risk-free asset more desirable compared to the risky asset and, therefore, puts downward pressure on the price of the risky asset. This discount rate effect is

also present in real-world financial markets (see footnote 3). Our asset pricing framework abstracts away from intertemporal and risk dimensions that are associated with interest rates in the real world. We only consider the discount rate effect of interest rates and its interaction with expectation formation, since these two elements are key to the formation and evolution of bubbles.

We include a “leaning against the wind” policy rule that increases the interest rate in response to asset price bubbles. The interest rate is set according to a Taylor-type rule with a zero lower bound (ZLB):

$$r_t = \max \left\{ r^* + \phi \left(\frac{p_{t-1} - p^*}{p^*} \right), 0 \right\}, \quad (2)$$

where the target interest rate is $r^* = 5\%$ and the target price is $p^* = 60$, in line with the asset pricing model with a fixed interest rate of Hommes et al. (2008).⁷ The parameter ϕ determines the strength of the rule: the interest rate is increased by ϕ percentage points for a one percentage point rise in the asset price relative to the steady-state value.

Taylor-type rules that endogenously set the interest rate in response to deviations from steady-state values are often used in other macroeconomic settings, such as New Keynesian models. The rule gives a smooth interest rate response to asset price bubbles. Moreover, this policy has been inspired by the influential paper of Bernanke and Gertler (1999). We use a version of their policy rule that is adapted to our setting: we abstract from inflation and output in our asset pricing model, and we do not use log differences to approximate the percentage deviation from the steady state, since this approximation is only appropriate for small deviations.

Equations (1) and (2) form a dynamical system with $r^* = 5\%$ and $p^* = 60$ as the unique steady-state equilibrium.⁸ Online Appendix A presents derivations and details about the properties of the dynamical system. For our experiment, these properties imply that convergence to the steady state, oscillations around the steady state and rational bubbles are all among the outcomes that we could potentially observe.

2.2 General Design

The experimental asset markets consist of six participants each. They have the role of advisors to a large pension fund, and their only task is to submit two-period-ahead forecasts of the price of the risky asset for 51 periods. The pension fund calculates its

7. Note that the interest rate rule is based on the most recent observation of the asset price, p_{t-1} . It is not possible to implement a contemporaneous rule using p_t instead, because p_t depends on p_{t+1}^e . When these expectations are formed in period t , the interest rate r_t for that period should be known, otherwise there is no risk-free investment. Hence, r_t cannot depend on p_t .

8. With a constant interest rate of 5%, the fundamental price of the asset is $p^f = \bar{y}/r = 60$. But with a varying interest rate, the fundamental price depends on interest rate expectations. Hence, $p^* = 60$ cannot be called the fundamental, but it still is the steady-state rational expectations equilibrium. See Online Appendix A for details.

optimal demand for the asset based on the price forecast, so trading is computerized. The market price follows from equations (1) and (2). Participants are paid for their prediction accuracy:

$$e_{it} = \max \left\{ 1, 300 - \frac{1,300}{49} * (p_t - p_{it}^e)^2, 0 \right\}. \quad (3)$$

A lower quadratic forecast error $(p_t - p_{it}^e)^2$ results in higher earnings. The experimental points e_{it} are converted into euros using an exchange rate of € 0.5 per 1,300 points.

The instructions for the experiment are largely the same as in Hommes et al. (2008), except for the parts about the interest rate (see Online Appendix B). Participants receive only qualitative information about the asset market. They are informed that there is a risky asset with a mean dividend of $\bar{y} = 3$ and a risk-free asset with a variable interest rate that starts at 5%. This gives participants enough information to calculate the steady-state price, assuming that the interest rate does not change: $p^* = 3/0.05 = 60$. They can also infer that there is positive expectations feedback. As in Hommes et al., there is an upper bound on predictions of 1,000, but that is not known beforehand. Participants receive a message about the upper bound when they try to enter a prediction higher than 1,000. It is important to note that participants are not informed about the market pricing equation or the interest rate rule.

At the beginning of the experiment, instructions are provided both on screen and paper. To ensure understanding of the instructions, participants have to correctly answer a number of control questions before they can proceed with the experiment. The main task consists of a series of 51 price predictions. In the first two periods, participants only know that the interest rate is 5% and that it is very likely that the price will be between 0 and 100. After submitting two price predictions, the first price becomes known, earnings are calculated and the interest rate may change. Subsequently, in each period t , subjects have to predict the price for period $t + 1$ knowing only prices up to period $t - 1$. Furthermore, participants have information on their own past predictions up to period t , current and past interest rates up to period t , and period and total earnings up to period $t - 1$. Figure 1 gives an example of the computer screen, showing graphs of past prices, predictions and interest rates, and a table with all the available information. The current interest rate r_t and the mean dividend $\bar{y} = 3$ are also indicated separately. After completing the prediction task, subjects fill in a short questionnaire, which includes open questions about their prediction strategy.

2.3 Treatments

We conduct five different experimental treatments to study the effects of monetary policy under various scenarios. These treatments differ in the interest rate rule that is used, the strength of the rule that is implemented, and the information that is given to participants. We explain the treatments below and give an overview in Table 1.

First, we consider a baseline treatment with a weak interest rate response to asset price bubbles. In this Weak Rule treatment, we set the strength of the rule in equa-

Prediction

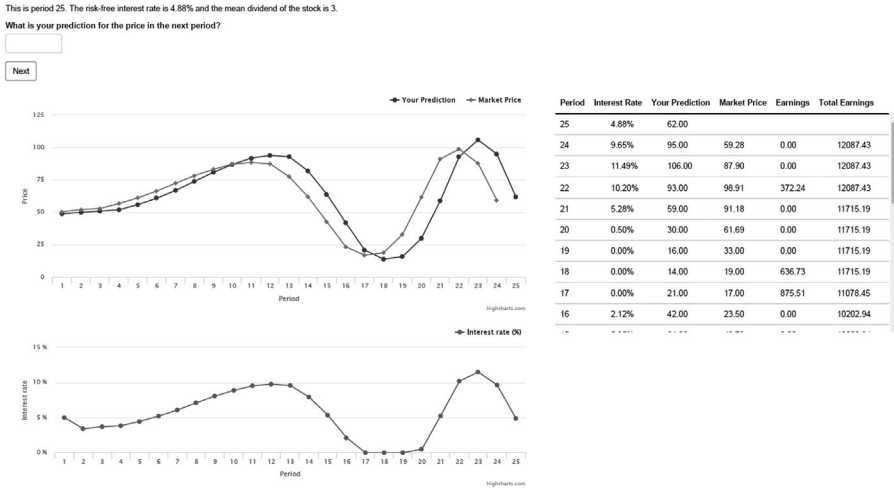


Fig. 1. Screenshot of the Experiment.

NOTES: This screen is seen by participants in all but the No Information treatment. In that treatment, the current interest rate is replaced by the target interest rate of 5%, the graph of past interest rates is removed, and the column in the table with the past interest rates is not shown.

TABLE 1
OVERVIEW OF TREATMENTS

Treatment	Interest rate rule	Strength	Information for participants
Weak Rule (WR)	Known p^* (equation (2))	$\phi = 0.001$	Current and past interest rates
Strong Rule (SR)	Known p^* (equation (2))	$\phi = 0.1$	Current and past interest rates
No Information (NI)	Known p^* (equation (2))	$\phi = 0.1$	Only target rate of 5%
Communication (C)	Known p^* (equation (2))	$\phi = 0.1$	Goal of policy
Sample Average (SA)	Unknown p^* (equation (4))	$\phi = 0.1$	Current and past interest rates

tion (2) to $\phi = 0.001$, to ensure that the interest rate changes are very small and the interest rate stays close to 5%. With such a weak policy response, we expect that large bubbles are still present in the market. We compare this with a Strong Rule treatment with $\phi = 0.1$, to see if this policy is able to stabilize the asset markets.⁹ In both treatments, participants receive information about the current and past interest rates as described in Section 2.2.

9. A behavioral heuristics switching model captures the price patterns in previous asset pricing experiments quite well (Anufriev and Hommes 2012, Bao et al. 2020). Simulations with this model guided the policy choices for the experiment. The simulations suggest that bubbles are still large for $\phi = 0.001$, whereas the market is quite stable with only small oscillations around the steady-state price for $\phi = 0.1$. Moreover, $\phi = 0.1$ is the parameter value that is used in Bernanke and Gertler (1999).

When the interest rate is increased, this lowers the price via the discount rate effect in equation (1). But it might also lower predictions by giving a signal to participants that the price of the asset is too high. In the Strong Rule treatment, we are not able to tell these two effects apart. To disentangle the effects, we run a No Information treatment with a strong interest rate rule ($\phi = 0.1$), where we do not give participants any information about the interest rate changes. The instructions tell them that the target interest rate is 5% and that the pension fund knows the current interest rate. During the prediction task, participants do not see the current and past interest rates in the graph and table on their computer screen. Hence, an interest rate change has no signaling effect. By comparing this treatment to the Strong Rule treatment, we can find out if participants respond to the information about interest rate changes.

Instead of giving less information, the central bank can also choose to give more information about the interest rate policy and be transparent about its goal. This might increase policy effectiveness. We test this in a Communication treatment with a strong interest rate rule ($\phi = 0.1$) where we add a sentence to the instructions: "The policy of the central bank is to raise the interest rate above 5% when it considers the asset price to be too high, and to cut the interest rate below 5% when it considers the asset price to be too low." Comprehension of this statement is also tested in a control question. When participants observe the current and past interest rates (as in Figure 1), it should thus be clear what the interest rate changes mean. We compare the Communication treatment with the Strong Rule treatment to examine the effect of communicating the goal of the policy.

In reality, it could be difficult to determine whether there is an asset price bubble, because the central bank might not know the steady-state fundamental price. To account for this possibility, we study a simple policy rule where the sample average price p_{t-1}^{av} is used as a proxy for p^* :

$$r_t = \max \left\{ r^* + \phi \left(\frac{p_{t-1} - p_{t-1}^{av}}{p_{t-1}^{av}} \right), 0 \right\}, \quad (4)$$

where $p_{t-1}^{av} = 1/(t-1) * \sum_{i=1}^{t-1} p_i$. We again consider a strong policy response ($\phi = 0.1$) and compare this Sample Average treatment to the Strong Rule treatment. The Sample Average treatment is intended to give a first impression of what the effects of monetary policy could be if the fundamental price is unknown. The sample average rule is easy to implement, which could be an advantage in more complex settings.

2.4 Implementation

The experiment was run in the CREED laboratory at the University of Amsterdam in May 2017 and September 2017. We conducted eight markets of each treatment with six subjects per market, giving a total of 240 subjects. No subject participated in more than one session. A session lasted about 1.5 h in total. Earnings, including a €

10 lump-sum payment, ranged from € 10.70 to € 34.10 and averaged € 17.73.¹⁰ The experiment was programmed in oTree (Chen, Schonger, and Wickens 2016).

3. AGGREGATE RESULTS

3.1 Price Dynamics

Figure 2 shows the realized market prices and interest rates in all markets, plotted per treatment. In Online Appendix C, summary statistics are given and prices, predictions, and interest rates are plotted for each market separately. It is immediately clear that large bubbles, with prices approaching the upper limit of 1,000, only occur in the Weak Rule treatment. All four versions of the strong interest rate rule are successful in preventing or deflating large bubbles.

In treatment Weak Rule, five markets display large bubbles, while the other three markets are stable or have small oscillations around the steady-state price. The results of this treatment are very similar to related experiments without monetary policy (Hommes et al. 2008, Bao et al. 2020, Hommes, Kopányi-Peucker, and Sonnemans 2021), except that there are relatively more stable groups in our experiment.

There are some differences among the four treatments with a strong interest rate rule as well. In the Strong Rule treatment, seven markets exhibit small price oscillations that are persistent throughout the experiment. Prices are below 200, except for one outlier in group 7. Only one market is stable and converges to the steady state.

In treatment No Information, the price patterns seem to be more erratic. Five markets have more or less regular price oscillations, except for an outlier in group 1. However, three markets exhibit quite irregular price patterns, with sudden jumps or drifts in the price. In group 7, there is even a medium sized bubble with prices above 400. None of the markets is stable.

The Communication treatment looks somewhat more stable than the Strong Rule treatment. The price oscillations are generally slightly smaller and are dampening or even converging in three groups. There are also three markets that are stable, with only very small oscillations in two cases and full convergence within 25 periods in one case. This is the only market in our experiment that fully converged to the steady state.

The results of the Sample Average treatment vary greatly per group. In three markets, multiple medium sized bubbles with prices up to 600 form in the second half of the experiment. There are small, persistent oscillations around the steady state in another three groups. Two markets are stable, but prices remain slightly below the steady state of 60.

10. For the sessions that we ran on the first day (groups 1–4 of the Weak Rule treatment and groups 1–4 of the Strong Rule treatment), we paid participants € 15 whenever their earnings in the experiment were below this amount. Since this occurred more often than we expected (namely, for 46 out of 48 subjects), we decided to change this practice. From the second day onward, we paid a lump sum of € 10 on top of the earnings in the experiment. In both cases, the participants did not know about the extra payments in advance, so the incentives during the experiment were the same in all sessions.

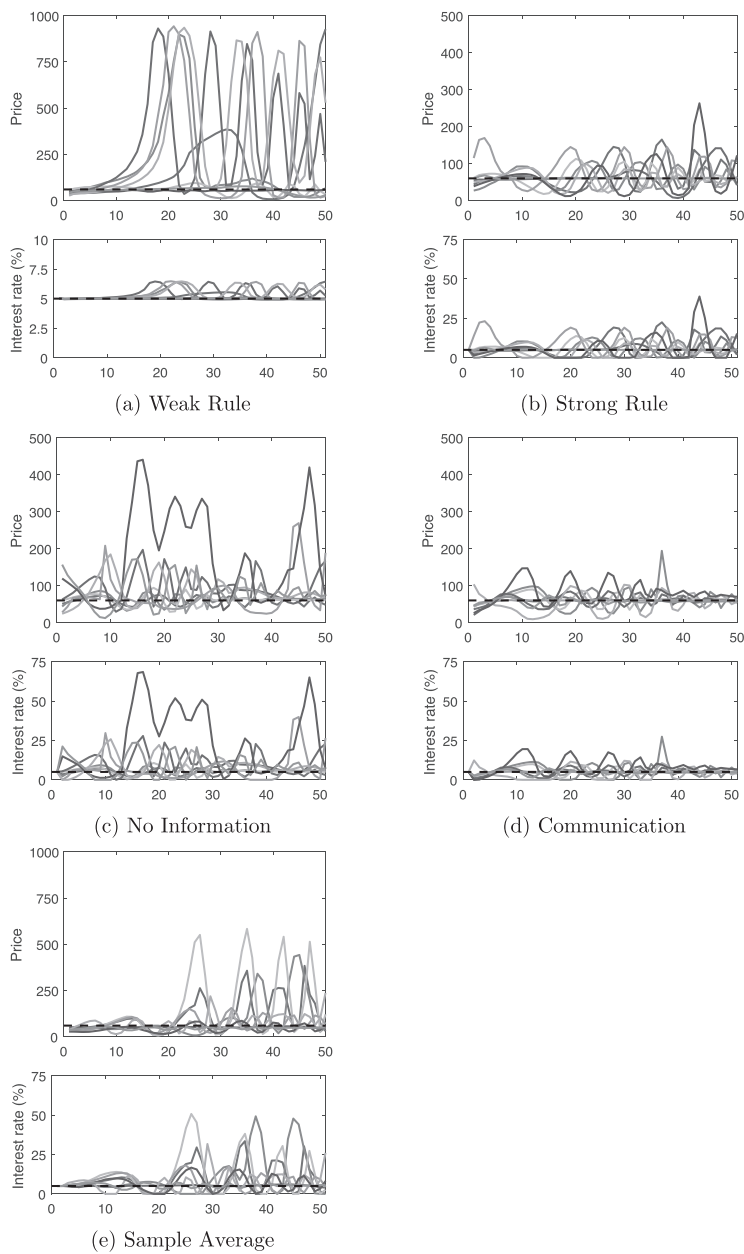


Fig. 2. Market Prices and Interest Rates in All Treatments.

NOTES: The dashed lines indicate the steady-state price of 60 and the steady-state interest rate of 5%. Note that the scale of the vertical axis may differ per treatment.

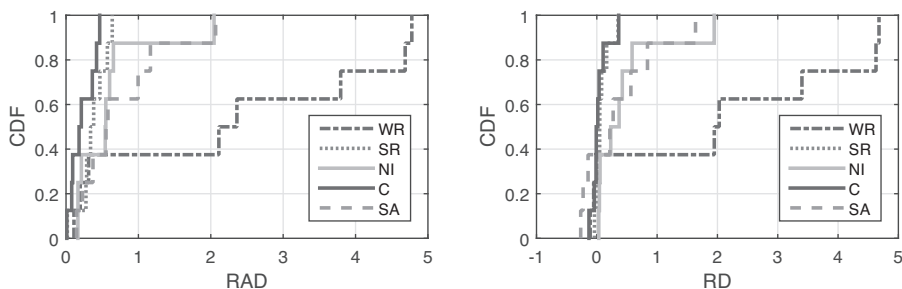


Fig. 3. Empirical Cumulative Distribution Functions of RAD and RD.

Note that the upper bound of 1,000 is only reached in the Weak Rule treatment. Naturally, the upper bound plays a role in the repeated bubbles and crashes in this treatment, just as in earlier studies (Bao et al. 2020, Hommes et al. 2008, Hommes, Kopányi-Peuker, and Sonnemans 2021). However, it is important to keep in mind that participants do not know about the upper bound until it is reached. By that time, the price is already more than 15 times higher than the steady-state fundamental value of 60, so we can safely say that a large bubble has formed. In the other four treatments, the upper bound of 1,000 is not reached and hence the dynamics are not affected by this feature of our design. Overall, the upper bound does not matter for our conclusion: large bubbles occur with a weak interest rate rule, but not with a strong rule.

3.2 Quantifying Mispricing and Overvaluation

The figures suggest that mispricing is largest in treatment Weak Rule, followed by Sample Average, No Information, Strong Rule and Communication. We quantify the bubble size in our markets with the Relative Absolute Deviation (RAD) and the Relative Deviation (RD) from the steady-state price $p^* = 60$, adapting the definitions of Stöckl, Huber, and Kirchler (2010):

$$RAD = \frac{1}{50} \sum_{t=1}^{50} \frac{|p_t - p^*|}{p^*}, \tag{5}$$

$$RD = \frac{1}{50} \sum_{t=1}^{50} \frac{p_t - p^*}{p^*}. \tag{6}$$

For example, $RAD = 0.5$ indicates that the price differs on average 50% from the steady state, while $RD = 0.5$ means that the price is on average overvalued by 50%.

Figure 3 shows the empirical cumulative distribution functions of RAD and RD for each treatment. In addition, Table C1 in Online Appendix C includes the values of RAD and RD for each group and the averages per treatment. The above order-

TABLE 2
 p-VALUES OF PAIRWISE TWO-SIDED MWW TESTS FOR RAD AND RD

Pairwise MWW tests for RAD				
	SR	NI	C	SA
WR	0.195	0.195	0.038**	0.279
SR		0.574	0.161	0.279
NI			0.050**	0.574
C				0.021**
Pairwise MWW tests for RD				
	SR	NI	C	SA
WR	0.279	0.442	0.130	0.083*
SR		0.065*	0.279	0.574
NI			0.010**	0.645
C				0.574

NOTE: ** and * indicate significance at the 5% and 10% level, respectively.

ing of treatments is confirmed by our measure of mispricing, the RAD. RD is always smaller than RAD, indicating that there are periods of undervaluation in each market, although the asset is on average overvalued ($RD > 0$) in 30 out of 40 markets. Undervaluation is relatively larger and more common in the Sample Average treatment, where $RD < -0.1$ in three groups (against one group each in treatments Weak Rule and Communication and zero in the other two treatments).

We test if the treatment differences are significant using pairwise two-sided Mann–Whitney–Wilcoxon tests at the 5% level. The null hypothesis is that the RAD or RD of the two groups have the same distribution. Table 2 presents the p -value of all pairwise MWW tests.

Despite the fact that RAD and RD are on average much larger for treatment Weak Rule, the difference in mispricing (as measured by RAD) is only significant compared with treatment Communication. This result suggests that simply implementing a strong interest rate rule is not enough to significantly reduce mispricing, but including communication about the rule is. Comparing the four treatments with a strong interest rate rule, the MWW test indicates that including communication leads to significantly less mispricing than giving no information or using the sample average. However, the differences between treatment Strong Rule and the other treatments are not significant, even though the RAD is on average higher in treatments No Information and Sample Average, and lower in treatment Communication. The low significance of the results could be due to the small sample size (eight markets per treatment) and the heterogeneity in market realizations within treatments, particularly in treatment Weak Rule.

In terms of overpricing (as measured by RD), the only difference that is significant at the 5% level is found between treatments No Information and Communication. Since many markets oscillate around the steady-state price, RD is close to zero in these markets. Therefore, no significant differences in overpricing can be detected between the other treatments.

4. INTEREST RATES

4.1 *Interest Rate Dynamics*

In treatment Weak Rule, the interest rate does not get higher than 6.5%. Clearly, this increase is not big enough to prevent large price bubbles. In the three treatments using the strong-steady state rule (equation (2) with $\phi = 0.1$), the highest realized interest rate is 68.4%. However, rates this high are uncommon: in 96% of the periods, the interest rate is below 20%. Most of the time, an increase to this level is enough to reverse an upward trend and deflate a bubble. Similarly, in the Sample Average treatment (equation (4) with $\phi = 0.1$), the highest realized rate is 50.7%, but the interest rate is below 20% in 93% of the periods. Only in the three markets with medium bubbles, the interest rate is above this level for multiple periods, preventing the bubbles from growing larger.

As can be seen from equation (1), the interest rate affects how much weight is given to next period's price expectations in determining this period's price. The factor $\lambda_t = 1/(1 + r_t)$ is called the feedback strength. The higher the interest rate r_t , the lower the feedback strength λ_t , so the weaker the expectations feedback and the more high prices are being pushed down. In related market experiments, Sonnemans and Tuinstra (2010) and Bao and Hommes (2019) found that markets with a feedback strength of $\lambda = 0.95$ (i.e., $r = 5\%$) are unstable, markets with $\lambda = 0.86$ (i.e., $r = 16\%$) are relatively stable but do not converge, and markets with $\lambda = 0.71$ (i.e., $r = 40\%$) or higher are stable and converge quickly. Our results are in line with these findings. We observe that higher interest rates and, therefore, lower feedback strengths can dampen bubbles and make the market less unstable. However, this does not always lead to convergence because the interest rate is not kept at a high level. In many markets, there still seems to be coordination on destabilizing trend-following expectations, causing persistent price oscillations. This is consistent with the findings of Sonnemans and Tuinstra, who conclude that coordination of expectations appears to be independent of the feedback strength, but convergence is mainly due to the prices being pushed more toward the fundamental value when the feedback strength is low.

By construction, the interest rate can only become zero in the four treatments with a strong interest rate rule.¹¹ The ZLB is reached in 125 out of 1,600 periods (8%). There are differences both across and within treatments. With the steady-state rule, the ZLB is hit when the price drops below 30. This happens most often in treatment Strong Rule (in total 47 times in seven markets), because most markets oscillate around the steady state. In the other two treatments, No Information and Communication, the

11. Of course, we cannot know exactly what prices would have been without a ZLB in place. Nevertheless, we can calculate what the negative interest rate and the corresponding price would have been, assuming that predictions would not have changed. This exercise shows that on average, the negative interest rate would have been -1.6%, and the lowest rate would have been -4.0%. This would have given prices that are on average 0.5 units and at most 4.3 units higher than the realized prices in the experiment, and the differences of more than one unit are all in the Sample Average treatment. We believe that these minor differences would not have changed the price dynamics in the experiment.

ZLB is reached less often because there is either mostly overpricing or the price oscillations are smaller, so that the price is above 30 most of the time. In treatment Sample Average, the ZLB is hit when the price is 50% lower than the sample average price. This happens in total 43 times in six markets, caused by relatively large oscillations and regular low prices.

4.2 Performance of the Sample Average Rule

The sample average rule performs worse than the steady-state rule, simply because the sample average price is generally not a good proxy for the steady-state price. As a result, the interest rate can increase above 5% even though the price is below the steady state, and vice versa. The sample average price starts out too low in all groups of the Sample Average treatment and stays too low in three groups, while it becomes too high in the other five groups. When the sample average price is too low, the sample average rule can reinforce the underpricing by setting an interest rate that is higher than it should be. This often happens in groups 4 and 8, where the price consistently stays below $p^* = 60$. Nevertheless, the sample average rule pushes the price down when there is overpricing. If preventing large bubbles is the main goal of the monetary policy, the sample average rule might be a useful alternative if the steady-state price is not known.

5. INDIVIDUAL EXPECTATIONS

5.1 Expectation Dynamics

Plots of individual predictions in all markets can be found in Online Appendix C. Predictions are quite close to each other most of the time, indicating that there is coordination of expectations. Many participants seem to use trend-following prediction strategies.¹² This leads to some large bubbles in the Weak Rule treatment, but bubbles are dampened in the four treatments with a strong interest rate rule. In stable markets, predictions seem to follow adaptive or naive strategies. Naturally, in markets with higher coordination and more stability, forecasting performance and, therefore, earnings are also better.

Most markets with a strong interest rate response exhibit small price oscillations, typically with the following dynamics. The price displays an upward trend in the beginning and increases above the steady state, so the interest rate is increased above 5%. This pushes the price down and thus flattens the upward trend. Participants lower their predictions in the next period(s) in response, which ultimately reverses the trend. The process repeats itself with both upward and downward trends. The amplitude of the oscillations usually becomes smaller because participants learn to anticipate the trend reversals. Large bubbles are thus prevented, not only because of the direct effect

12. This observation is supported by the questionnaire, in which more than half of the participants describe their strategy as some form of trend following.

of the interest rate on the price, but also because of the indirect effect on expectations. It seems that trend extrapolation becomes less strong, although it continues to cause price oscillations.

While there is generally consensus about future prices, there are also subjects who submit so-called “spoilers”: sudden large and erratic deviations in individual predictions (Sonnemans and Tuinstra 2010). In markets of six, predictions of a single participant have a substantial effect on the price, so these spoilers can change the price dynamics in the experiment. In treatment Weak Rule, three participants in different groups try to bring down the price by submitting a very low prediction. These attempts are unsuccessful in two cases, but two other bubbles in groups 1 and 2 remained smaller due to these low predictions. Treatment Strong Rule, No Information and Communication all have one market where a single spoiler leads to a sudden jump in the price, followed by a jump in predictions of the other subjects in the market, which temporarily destabilizes the market. A small typo in a stable market can also lead to destabilization, which probably happened in group 8 of treatment Weak Rule and group 4 of treatment Strong Rule. Lastly, there are some participants who submit repeated spoilers and, therefore, have a great effect on the price dynamics. In the No Information treatment, one subject in group 5 and two subjects in group 7 cause erratic price patterns with their spoilers. In the Sample Average treatment, repeated spoilers in groups 1, 2, and 6 lead to price peaks and irregular oscillations. However, the general upward trend in groups 1 and 2 suggests that the medium bubbles also would have formed without those outliers, as was the case in group 3.

5.2 Quantifying Coordination

Coordination and average forecasting performance can be quantified by splitting up the quadratic forecast error, averaged over time and individuals:

$$\frac{1}{45} \cdot \frac{1}{6} \sum_{t=6}^{50} \sum_{i=1}^6 (p_{it}^e - p_t)^2 = \frac{1}{45} \cdot \frac{1}{6} \sum_{t=6}^{50} \sum_{i=1}^6 (p_{it}^e - \bar{p}_t^e)^2 + \frac{1}{45} \sum_{t=6}^{50} (\bar{p}_t^e - p_t)^2, (7)$$

where $\bar{p}_t^e = 1/6 * \sum_{i=1}^6 p_{it}^e$ is the average prediction for period t . The first five periods are omitted to allow for some learning. The first term is called the average dispersion error, which is relatively small if there is coordination of expectations. The second term is called the average common error, which is relatively small if expectations are approximately correct in the aggregate, in line with Muth's (1961) formulation of the rational expectations hypothesis.

Figure 4 plots the empirical cumulative distribution functions of the average individual quadratic forecast error and the percentage of the average dispersion error for each treatment. Obviously, errors are larger in markets with large or medium bubbles, and spoilers also lead to more errors. This is directly reflected in the earnings of the participants, since these are based on the quadratic forecast error as well. In terms of percentages, the average dispersion error is usually lower than the average common error. This indicates that there is coordination, despite being on the

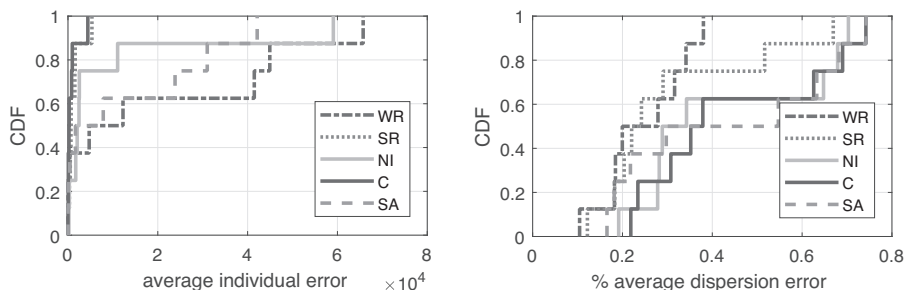


Fig. 4. Empirical Cumulative Distribution Functions of Average Individual Quadratic Forecast Errors (left) and Percentages of Average Dispersion Error (Right).

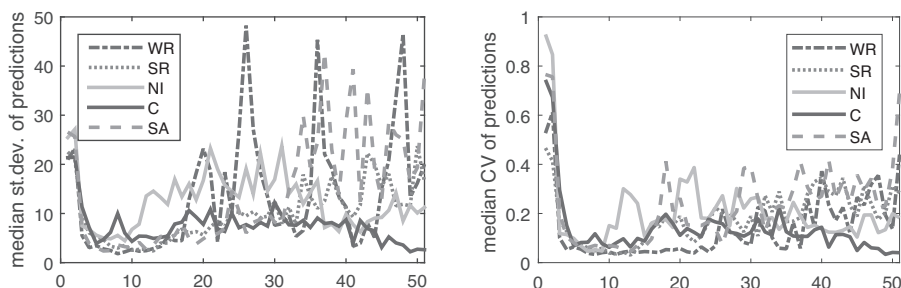


Fig. 5. Time Series of Median Standard Deviation of Predictions (Left) and Median Coefficient of Variation of Predictions (Right).

wrong price. Forecast errors generally do not cancel out at the aggregate level, so expectations cannot be called rational in the sense of Muth (1961).

The average dispersion error in absolute terms is on average higher in the No Information treatment than in the Strong Rule treatment. On the other hand, treatment Strong Rule and Communication are comparable in terms of average dispersion errors. These results suggest that coordination is less strong without providing information about interest rate changes, but providing communication about the interest rate rule does not make coordination stronger. However, pairwise MWW tests indicate that only the difference between treatment No Information and Communication is statistically significant (p -value = 0.028), not the differences with treatment Strong Rule.

Note that the average dispersion error is equal to the population variance of individual predictions, averaged over time. We take a closer look at coordination by instead considering the sample standard deviation of predictions in each period of each market. This measure is expressed in the same units as the predictions and gives us insight into the dynamics of coordination. The time series of the median standard deviation of predictions in each treatment is shown in the left panel of Figure 5.

All treatments show a sharp drop in heterogeneity of expectations after the first two periods, indicating that participants use the market price as a coordination device. Coordination is generally strong in the beginning, but breaks when large or medium bubbles form or when spoilers are submitted. For this reason, heterogeneity is often larger in treatment Weak Rule, No Information and Sample Average. In the Strong Rule treatment, the median standard deviation of predictions increases toward the end of the experiment, which reflects the persistent oscillations in most markets of this treatment. By contrast, heterogeneity decreases over time in the Communication treatment, reflecting the dampening oscillations or convergence in this treatment.

The right panel of Figure 5 displays the median coefficient of variation (CV) of predictions over time. The CV is defined as the ratio of the standard deviation to the mean of predictions and can thus be interpreted as a measure for the relative heterogeneity in expectations. The time series of the CV also illustrate the sharp drop in heterogeneity in the beginning of all treatments. The Weak Rule treatment shows a relatively low value of the CV, especially in the first half of the experiment. This suggests that the first large bubbles in these markets are caused by relatively strong coordination of expectations. In the Strong Rule, No Information and Sample Average treatments, heterogeneity is relatively high, reflecting that expectations and prices do not completely stabilize in most markets. The CV again reveals an increase in coordination toward the end in the Communication treatment.

Looking at both mispricing and coordination and comparing the three treatments with differences in information for participants, it seems that giving more information is helpful. We observe that markets are less stable and coordination is less strong in treatment No Information, where there is no signaling effect of the interest rate. On the other hand, markets are slightly more stable in treatment Communication, where the signaling effect is more pronounced because of the extra information about the policy. The signal given by the interest rate thus seems to aid coordination and stabilization, although the results are somewhat noisy.

5.3 Estimating Prediction Strategies

To further analyze the prediction strategies that participants use, we start by estimating a general specification for each individual i :¹³

$$p_{i,t+1}^e = \alpha + \sum_{k=1}^4 \beta_k p_{t-k} + \sum_{l=0}^3 \gamma_l p_{i,t-l}^e + u_t. \quad (8)$$

We regress the individual predictions on a constant, the last four observations of the market price and the last four own predictions. To allow for a short learning phase, the forecasting rule is estimated from period $t = 5$. We then delete the least significant

13. The forecasting rule is estimated after removing outliers, that is, predictions that differ substantially from what would be expected from the general pattern. A total of 13 outliers, all for different participants, were removed by linear interpolation (0.1% of all predictions).

TABLE 3
MAIN RESULTS OF ESTIMATED FORECASTING RULES

	WR	SR	NI	C	SA	Overall
% successful	96%	85%	94%	81%	90%	89%
Mean adjusted R^2	0.87	0.76	0.68	0.69	0.73	0.75
% used (nonzero coeff.)						
β_1	89%	83%	89%	79%	79%	84%
β_2	76%	68%	76%	79%	60%	72%
β_3	46%	46%	58%	54%	42%	49%
β_4	28%	37%	40%	54%	35%	38%
γ_0	41%	39%	29%	46%	53%	42%
γ_1	35%	32%	24%	28%	28%	29%
γ_2	33%	24%	16%	21%	9%	21%
γ_3	24%	29%	13%	10%	28%	21%
Mean coefficient						
α	38.88	22.75	23.56	26.05	20.60	26.56
β_1	1.88	1.69	1.76	1.51	1.65	1.71
β_2	-1.39	-1.33	-1.22	-1.21	-1.23	-1.28
β_3	0.68	0.58	-0.02	0.65	0.37	0.43
β_4	-0.48	-0.56	0.35	-0.36	-0.05	-0.20
γ_0	0.32	0.36	0.31	0.59	0.46	0.42
γ_1	-0.46	-0.40	-0.34	-0.25	-0.44	-0.39
γ_2	0.07	0.31	0.56	0.03	-0.02	0.19
γ_3	0.27	0.09	-0.45	0.00	0.02	0.03

regressors one by one, until all remaining regressors are significant at the 5% level. We call the estimation successful if there is no autocorrelation in the residuals of the final rule (Breusch–Godfrey test, two lags).

Table 3 presents the main estimation results per treatment and overall: the percentage of successful rules, the mean value of the adjusted R^2 , the percentage of subjects using each regressor, and the mean value of all nonzero coefficients for each regressor. In total, 214 out of 240 rules (89%) are successfully estimated. Of those successful estimations, the adjusted R^2 is generally quite high, indicating that the estimated forecasting rules provide a good fit.

In all treatments, the last observation of the market price (p_{t-1}) is the most important regressor: 79–89% of the participants use this variable in their forecasting rule. A large majority (60–79%) also considers p_{t-2} . The corresponding coefficient β_2 is almost always negative (with just four exceptions), indicating trend-following behavior. The last own prediction (p_t^e) is also an important regressor, used by 29–53% of the subjects. These three regressors form the basis of benchmark heuristics, such as adaptive, trend-following, and anchoring and adjustment rules. The estimation results confirm the key role of these variables, but also indicate that many participants use more sophisticated forecasting rules, involving higher lags of prices and predictions.

The effect of the interest rate on predictions cannot be easily identified, since the interest rate rule makes r_t perfectly correlated with p_{t-1} . Recall that participants in treatment No Information do not know anything about the interest rate changes. We can compare this treatment to the Strong Rule treatment, where participants do know the current and past interest rates, and to the Communication treatment, where partic-

ipants additionally receive information about the goal of the policy. Pairwise MWW tests only find a significant difference in γ_0 between treatments No Information and Communication (p -value = 0.040). The insignificance of the differences in coefficients suggests that participants do not change their prediction strategy if they know about the interest rate changes. However, this conclusion is not in line with the questionnaire, where 122 out of 192 participants (64%) state that the interest rate affected their strategy in some way. While a few participants correctly interpret an interest rate above 5% as a signal that the price is too high, the questionnaire also reveals several misunderstandings of the interest rate rule. For example, 17 participants indicate that they increased their predictions after an interest rate increase. This is not the desired response, as it reinforces trend chasing and has a destabilizing effect on prices.

6. CONCLUSION

We study the effect of monetary policy on asset price bubbles in a learning-to-forecast experiment, where prices are driven by the expectations of participants in the asset market. Our “leaning against the wind” Taylor-type policy rule sets the interest rate in response to relative deviations from the steady-state price. The success of the policy crucially depends on individual expectations: a rational bubble grows faster after an interest rate increase, but bubbles caused by boundedly rational expectations might be managed or even prevented.

We find that a weak policy response is not able to prevent large price bubbles, since destabilizing trend-following expectations are too strong. By contrast, large bubbles do not occur in any of our four treatments with a strong interest rate response. Most of the time, an interest rate increase up to 20% is enough to stop the formation of a bubble. Yet, most markets are not completely stabilized. While an interest rate increase pushes the price down and thus dampens a bubble, there is often still coordination on trend-following expectations, causing persistent price oscillations.

In our baseline setting, current and past interest rates are known. To remove the signaling effect of the interest rate, we conduct a treatment where we do not inform participants about the interest rate changes. Price patterns are more erratic and the absence of the signaling effect seems to decrease coordination. On the other hand, when we communicate the goal of the policy, markets are slightly more stable.

The steady-state fundamental price of an asset may be unknown. When we base the interest rate on the sample average price instead, the results are mixed: markets exhibit medium sized bubbles, small price oscillations, or persistent underpricing. The policy is less effective because the sample average price is usually not a good proxy for the steady state. As a result, underpricing can be reinforced. Nonetheless, the sample average rule pushes the price down in a bubble and might, therefore, be a useful alternative for the steady-state rule. It seems likely that the policy would work better if the central bank would have more information to estimate the fundamental, so that the policy rule can be improved.

The bubbles in our experiment are not based on rational expectations. Regressions show that many participants use the last two observations of the market price and the last own prediction to form new predictions. This is in line with benchmark heuristics, such as adaptive, trend-following, and anchoring and adjustment rules. Many prediction strategies have a trend-following component. Most participants pay attention to the interest rate changes, but they do not seem to adapt their strategies in a significant way.

Our experimental results suggest that a strong interest rate rule is successful in deflating large price bubbles. Even though the policy cannot always prevent coordination on destabilizing trend-following expectations, it can substantially dampen price oscillations. Communicating the goal of the policy is necessary to significantly decrease mispricing and increase coordination. There seems to be room for improvement by explaining the policy to market participants more carefully, so that interest rate changes are not misunderstood and expectations can be managed even more. It would also be interesting to study whether adding communication to a weak rule or a sample average rule would help to stabilize markets.

An argument that is often raised against a monetary policy response to asset prices is that deflating a bubble is likely to have negative side effects on the economy. Our partial equilibrium asset pricing model disregards important economic variables, such as inflation and output. It is possible that an interest rate policy successfully stabilizes asset markets, but harms other parts of the economy. Embedding an asset market in a general equilibrium framework to experimentally study the effects of monetary policy on bubbles in a more realistic setting is an important topic for future work. One suggestion would be to implement the production economy of Fenig, Mileva, and Petersen (2018) as a learning-to-forecast experiment, where subjects submit expectations but other decisions are optimized by the computer. This would bridge the gap between our study and the study of Fenig, Mileva, and Petersen by making it possible to focus on the role of expectations in a general equilibrium setting. Another option would be to design an experiment using a New Keynesian framework with an asset market. Since the New Keynesian model is widely used by central banks for policy analysis, this would be an interesting framework to study as well.

An additional opportunity for further research is to extend our setting to include trading decisions. Our learning-to-forecast design assumes that agents trade optimally given their expectations. The implications of this assumption are addressed in so-called learning-to-optimize experiments, where subjects need to decide how many assets to buy or sell and are paid based on realized profits. Bao, Hommes, and Makarewicz (2017) show that bubbles are even larger in a learning-to-optimize setting compared to a learning-to-forecast setting—bubble formation is thus a robust feature of markets with positive feedback. Studying whether monetary policy can stabilize bubbles in a learning-to-optimize asset market experiment would be a fruitful next step.

Our present experiment is a first step in gaining insight in how individual expectations and asset prices interact with interest rate policy in a simple environment. Our results could help disentangle the effects in a more complex setting by providing a

baseline for the effect of the policy on expectations and asset prices without any interaction with other economic variables. We believe that further experimental research would be valuable, so that the various approaches to study the effects of monetary policy in asset markets can complement each other and advance the literature on this topic.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Figure A1: Simulations of rational bubbles

Figure A2: Simulations with homogeneous expectations

Table C1: Summary statistics

Figure C1: Market prices, predictions, and interest rates in treatment Weak Rule

Figure C2: Market prices, predictions, and interest rates in treatment Strong Rule

Figure C3: Market prices, predictions, and interest rates in treatment No Information

Figure C4: Market prices, predictions, and interest rates in treatment Communication

Figure C5: Market prices, predictions, and interest rates in treatment Sample Average