

Experiences and expectations in asset markets: an experimental study

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Abstract

This paper presents experimental evidence that experienced price patterns in asset markets have a large impact on expectations and thereby affect the (de)stabilization of asset prices in the future. In a controlled learning-to-forecast experiment, subjects first experience a stable or a bubbly asset market before entering into a same- or mixed-experience market. In markets where all subjects experienced stability, convergence to the fundamental price is faster. Bubble formation is faster in markets where all subjects experienced bubbles. In mixed-experience markets, dynamics can go both ways: prices either stabilize or destabilize. Heterogeneity in expectations is larger when more subjects have experienced bubbles before.

JEL codes: C92, D84, G12, G41

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1 Introduction

Personal experiences shape expectations in asset markets and can therefore affect future market dynamics. I demonstrate that experiences with price stability or bubbles play a key role in the (de)stabilization of asset markets in a laboratory experiment. In my experiment, subjects gain experience in a stable or a bubbly market, before entering into a same- or mixed-experience market. The experimental approach complements empirical studies by providing a controlled environment. This control makes it possible to induce and mix experiences, observe individual expectations and market dynamics, and gain insight in how experiences affect individual and aggregate behavior.

A growing body of empirical literature, including the influential studies of Malmendier and Nagel (2011, 2016), states that personal experiences affect expectations about asset prices and returns, inflation and house prices, and investment decisions for stocks, bonds, IPOs, mortgages and savings.¹ Investors put more weight on personal experiences than on other available historical data. For example, experiencing high returns leads to optimism about future prices and an increase in investments, particularly among younger individuals. With this trend-chasing behavior, inexperienced investors contributed to the formation of the technology stock bubble in 1997–2000 and the US housing bubble in 2003–2007 (Chernenko et al., 2016; Greenwood and Nagel, 2009).

The role of experience in asset markets has also been studied experimentally. In trading experiments using the design of Smith et al. (1988), experience almost always eliminates bubbles if the market environment stays constant.² Haruvy et al. (2007) show that convergence to fundamental values occurs because expectations are updated adaptively. Experienced subjects seem to play a best response under the assumption that other subjects behave the same as in the previous round.³

¹Studies examining experience effects in stock markets are Ampudia and Ehrmann (2017); Chernenko et al. (2016); Cordes and Dierkes (2017); Greenwood and Nagel (2009); Hoffmann et al. (2017); Hoffmann and Post (2017); Malmendier and Nagel (2011); Nagel (2012); Strahilevitz et al. (2011) and Vissing-Jorgensen (2003). Anagol et al. (2018); Chiang et al. (2011) and Kaustia and Knüpfer (2008) focus on IPOs. Fajardo and Dantas (2018); Madeira and Zafar (2015); Malmendier and Nagel (2016) and Malmendier et al. (2017) consider inflation, Kuchler and Zafar (2019) and Malmendier and Steiny (2017) investigate the housing market and Choi et al. (2009) study 401(k) savings.

²Bubbles are eliminated with experience in Haruvy et al. (2007); King (1991); King et al. (1993); Smith et al. (1988) and Van Boening et al. (1993). Hussam et al. (2008) show that bubbles can be rekindled with experienced subjects when the market is shocked with an increase in liquidity and dividend uncertainty. The admission of inexperienced subjects can also rekindle bubbles, but these bubbles are usually smaller because experienced subjects act as price stabilizers (Akiyama et al., 2014; Dufwenberg et al., 2005; Kirchler et al., 2015; Xie and Zhang, 2012). Counterexamples of the result that experience eliminates bubbles are found by Hong et al. (2018); Kopányi-Peucker and Weber (2018) and Oechssler et al. (2011).

³Similar behavior is observed in beauty contest games: experienced players anticipate the

In the market setting of Smith et al. (1988), such a trading strategy mitigates bubbles. By contrast, Kopányi-Peuker and Weber (2018) show that stationary repetition does not eliminate bubbles in an asset market learning-to-forecast experiment. They observe that bubbles emerge even faster in the second and third repetition, but do not analyze the role of experience in detail.

To learn more about the effect of experiences in asset markets, I conduct a learning-to-forecast experiment that induces and mixes experiences. My experimental design builds on Hommes et al. (2005, 2008). Subjects predict the price of an asset, which in turn depends positively on the average price forecast of all traders in the market. As in real world asset markets, price bubbles occur in this setting when subjects exhibit strong trend-extrapolating behavior.⁴ In the first stage of my experiment, each subject is paired with five robots that make predetermined predictions, to ensure that subjects have very similar experiences. Two typical price patterns from previous learning-to-forecast experiments are considered: a stable market with small, dampening oscillations that converge to the fundamental price, and a bubbly market with two large price bubbles and crashes. In the second stage, markets are formed with six subjects who either all have the same experience (stable or bubbly) or an equal mix of experiences, without informing them about this composition.

If all subjects act rationally in stage 2, they should all predict the fundamental price – accurately predicting bubbles is difficult and usually leads to large forecast errors and low earnings. Nevertheless, the experienced price patterns in the first stage have a large effect on expectations and price dynamics in the second stage. In markets where all subjects experienced stability, convergence is faster even though the fundamental price is slightly changed. Bubble formation is faster in markets where all subjects experienced bubbles. In mixed-experience markets, dynamics can go both ways: prices stabilize in five markets and destabilize in three markets. Markets are more unstable and heterogeneity in expectations is larger when more subjects have experienced bubbles before. An analysis of the individual prediction strategies suggests that many subjects use trend-following or anchoring and adjustment rules. Subjects in stable-experience markets generally learn to put more weight on the fundamental value, whereas subjects in bubbly-experience markets have heterogeneous expectations that cannot always be captured by sim-

choices of their inexperienced opponents and play a best response (Skeath and Livingston, 2010; Slonim, 2005).

⁴Large bubbles driven by trend-following expectations are found in the asset market learning-to-forecast experiments of Bao et al. (2020), Hennequin and Hommes (2019) and Hommes et al. (2005, 2008, 2018). The empirical literature also provides ample evidence of trend extrapolation by investors, potentially contributing to bubble formation (see e.g. Barberis et al., 2018; Greenwood and Shleifer, 2014; Hirshleifer, 2001; Shiller, 2002; Shleifer and Summers, 1990).

ple heuristics. The tendency of subjects to extrapolate trends might contribute to the stabilization or destabilization in mixed-experience markets.

My experiment differs from the repeated learning-to-forecast experiment of Kopányi-Peucker and Weber (2018) in three main respects. First, I induce either a stable or a bubbly experience, such that the effect of both sorts of experiences can be studied.⁵ Second, I form mixed-experience markets in addition to same-experience markets. Third, unlike stationary repetition, the fundamental price is not the same in the two stages of the experiment and subjects do not know about the experiences of others in the market. While several asset trading experiments consider markets with a mix of experienced and inexperienced subjects (Akiyama et al., 2014; Dufwenberg et al., 2005; Kirchler et al., 2015; Xie and Zhang, 2012), inducing and mixing different experiences has not been done in this type of experiments either.

Altogether, my experiment sheds new light on the effect of experience on individual expectations and market dynamics. My results show that expectations of future prices are strongly affected by experiences with price stability or bubbles. This experimental evidence supports the findings of Malmendier and Nagel (2011, 2016) and other empirical studies. Furthermore, my study demonstrates that experience can both have a stabilizing and a destabilizing effect in asset markets, which contrasts the results of experiments using the design of Smith et al. (1988). When the setting is more complex than their simple market with a short-lived asset, experiencing bubbles can thus lead to new bubble formation.

2 Experimental design

2.1 Two-stage asset market experiment

The general design of the experiment is based on the asset market learning-to-forecast experiment of Hommes et al. (2008). Six traders interact in a simple asset market. In each period t , they can invest in an infinitely lived risky asset paying an i.i.d. dividend y_t with mean \bar{y} , or a risk-free asset paying a fixed interest rate $r = 5\%$. Consequently, the risky asset has a constant fundamental value of $p^f = \bar{y}/r$. Given their expected price of the risky asset in the next period,

⁵Lejarraga et al. (2016) and Safford et al. (2018) also induce experiences of booms or crashes in the lab, but they study behavior in an experimental investment task where subjects repeatedly allocate a portfolio between a risky and a risk-free asset. Subjects who experienced a crash allocate less of their portfolio to the risky asset, expect that future returns on the risky asset will be lower, and increase their belief that another market crash is possible. Using the same type of experiment, Gong et al. (2013) find that real asset market experiences have an impact as well: subjects who personally experienced a boom in the Shanghai Stock Exchange make bigger trades and hold more shares than cash, as opposed to subjects who experienced a crash.

$E_{it}(p_{t+1}) = p_{i,t+1}^e$, traders calculate their optimal demand for shares using myopic mean-variance optimization. The market price is determined by the equilibrium between demand and supply:

$$p_t = \frac{1}{1+r} \left[\frac{1}{6} \sum_{i=1}^6 p_{i,t+1}^e + \bar{y} \right]. \quad (1)$$

The price of the risky asset thus depends positively on the average price prediction for the next period of all traders in the market. A detailed derivation of Equation (1) can be found in Appendix A.

In the experiment, traders are large pension funds, and subjects have the role of financial advisors. Appendix B provides the full instructions. Subjects first get instructions for the first stage, knowing that a second stage will follow. Most information is the same for both stages: subjects get qualitative information about the asset market and their role. Their only task is to predict the price of the risky asset in the next period for 36 consecutive periods in each stage. The market price is then determined by Equation (1), although subjects are not informed about this equation. Subjects earn points for their prediction accuracy, as measured by the quadratic forecast error:

$$e_{it} = \max \left\{ 1300 - \frac{1300}{49} (p_t - p_{it}^e)^2, 0 \right\}. \quad (2)$$

The total number of points earned in stage 1 and 2 is converted into euros using an exchange rate of €1 per 2000 points. In addition, subjects receive a fixed participation fee of €10.

In stage 2, the pension funds invest in a different asset than in stage 1. This is reflected in a slightly different value of the mean dividend \bar{y} and thus in a slightly different fundamental price $p^f = \bar{y}/r$. The change in fundamentals makes sure that learning is not too simple in stage 2, especially when a stable experience is induced in stage 1. However, I keep the difference in fundamentals small to avoid that markets destabilize because the shock in fundamentals is too big. In each treatment, half of the markets have a fundamental of $p^f = 62$ in stage 1 and $p^f = 68$ in stage 2, and vice versa for the other half. By having both an increase and a decrease in fundamentals, it is easier to see if the change in fundamentals affects the results. If this is not the case, then the two types of markets in each treatment can be pooled in the data analysis.

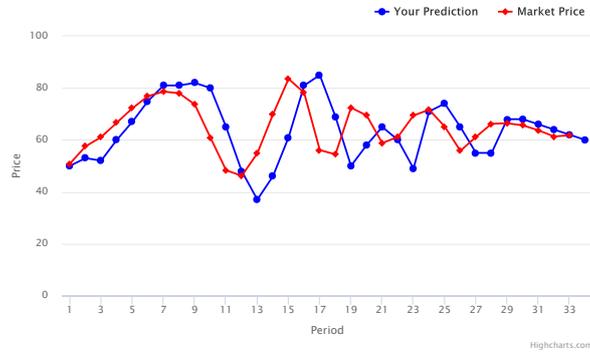
The fundamental price is not given in the instructions, but subjects are informed about the interest rate $r = 5\%$ and the value of the mean dividend \bar{y} (which equals either 3.1 or 3.4, depending on the market and the stage). This information makes

Prediction

This is period 34. The risk-free interest rate is 5% and the mean dividend of the stock is 3.4.

What is your prediction for the price in the next period?

Next



Total Earnings (Part 1):

Period	Your Prediction	Market Price	Earnings
34	60.00		
33	62.00	61.81	1299.04
32	64.00	61.33	1111.34
31	66.00	63.71	1161.39
30	68.00	65.62	1149.60
29	68.00	66.41	1233.16
28	55.00	66.25	0.00
27	55.00	61.17	288.50
26	65.00	55.78	0.00
25	74.00	65.14	0.00
24	71.00	71.65	1288.76

Figure 1: Example of the screen that subjects see during the prediction task

it possible to calculate the fundamental price. Still, even if subjects do not calculate the fundamentals, the instructions make clear that the markets in stage 1 and 2 are not completely the same.

Subjects know that there are five other pension funds active in the asset market. In the first stage, they are told that the other pension funds make use of computer traders with a trading strategy based on a previous experimental asset market. In the second stage, they learn that each pension fund is now advised by a subject of the experiment. The instructions mention that other subjects may have encountered the same or different computer traders in stage 1. Yet, subjects do not know the trading strategies of the computer traders or the experiences of the other subjects.

The instructions are available on the computer screen throughout the entire experiment. Understanding is checked with a number of control questions before subjects can proceed with the prediction task. In the first two periods of the prediction task, there is no information about past prices, but the instructions indicate that it is very likely that the first two prices will be between 0 and 100. In the subsequent periods, subjects see a computer screen as in Figure 1. It shows a graph of past prices up to the previous period and their own predictions up to the current period. It also includes a table with prices, predictions and earnings in each period, and total earnings so far. Furthermore, the value of the mean dividend \bar{y} and the interest rate r are indicated. Subjects have to submit a price prediction for the next period (i.e. a two-period-ahead prediction) for 36 periods.

When subjects reach the second stage, they are informed about the new asset with the corresponding mean dividend value \bar{y} , and the presence of other subjects in the market instead of computer traders. A control question checks their understanding of these two changes before continuing with stage 2 of the prediction task. After completing the two prediction stages of the experiment, subjects fill in a short questionnaire, which includes demographic information as well as open questions about their forecasting strategy.

2.2 Robots in stage 1

In the first stage of the experiment, markets consist of one subject and five robots (i.e. computer traders). The predictions of the robots are based on human behavior in the first 36 periods of a previous asset market learning-to-forecast experiment. Two markets with price patterns that typically occur in this type of experiment are considered: a stable market with small, dampening oscillations that converge to the fundamental, and a bubbly market with two large bubbles and crashes.⁶ The predictions of subjects 2–6 in these markets are taken and adjusted to match the fundamental price in stage 1 of this experiment.⁷

Figure 2 shows the predictions of the five robots and the price patterns that they generate. In my experiment, the robots' predictions have a total weight of $\frac{5}{6}$ in the the market price (Equation (1)), while the subject's prediction has a weight of $\frac{1}{6}$. Hence, the experience of subjects in stage 1 depends on their own predictions, but the price pattern will look very similar to the stable or bubbly pattern that the robots generate, so that subjects have comparable experiences.⁸

In the previous learning-to-forecast experiment, the large bubbles crashed because there was an upper bound on predictions of 1000. In this experiment, I increase this upper bound to 2000. Subjects do not know about the upper bound beforehand, but they receive a message when they try to enter a prediction above

⁶The markets are taken from Hennequin and Hommes (2019). Group 8 in treatment Communication is the stable market and group 4 in treatment Weak Rule is the bubbly market. Similar price patterns can also be observed in other groups and in other asset market learning-to-forecast experiments.

⁷The fundamental in Hennequin and Hommes (2019) is $p^f = 60$, so all predictions are increased by either 2 or 8 units. This ensures that the price pattern remains the same, but the stable market converges to the fundamental of $p^f = 62$ or $p^f = 68$.

⁸A difference between a market with one subject and five robots and a market with six subjects is that the robots do not react to the subject's predictions. If a subject makes a typo or an outlier prediction in a market with robots, this has a direct effect on the price in the current period, but it does not change the overall price pattern. In a market with human subjects, a sudden price change caused by one subject might have an indirect effect on the predictions of other subjects, so that it could change the market dynamics. For example, a stable market with six subjects might be destabilized after a single typo, but this cannot happen in a market with robots.

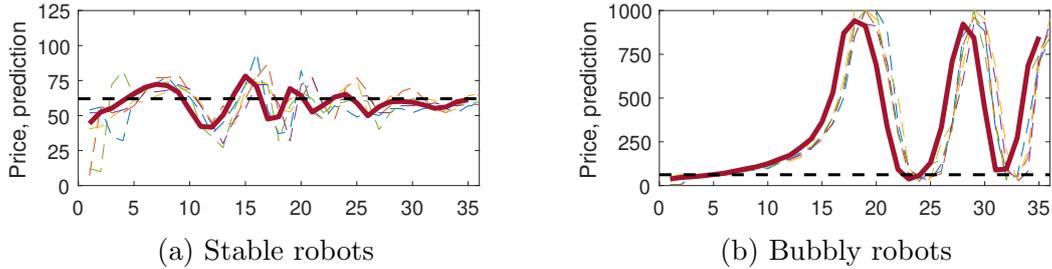


Figure 2: Price patterns generated by robots in stage 1

Notes: The colored dashed lines are the predictions of the five robots, the solid line is the price pattern that they generate. The black dashed line indicates the fundamental price of $p^f = 62$ (this holds for half of the markets – for the other half, all lines are shifted upwards to match the fundamental of $p^f = 68$).

2000. Even if a subject submits the maximum prediction in stage 1 at the peak of the bubble, the robots ensure that the price does not become higher than 1100. The increased upper bound gives the opportunity to see if bubbles grow larger in stage 2, and if there is a crash before the upper bound is reached.

2.3 Treatments in stage 2

In the second stage of the experiment, markets are formed with six experienced subjects. I consider three treatments: all subjects have a stable experience (treatment 6S), all subjects have a bubbly experience (treatment 6B), or three subjects have a stable experience and three subjects have a bubbly experience (treatment 3S3B). The composition is not known to the subjects. The market setting in this stage is essentially the same as in Hommes et al. (2008), except for the increased upper bound on predictions and the experiences of the subjects.

If all subjects act rationally in stage 2, they should predict the fundamental price and achieve maximal earnings. Accurately predicting price bubbles is much harder and usually leads to large forecast errors and low earnings. It is possible that entering into a new market with new traders gives subjects the opportunity to “start over” and discard suboptimal forecasting strategies that they might have experimented with in the beginning. If all experiences lead to more rationality, this would manifest in more stability in stage 2 in all treatments. Another possibility is that subjects (initially) expect the same price pattern as in the market they just experienced and play a best response, similar to the observation of Haruvy et al. (2007). This could lead to faster convergence in treatment 6S and faster bubble formation in treatment 6B.⁹ In treatment 3S3B, the dynamics could go

⁹Assuming that other traders behave the same as in the previous market, it is optimal for a subject to be one step ahead of the others and predict a price close to the predictions of others *in the next period*, since prices depend on next period’s predictions. Therefore, the best response to the stable experience is to predict earlier trend reversals, leading to faster convergence, and the

both ways: some subjects will need to adjust their initial expectations of the price pattern. Hence, a mixed-experience market could become stable when subjects who initially expect bubbles change their strategy, or it could become bubbly when subjects who initially expect stability change their strategy. If different experiences affect expectations differently, this would lead to distinctions in market dynamics in treatments 6S, 6B and 3S3B.

2.4 Implementation

The experiment took place in the CREED laboratory at the University of Amsterdam in May and June 2018. I programmed the experiment in oTree (Chen et al., 2016). I conducted eight markets per treatment, giving a total of 144 subjects (mostly students in economics or social sciences).¹⁰ A session lasted for about two hours in total. Earnings were on average €21.63 and ranged from €10 to €40.90, including the participation fee of €10.

3 Experimental results

3.1 Market dynamics

Figure 3 shows the prices and predictions of all subjects in stage 1, plotted separately for the two experiences (stable or bubbly) and the two fundamentals ($p^f = 62$ or $p^f = 68$). Subjects indeed have very similar experiences: each panel includes 36 subjects, but the solid lines representing the realized prices are close together. A small number of extreme predictions in the bubbly markets cause kinks in the price pattern for these subjects. Nevertheless, all subjects experienced either small, dampening oscillations or large bubbles and crashes.

The prices and predictions in each market in stage 2 are shown in Figure 4 (treatment 6S), Figure 5 (treatment 6B) and Figure 6 (treatment 3S3B). Clearly, the experienced price patterns in stage 1 have a large effect on the market dynamics in stage 2. All markets in treatment 6S have stable prices, whereas all markets in

best response to the bubbly experience is to predict faster price increases and decreases, leading to faster bubble formation.

¹⁰Since I am investigating the role of experience, I recruited at first from a pool of subjects who did not participate in closely related asset market learning-to-forecast experiments. However, this led to a shortage of subjects – only fourteen markets could be formed. Furthermore, a majority of these subjects (56%) indicated they had participated in learning-to-forecast experiments before (but most likely in different market settings). Therefore, I dropped the exclusion criteria for the last ten markets (group 7–8 in 6S, group 7–8 in 6B, and group 3–8 in 3S3B). I am confident that this did not change the results, since there are no significant differences between the markets with or without exclusion criteria. The experience induced in stage 1 of this experiment is more salient and relevant than previous experiences in different experiments.

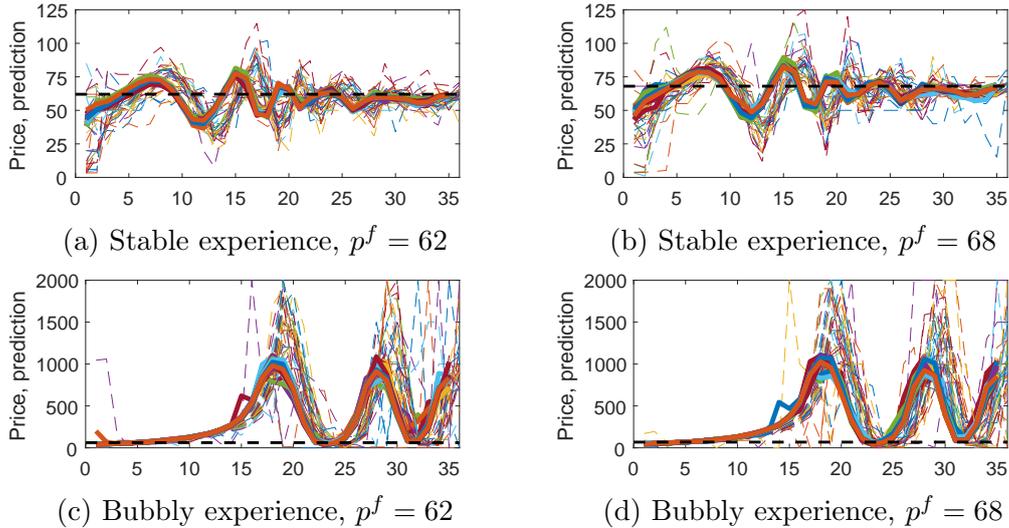


Figure 3: Market prices and predictions of all subjects in stage 1

Notes: The colored dashed lines are the predictions of subjects, the colored solid lines are the realized prices. The dashed black line indicates the fundamental price. The upper bound on predictions is 2000. Shown in (a) are all subjects in group 1, 3, 5 and 7 of treatment 6S and subjects 1–3 in group 1, 3, 5 and 7 of treatment 3S3B. Shown in (b) are all subjects in group 2, 4, 6 and 8 of treatment 6S and subjects 1–3 in group 2, 4, 6 and 8 of treatment 3S3B. Shown in (c) are all subjects in group 1, 3, 5 and 7 of treatment 6B and subjects 4–6 in group 1, 3, 5 and 7 of treatment 3S3B. Shown in (d) are all subjects in group 2, 4, 6 and 8 of treatment 6B and subjects 4–6 in group 2, 4, 6 and 8 of treatment 3S3B.

treatment 6B exhibit large bubbles. Treatment 3S3B shows mixed results: four markets are stable with prices remaining close to the fundamental, one market is relatively stable around a price that is about two times too high, and three markets show large bubbles with prices exceeding twenty times the fundamental. Experience thus plays a role in the (de)stabilization of asset markets.

In treatment 6S, oscillations are generally even smaller than in stage 1. Five of the eight markets converge to the new fundamental. This is remarkable, since most subjects do not know how to calculate the fundamental price.¹¹ Yet, instead of simply repeating the same equilibrium that they have seen in stage 1, they were able to learn the new equilibrium. Not all markets managed to do this: groups 1 and 7 exhibit prices that remain too low after the increase in fundamental, while group 4 exhibits prices that remain too high after the decrease in fundamental. In each of these three markets, there is one subject trying to coordinate on a round number (50 in the former two cases, 70 in the latter case), preventing the price from getting closer to the fundamental. Once the price stabilizes not too far from the fundamental, earnings are relatively high already, so the incentives to get closer to the fundamental are not very strong. This could explain why not all groups fully converge.

¹¹Subjects were asked in the questionnaire if they know the fundamental value of an infinitely lived asset with a mean dividend of D (for example $D = 3.1$) and an interest rate of 5%. The correct answer is given by 16% of the subjects, but a large majority (84%) does not know.

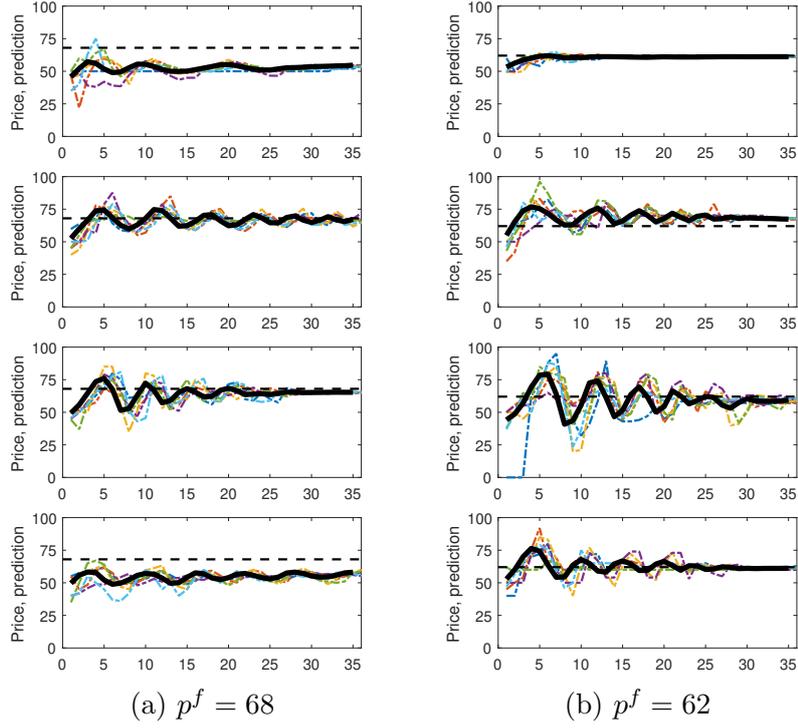


Figure 4: Market prices and predictions in stage 2, treatment 6S
 The solid black line is the market price, the colored lines are the individual predictions. The dashed black line indicates the fundamental price. Odd-numbered groups have $p^f = 68$, even-numbered groups have $p^f = 62$.

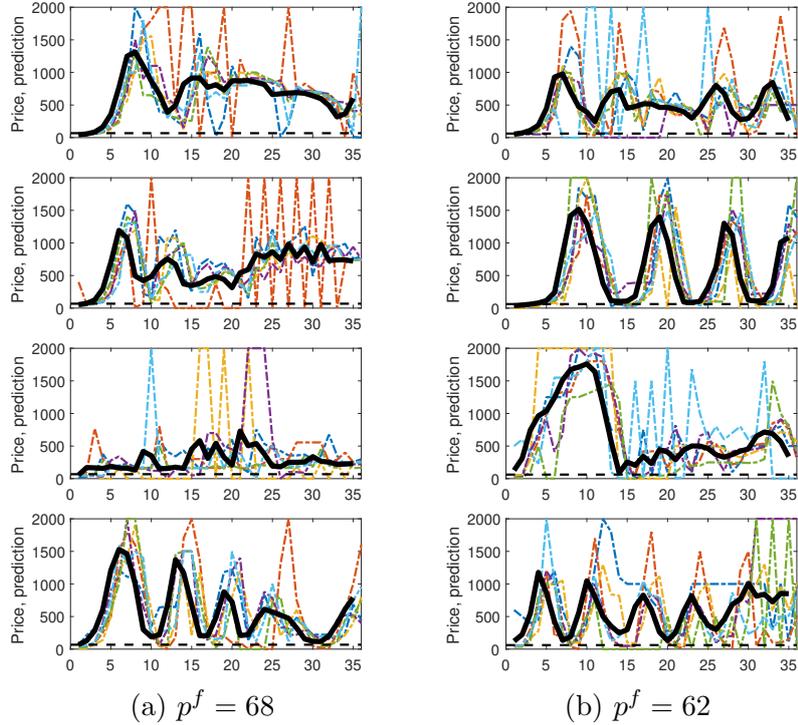


Figure 5: Market prices and predictions in stage 2, treatment 6B
 The solid black line is the market price, the colored lines are the individual predictions. The dashed black line indicates the fundamental price. Odd-numbered groups have $p^f = 68$, even-numbered groups have $p^f = 62$. The upper bound on predictions is 2000.

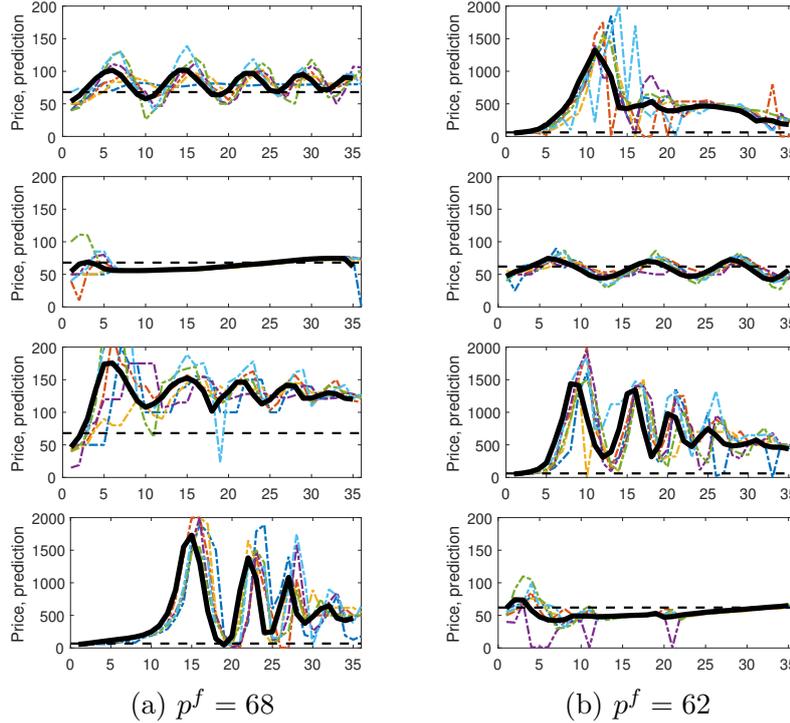


Figure 6: Market prices and predictions in stage 2, treatment 3S3B. The solid black line is the market price, the colored lines are the individual predictions. The dashed black line indicates the fundamental price. Odd-numbered groups have $p^f = 68$, even-numbered groups have $p^f = 62$. The upper bound on predictions is 2000. Note that the scale of the vertical axis may differ per group.

Bubbles form faster and grow larger in treatment 6B, compared to stage 1 (except in group 5). The fundamental price does not play a role at all in these markets. In most markets, the price pattern becomes irregular after one or more bubbles. This is due to extreme predictions by some subjects, causing unpredictable jumps in prices. The questionnaire reveals that these subjects are either trying to manipulate the price in the hope of giving it a more predictable direction, or they got frustrated and simply gave up predicting accurately. The upper bound on predictions of 2000 allowed bubbles to grow larger than in stage 1. However, only in group 6 does the price approach the maximum value – in other groups, the first bubble crashes before most subjects have reached the upper bound. Subjects thus seem to expect a crash because of their experience in stage 1.

In the mixed-experience treatment 3S3B, results are mixed. Group 3 and 8 are very stable and have prices close to the fundamental. Group 1 and 4 exhibit small oscillations around the fundamental. Group 5 is relatively stable with dampening oscillations around a price of 120 (about twice the fundamental). By contrast, group 2, 6 and 7 destabilize, and bubbles form faster and grow larger compared to the bubbly experience in stage 1. It is not immediately clear why a mixed-experience market stabilizes or destabilizes, but looking closely at individual

predictions and subjects' responses in the questionnaire gives some idea. It seems that a market stays stable if none of the subjects is predicting large price changes (be it deliberately or not), and if at least one subject is aiming to stabilize the price by submitting (almost) constant predictions or by submitting low predictions whenever the price goes up too quickly.¹² On the other hand, a market destabilizes if subjects do nothing to stop the acceleration of the upward trend in the beginning. Attempts to stabilize the market later on are unsuccessful, since it is extremely hard to achieve coordination once the price is too far from the fundamental and the fluctuations are too big.

In all treatments, there are some benefits from entering into a new market: several subjects indicate in the questionnaire that they learned during stage 1 that predicting large price changes is not a successful strategy, and that the price should remain stable in order to make money. In stage 2, they have the opportunity to start over and abandon this suboptimal behavior. However, aiming for stable prices only works if the other subjects in the market do not spoil the attempts by predicting high prices or large changes. For this reason, stabilizing strategies are very successful in stable-experience markets, unsuccessful in bubbly-experience markets, and successful in some (though not all) mixed-experience markets. The results in the first market could also have a negative influence on the new market: some subjects with a bubbly experience become frustrated, causing further destabilization.

The figures suggest that there are no substantial differences in results for the two levels of the fundamental within each treatment. To formally test this, I consider a range of summary statistics, presented in Table 4 in Appendix C. The fundamental is normalized to $p^f = 62$ in all markets to allow for comparison between markets with different fundamentals.¹³ The summary statistics confirm that the differences between the two levels of the fundamental are not significant: pairwise Mann-Whitney-Wilcoxon (MWW) tests, comparing odd-numbered groups with even-numbered groups, all have a p -value > 0.05 for each statistic in each treatment (see Table 5 in Appendix C). Hence, the change in fundamentals does not matter for the results.

¹²A number of subjects describe stabilizing strategies for stage 2 in the questionnaire, using phrases such as “trying to maintain as constant a price as possible”, “mitigating fluctuations”, and “preventing a bubble from forming by predicting a price of 1”. Some of these subjects experienced stability in stage 1, some of them experienced bubbles.

¹³Normalization to $p^f = 62$ means that all predictions and prices are shifted downwards by six units in markets with $p^f = 68$, before the summary statistics are calculated. This procedure implies that the mean, maximum and minimum price are lowered by six units, while the standard deviation and the range of prices remain the same. The RAD and RD (see Section 3.2) yield slightly higher numbers when $p^f = 68$ is changed to $p^f = 62$, but comparison is only meaningful if the same fundamental is used in the calculation for all markets.

3.2 Volatility and mispricing

There are clear differences in market volatility and mispricing across the three treatments. To quantify these results, I measure volatility using the standard deviation of prices. However, this only measures fluctuations around the mean price, without considering the fundamental price. Therefore, I also measure mispricing using the Relative Absolute Deviation (RAD) from the fundamental, defined according to Stöckl et al. (2010):

$$\text{RAD} = \frac{1}{36} \sum_{t=1}^{36} \frac{|p_t - p^f|}{p^f}. \quad (3)$$

For instance, a value of $\text{RAD} = 0.5$ indicates that the price differs on average 50% from the fundamental.¹⁴ Figure 7 shows the empirical cumulative distribution functions (CDFs) of the volatility and mispricing measures for the two experiences in stage 1 and the three treatments in stage 2. The precise values of the measures in each market can be found in Table 4 in Appendix C.

Figure 4–6 show that markets are more unstable when more subjects have experienced bubbles before: bubbles are largest in treatment 6B, followed by 3S3B and 6S. To find out if the differences between treatments are statistically significant, I conduct pairwise MWW tests. The null hypothesis is that there are no differences in volatility and mispricing in stage 2. The p -values of these tests can be found in the last two columns of Table 1. The tests indicate that the differences between treatment 6S and 6B are highly significant for both measures. The differences between 3S3B and 6S are significant at the 5% level in terms of both volatility and mispricing. Mispricing in 3S3B is also significantly different from 6B at the 5% level, but the difference in volatility is only significant at the 10% level, due to the mixed results in 3S3B. Considering the two types of results in 3S3B separately, the standard deviation of prices is significantly different in the stable markets compared to 6S, but RAD is only significantly different at the 10% level. This implies that the mixed-experience markets are slightly less stable than the stable-experience markets, but it only has a marginal effect on mispricing. Both measures are not significantly different in the bubbly markets compared to 6B, indicating that the results in all bubbly markets are comparable.

Compared to stage 1, the stable-experience markets of 6S become more stable, the bubbly-experience markets of 6B become more bubbly, and the mixed-

¹⁴The Relative Deviation (RD) measures overvaluation and is defined in a similar way as RAD, but without taking the absolute value. RD is less informative for my experimental data, since it is close to zero in markets that oscillate around the fundamental price and close to RAD in markets with large bubbles.

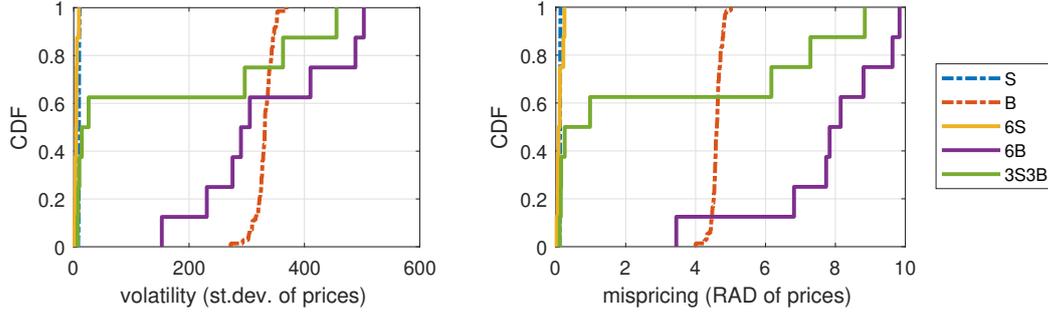


Figure 7: Empirical CDFs of volatility and mispricing measures

Notes: The dashed lines are the two experiences in stage 1 (“S” for stable and “B” for bubbly), including 72 markets each. The solid lines are the three treatments in stage 2 (6S, 6B and 3S3B), including 8 markets each.

Table 1: p -values of pairwise MWW tests for volatility and mispricing

Pairwise MWW tests for st.dev. of prices					Pairwise MWW tests for RAD				
	S	B	6S	6B		S	B	6S	6B
6S	0.000**				6S	0.064*			
6B		0.301	0.000**		6B		0.001**	0.000**	
3S3B	0.025**	0.022**	0.001**	0.083*	3S3B	0.000**	0.252	0.010**	0.015**
3S3B-S	0.515		0.006**		3S3B-S	0.018**		0.093*	
3S3B-B		0.324		0.630	3S3B-B		0.004**		0.630

Notes: ** and * indicate significance at the 5% and 10% level, respectively. “S” and “B” stand for the stable and bubbly experiences in stage 1; “3S3B-S” stands for the stable markets (group 1, 3, 4, 5 and 8) and “3S3B-B” stands for the bubbly markets (group 2, 6 and 7) of treatment 3S3B in stage 2. The treatments in stage 2 (rows) are compared with each other and with the relevant experiences in stage 1 (columns).

experience markets of 3S3B show mixed results. The first two columns of Table 1 present p -values of pairwise MWW tests comparing the treatments in stage 2 with the relevant experiences in stage 1. Treatment 6S is significantly different from the stable experience in terms of volatility. The difference in terms of mispricing is only significant at the 10% level, due to the three markets that do not converge to the new fundamental. Treatment 6B is significantly different from the bubbly experience in terms of mispricing, but volatility is comparable. Treatment 3S3B as a whole is significantly different from the stable experience in terms of volatility and mispricing, and from the bubbly experience in terms of volatility. Comparing the stable markets in 3S3B with the stable experience and the bubbly markets with the bubbly experience, volatility is not significantly different, but mispricing is: both types of markets deviate more from the fundamental in stage 2.

3.3 Coordination of expectations

The experiences of subjects also affect coordination of expectations in stage 2. To illustrate this, Figure 8 plots the coefficient of variation (CV) of predictions over

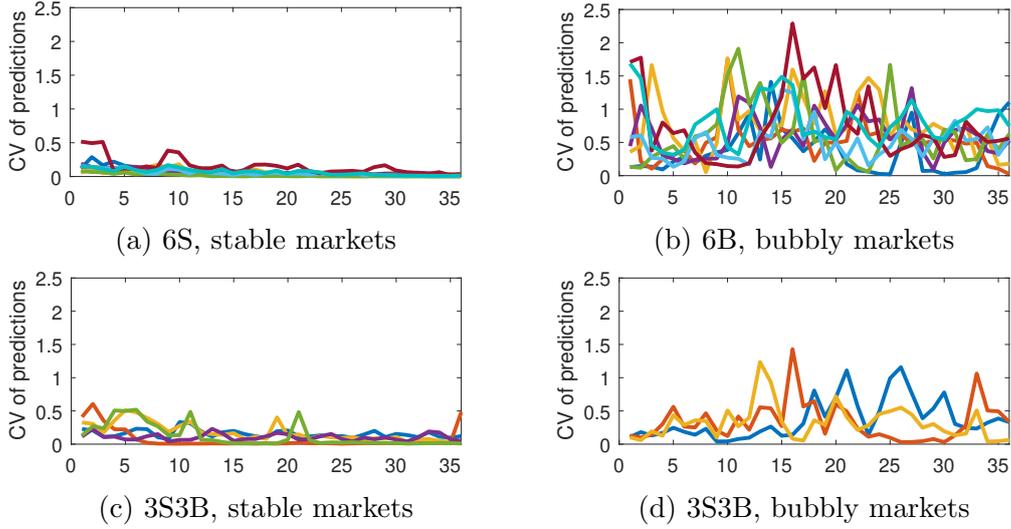


Figure 8: Coefficient of variation of predictions over time in stage 2
Notes: Each colored line represents a different market. Panel (a) contains all 8 groups of treatment 6S, panel (b) contains all 8 groups of treatment 6B, panel (c) contains group 1, 3, 4, 5 and 8 of treatment 3S3B, and panel (d) contains group 2, 6 and 7 of treatment 3S3B.

time for treatment 6S, 6B and the stable and bubbly markets of 3S3B separately. The CV is defined as the ratio of the standard deviation to the mean of predictions and thus measures the relative heterogeneity in expectations. A low CV indicates that subjects coordinate on a common prediction strategy. In the stable markets of treatment 6S, coordination is strong and increasing over time. The stable markets of 3S3B show an increase in coordination in most markets as well, but there is slightly more heterogeneity in expectations than in 6S. By contrast, coordination is low in the bubbly markets of 6B. Notably, the CV is relatively high in the first two periods, suggesting that a bubbly experience leads to heterogeneity in expectations right from the beginning of the new market. This disagreement makes it harder to achieve coordination, leading to more fluctuations in the price, which in turn reinforces the disagreement.¹⁵ Heterogeneity in predictions is also large in the bubbly markets of 3S3B, though somewhat smaller than in 6B. The differences in the average CV of predictions are significant for each comparison (p -value < 0.05 for all pairwise MWW tests). Coordination is thus strongest in stable-experience markets, but mixed-experience markets exhibit less heterogeneity in expectations than bubbly-experience markets.

¹⁵The interplay between price bubbles and heterogeneity in expectations is in line with the model of Barberis et al. (2018), where investors with extrapolative expectations differ in the weight they put on the asset’s past price changes (the “growth signal”) and the degree of overvaluation (the “value signal”). Since the difference between the two signals becomes larger in a bubble, the heterogeneity in expectations increases, generating high trading volumes and fueling the bubble.

3.4 Earnings efficiency

The performance of subjects in the prediction task is reflected by their earnings, which are based on prediction accuracy. The highest possible earnings in each stage are €22.75 (35 periods times €0.65 per period). Earnings efficiency can be measured by dividing the actual earnings in the experiment by the theoretical maximum. Figure 9 displays the empirical CDFs of the earnings efficiency of each subject for the two experiences in stage 1 and the three treatments in stage 2.

For subjects with a stable experience in stage 1, earnings efficiency is only 30% on average, implying that subjects make quite some forecast errors even in markets that are relatively stable. In treatment 6S, performance is substantially better in stage 2, with an average earnings efficiency of 66%. Group 2 even reached an earnings efficiency of 95% on average. Subjects in markets with stable prices slightly above or below the fundamental value could achieve relatively high earnings as well: for instance, average earnings efficiency is 80% in group 1. There is room for improvement, but the incentives might not be sharp enough for subjects to respond to this. Average earnings efficiency is 45% in the stable markets of 3S3B, reflecting that oscillations in these markets are generally slightly larger than in 6S.

It is not surprising that earnings efficiency is much lower in bubbly markets, where it is harder to predict the large price changes. Earnings efficiency is 6% on average for subjects with a bubbly experience in stage 1. Performance is even worse in treatment 6B: average earnings efficiency is only 2%, due to the erratic market prices in stage 2. In the bubbly markets of 3S3B, average earnings efficiency is 5%. There are differences in performance even in bubbly markets: while some subjects do not earn anything, others manage to achieve an earnings efficiency of 10–17%. Judging by their individual predictions and responses in the questionnaire, it seems that most subjects still try to form accurate predictions despite the low earnings in bubbly markets.

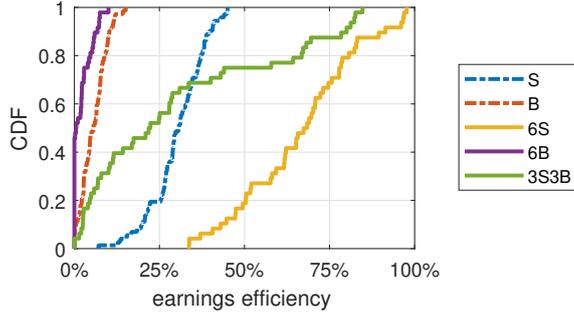


Figure 9: Empirical CDFs of earnings efficiency

Notes: Earnings efficiency is measured by dividing the actual earnings of the subject in the experiment by the theoretical maximum of €22.75 per stage. The dashed lines are the two experiences in stage 1 (“S” for stable and “B” for bubbly), including 72 subjects each. The solid lines are the three treatments in stage 2 (6S, 6B and 3S3B), including 48 subjects each.

4 Individual forecasting heuristics

4.1 Procedure for classifying heuristics

To get insight in the type of prediction strategies that subjects use, I compare their actual predictions to a range of simple heuristics and identify the heuristic with the best fit. Mirdamadi and Petersen (2019) conduct a similar analysis for their learning-to-forecast experiment. The heuristics I consider have commonly found support in the experimental literature on expectation formation (see e.g. Bao et al., 2020; Cornand and M’baye, 2016; Hommes et al., 2005; Pfajfar and Žakelj, 2016). Table 2 presents the specifications of the heuristics. To see if subjects form expectations based on the rational expectations equilibrium of the asset pricing model, I first compare their forecasts to the fundamental price (FUN). Next, I check if subjects have naive expectations (NAI), meaning that their forecast is simply the last observed price. The third heuristic is constant gain learning (CGL), also known as adaptive learning, where the previous prediction is adapted in the direction of the last observed price, with a constant gain parameter γ . A related heuristic is decreasing gain learning (DGL) with gains $\gamma_t = \frac{\theta}{t}$, where the parameter θ determines whether more recently observed prices receive more weight ($\theta > 1$), less weight ($\theta < 1$) or equal weight ($\theta = 1$) compared to prices observed in the beginning of the experiment. The fifth heuristic is trend-following expectations (TR), in which the prediction is based on the last observed price and adjusted in the direction of the last observed price change. The trend extrapolation parameter ϕ is called weak for $\phi < 1$ and strong for $\phi > 1$. Lastly, a slightly more sophisticated heuristic is the anchoring and adjustment rule (AA), which takes a weighted average of the last observed price and the fundamental price as an anchor for the prediction and adjusts it based on the last observed price change, with a weighting parameter α

Table 2: Specification of heuristics

Heuristic	Specification	Parameters
Fundamental (FUN)	$p_{i,t+1}^e = p^f$	
Naive (NAI)	$p_{i,t+1}^e = p_{t-1}$	
Constant gain (CGL)	$p_{i,t+1}^e = p_{i,t}^e + \gamma(p_{t-1} - p_{i,t}^e)$	$\gamma = \{0.1, 0.2, \dots, 0.9\}$
Decreasing gain (DGL)	$p_{i,t+1}^e = p_{i,t}^e + \frac{\theta}{t}(p_{t-1} - p_{i,t}^e)$	$\theta = \{0.1, 0.2, \dots, 3.0\}$
Trend-following (TR)	$p_{i,t+1}^e = p_{t-1} + \phi(p_{t-1} - p_{t-2})$	$\phi = \{0.1, 0.2, \dots, 2.0\}$
Anchoring and adjustment (AA)	$p_{i,t+1}^e = \alpha p_{t-1} + (1 - \alpha)p^f + \beta(p_{t-1} - p_{t-2})$	$\alpha = \{0.0, 0.1, \dots, 0.9\},$ $\beta = \{0.0, 0.1, \dots, 2.0\}$

and a trend extrapolation parameter β . For the CGL, DGL, TR and AA heuristics, I consider a range of different parameterizations.¹⁶

The procedure for the classification is as follows. For each subject in each stage of the experiment, I compare their actual prediction for period $t + 1$ to the hypothetical predictions generated by the heuristics, using the actual prices and predictions up until period t .¹⁷ This is done from the prediction for period 4 onwards (i.e. $t \geq 3$), such that all past prices and predictions are defined. As a measure of fit, I use the mean absolute error (MAE), which does not penalize large errors as much as the root mean squared error (RMSE). Since my data includes large fluctuations and outliers in the bubbly markets, the MAE provides a better indication of the fit of the heuristics than the RMSE. For all heuristics, the MAE over all time periods is calculated, and the heuristic with the lowest MAE is assigned to the subject. It does not have to be the case that the subject actually used the assigned heuristic to form forecasts – the heuristic simply provides the best description of the observed behavior in terms of a simple forecasting rule.

4.2 Classified heuristics

Figure 10 shows the composition of heuristics for the stable and bubbly experiences in stage 1, and for treatment 6S, treatment 6B, and the stable and bubbly markets of treatment 3S3B in stage 2. The mean parameter values of the CGL, DGL, TR and AA heuristics are given in Table 3. More details on the parameter values can be found in Appendix D, where Figure 11 displays the empirical CDFs of γ , θ , ϕ ,

¹⁶The gain sequences $\gamma_t = \gamma$ for CGL and $\gamma_t = \frac{\theta}{t}$ for DGL must satisfy $0 < \gamma_t \leq 1$ for all included periods (i.e. $t \geq 3$). Note that CGL with $\gamma = 1$ simplifies to naive expectations, so this parameter value is omitted. Furthermore, AA with $\alpha = 0$ and $\beta = 0$ simplifies to fundamental expectations, so this particular combination is not included either.

¹⁷An alternative approach would be to use hypothetical predictions instead of actual predictions to generate new hypothetical predictions. This approach generally worsens the fit of the CGL and DGL heuristics, since errors tend to accumulate over time. Moreover, taking actual predictions is more in line with taking actual prices. The other four heuristics do not use past predictions and are therefore not affected by this choice.

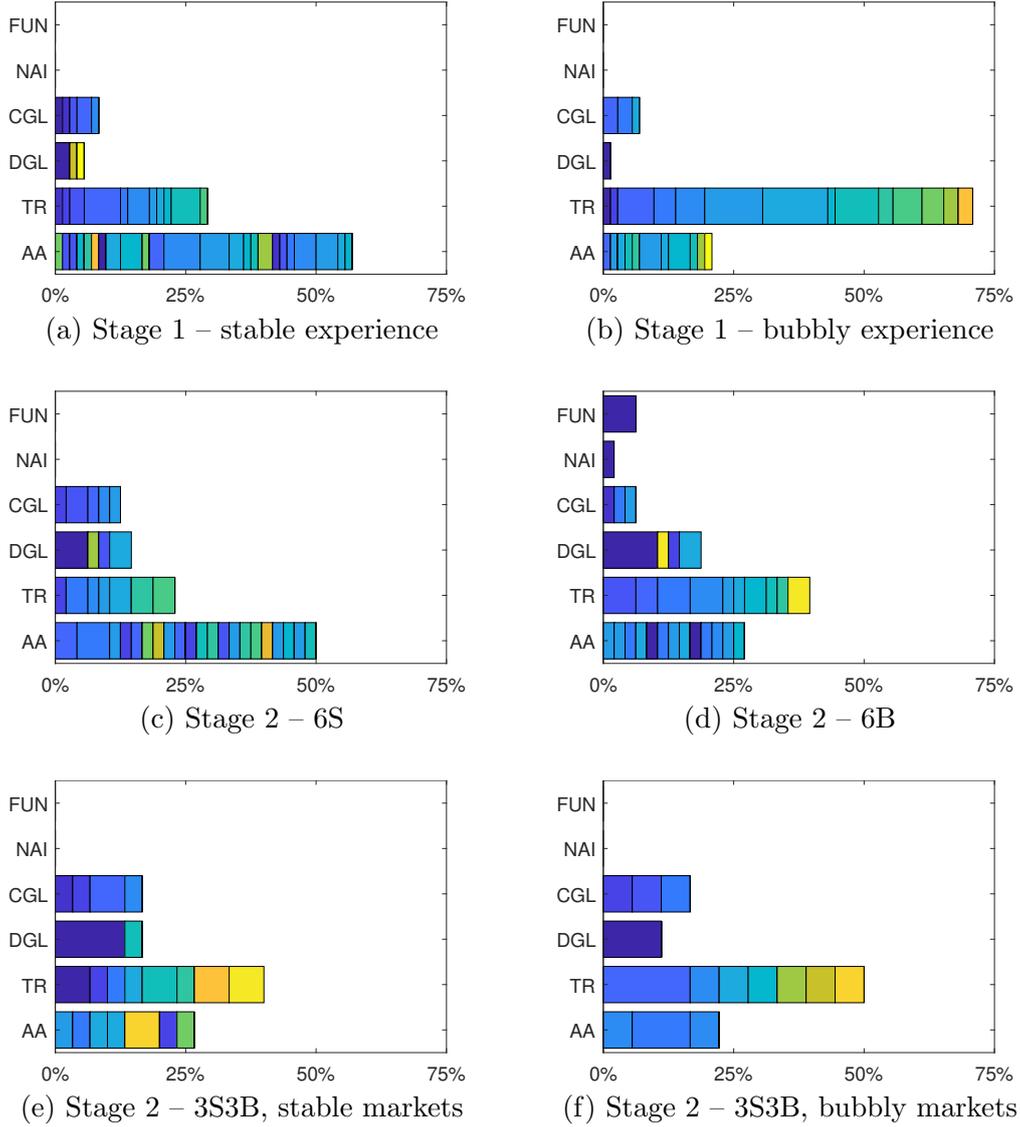


Figure 10: Composition of classified heuristics in stage 1 and stage 2

Notes: Each bar indicates the percentage of subjects that is assigned a certain type of heuristic. The colors of the bars illustrate the parameter values of the heuristics, with lighter colors generally representing higher values of γ , θ , ϕ and β . Panel (a) contains all subjects with a stable experience in stage 1, panel (b) contains all subjects with a bubbly experience in stage 1, panel (c) contains all 8 groups of treatment 6S in stage 2, panel (d) contains all 8 groups of treatment 6B in stage 2, panel (e) contains group 1, 3, 4, 5 and 8 of treatment 3S3B in stage 2, and panel (f) contains group 2, 6 and 7 of treatment 3S3B in stage 2.

α and β , as well as pairwise MWW tests that check for significant differences in parameter values across stages and treatments. Table 6 in Appendix D lists the classified heuristics and MAEs for each individual subject.

4.2.1 Stable and bubbly markets in stage 1

There is a clear difference in the composition of heuristics in the stable and bubbly experiences of stage 1. In the stable markets, 57% of the subjects are assigned an anchoring and adjustment heuristic. Generally, most weight is given to the last ob-

Table 3: Mean parameter values of classified heuristics

	CGL: γ	DGL: θ	TR: ϕ	AA: α	AA: β
Stage 1 – stable experience	0.40	0.98	0.71	0.74	0.75
Stage 1 – bubbly experience	0.62	0.10	0.94	0.85	0.93
Stage 2 – 6S	0.52	1.47	0.89	0.37	0.75
Stage 2 – 6B	0.53	1.21	0.85	0.78	0.57
Stage 2 – 3S3B, stable markets	0.44	0.30	1.08	0.78	0.99
Stage 2 – 3S3B, bubbly markets	0.43	0.10	1.01	0.85	0.55

served price, with a small weight on the fundamental, and the trend-extrapolation component is weak. Such a rule works well to predict the small, dampening oscillations that occur in these markets. 29% of the heuristics are classified as trend-following, with generally a weak trend extrapolation parameter. The remaining heuristics are identified as constant gain learning (8%) or decreasing gain learning (6%). In the bubbly markets of stage 1, a large majority of subjects (71%) is classified as trend followers, generally with a stronger trend extrapolation coefficient than in the stable markets. The difference in the values of ϕ is significant at the 5% level. 21% of the heuristics are of the anchoring and adjustment type, with a higher weight on past prices and a stronger trend-following component than in the stable markets. The difference in α is significant at the 5% level, while the difference in β is marginally significant at the 10% level. Both types of rules with a strong trend extrapolation coefficient are useful to predict the pattern of large bubbles and crashes in the bubbly markets of stage 1. Finally, constant gain learning is found for 7% and decreasing gain learning for 1% of the subjects, with no significant differences in parameters compared to the stable markets.

4.2.2 Stable-experience markets

In treatment 6S in stage 2, the types of heuristics are distributed in a similar way as in stage 1: 50% anchoring and adjustment, 23% trend-following, 15% decreasing gain learning and 13% constant gain learning. Nevertheless, there is a large shift in the parameter α of the anchoring and adjustment rule towards values that put less weight on the last observed price and more weight on the fundamental price. The difference is significant at the 5% level, whereas the other parameter values are not significantly different from the stable experience in stage 1. The value of α is also significantly lower in treatment 6S than in treatment 6B and 3S3B. The shift in α is not surprising, given the experience of the subjects with dampening oscillations that converge to the fundamental. Even though subjects might not realize immediately that the fundamental price is slightly different in the second

stage, the use of a forecasting rule that anchors around a fixed price facilitates stabilization and helps subjects to learn the new equilibrium price. Combined with adaptive learning and generally weak trend-following behavior, this composition of heuristics leads to markets that are very stable.

4.2.3 Bubbly-experience markets

The classified heuristics in stage 2 of treatment 6B do not show a clear pattern. Compared to stage 1, there is no longer a majority classified as trend-following: this rule is now found for 40% of the subjects. Furthermore, 27% of the heuristics are identified as anchoring and adjustment. Surprisingly, the trend extrapolation coefficients ϕ and β are slightly lower in stage 2 than in the bubbly markets of stage 1, and this difference is even significant at the 5% level for β and marginally significant at the 10% level for ϕ . Decreasing gain learning is assigned to 19% of the subjects, constant gain learning to 6%, and naive expectations to 2%. The classification of fundamental expectations for 6% of the subjects seems counterintuitive for these highly unstable markets, but the three subjects that are assigned this classification all submitted repeated predictions of 0 and 1, irregularly interspersed with high predictions (e.g. 250, 500, or 2000). Therefore, a constant prediction of p^f gives a better fit than the other heuristics, but fundamental expectations should not be seen as an accurate classification. In general, it seems that the bubbly experience in stage 1 mainly leads to heterogeneity in expectations, causing erratic predictions and prices and therefore even more heterogeneity in stage 2. This makes it hard to classify predictions as a certain simple heuristic.

4.2.4 Mixed-experience markets

For treatment 3S3B, I consider the five stable markets and the three bubbly markets in stage 2 separately. The composition of heuristics is similar: 40% trend-following, 27% anchoring and adjustment, 17% constant gain learning and 17% decreasing gain learning in the stable markets, versus 50% trend-following, 22% anchoring and adjustment, 17% constant gain learning and 11% decreasing gain learning in the bubbly markets. There are also no significant differences in parameters in the two types of markets. The composition of heuristics seems to be a mix of the heuristics found for the stable and bubbly experiences of stage 1, though with more adaptive learning rules. There are some differences in parameters compared to stage 1: α is marginally significantly smaller in the stable markets of 3S3B compared to the bubbly experience, and β is significantly smaller in the bubbly markets of 3S3B compared to the bubbly experience and marginally significantly smaller compared to the stable experience. The overall composition of heuristics does not explain

why some mixed-experience markets stabilize and others destabilize.

To shed light on the different dynamics in the mixed-experience markets, I divide the subjects in treatment 3S3B into four groups, based on whether they have a stable or bubbly experience in stage 1 and whether they are part of a stable or bubbly market in stage 2. Looking at the classified heuristics for these four groups in both stage 1 and stage 2, there are some notable differences in trend-following and anchoring and adjustment rules, which are assigned to a majority of subjects (85% in stage 1 and 69% in stage 2). Figure 12 in Appendix D displays the empirical CDFs of the weight parameter α (where $\alpha = 1$ for trend-following rules) and the trend extrapolation parameter ϕ or β in the four groups.

Interestingly, comparing subjects with a stable experience, subjects who are part of a stable market in stage 2 already have lower trend extrapolation parameters in stage 1 than subjects who are part of a bubbly market in stage 2. The difference is significant at the 5% level (MWW test, p -value = 0.033). The lower value might indicate that these subjects are less inclined to extrapolate trends in general, thereby contributing to stable prices in stage 2. The lower value of ϕ or β is generally combined with a higher value of α (implying less weight on the fundamental) – this difference is significant as well (MWW test, p -value = 0.045), but the weight parameter is less important for the amplitude of the oscillations than the trend extrapolation parameter. Trend extrapolation parameters in stage 1 are not significantly different for both groups of subjects with a bubbly experience (MWW test, p -value = 0.680), although all three subjects who are classified as very strong trend followers (ϕ or $\beta > 1.5$) in stage 1 are part of a bubbly market in stage 2. It is possible that the tendency of subjects to extrapolate trends affects the stabilization or destabilization of the markets in stage 2, but it is difficult to draw firm conclusions because of path dependence.

In the stable markets in stage 2, it is interesting to note that subjects with a stable experience have much lower values of ϕ and β than subjects with a bubbly experience, and this difference is highly significant (MWW test, p -value = 0.002). Hence, subjects with a bubbly experience make the market less stable, even though they do not cause large bubbles. Such an effect does not occur in the bubbly markets in stage 2: all subjects in these markets contribute to the large bubbles, also those with a stable experience.

4.2.5 Fit of classified heuristics

To illustrate the fit of the classified heuristics, Figure 13 in Appendix D shows the empirical CDFs of the mean absolute error. In all stable markets, the fit is good, with MAEs averaging 5.3 for the stable experience, 2.7 for treatment 6S and 6.1 for

the stable markets of 3S3B. MAEs are higher in all bubbly markets, with averages of 136.2 for the bubbly experience, 228.3 for treatment 6B and 190.1 for the bubbly markets of 3S3B, and a large dispersion around these values. Higher MAEs are to be expected in bubbly markets, because sudden large fluctuations in predictions and prices give rise to large errors for some periods, thereby increasing the mean error substantially. A visual inspection of actual versus hypothetical predictions suggests that the fit is reasonable for many subjects in bubbly markets, especially in the first stage and in treatment 3S3B, where the patterns of bubbles and crashes are more regular. Nevertheless, there are a dozen subjects in treatment 6B with MAEs above 300, whose predictions evidently cannot be captured by simple forecasting rules.

5 Conclusion

In this paper, I study how experiences of price patterns in asset markets affect expectations of future prices in a controlled learning-to-forecast experiment. Subjects first enter into a market with robots, so that they have very similar experiences in either a stable or a bubbly market. Subsequently, new markets are formed with subjects only, who either have the same experience or an equal mix of experiences. Subjects know that the other subjects in the market are experienced as well, but they do not know what kind of experiences the others have.

The results show that experiencing price stability or bubbles has a large effect on future market dynamics, despite the fact that the second market is in principle independent of the first market. Convergence is faster in markets where all subjects experienced stability, even though the fundamental price is slightly changed. Bubble formation is faster in markets where all subjects experienced bubbles. Results are mixed in mixed-experience markets: prices either stabilize or destabilize. When more subjects in a market have experienced bubbles before, heterogeneity in expectations is larger.

Many individual prediction strategies can be characterized as trend-following rules and anchoring and adjustment rules. In stable-experience markets, a high weight is put on the fundamental price, explaining the quick stabilization. Predictions are hard to describe by a simple heuristic in bubbly-experience markets, reflecting the heterogeneity in expectations. In mixed-experience markets, subjects with a bubbly experience usually cause somewhat larger oscillations in markets that stay relatively stable, whereas subjects with a stable experience do not decrease mispricing and volatility in markets that become bubbly. It may be that the stabilization or destabilization of a mixed-experience market is related to the general

tendency of subjects to extrapolate trends.

My experimental results illustrate that experience can work both stabilizing and destabilizing. Experiencing bubbles leads to expecting more bubbles and can therefore cause the formation of new bubbles. The result that experience does not eliminate bubbles is also observed in the learning-to-forecast experiment with stationary repetition of Kopányi-Peucker and Weber (2018), and contradicts a robust finding in experiments à la Smith et al. (1988). In these trading experiments, subjects buy and sell an asset for about fifteen periods in a simple market. Assuming that other traders behave the same as in the previous market, the best response to a bubble experience in both types of experiments is to be one step ahead of the other traders, either by buying into the bubble and selling all assets right before the crash is expected to happen, or by predicting price increases or decreases one period earlier than the others. However, the market setting in learning-to-forecast experiments is less transparent and has a longer time horizon, making it more difficult to determine how behavior should be optimally adjusted. Hence, bubbles do not always disappear with experience in more complex market settings. On the other hand, my experiment suggests that experiencing stability helps expectations to remain stable, which is a novel finding.

Empirical studies have found that inexperienced traders play a role in the formation of bubbles, as they are more susceptible to optimistic thinking and trend chasing (Chernenko et al., 2016; Greenwood and Nagel, 2009). To some extent, my experimental results are in line with this: inexperienced subjects often have trend-following expectations, thereby contributing to bubbles. However, subjects in my experiment cannot opt out of the market after experiencing a bubble and crash, whereas traders in real-world asset markets generally lower their investments in risky assets after a negative experience (see e.g. Ampudia and Ehrmann, 2017; Malmendier and Nagel, 2011). An interesting direction for future research is therefore to study the effect of experiencing stability or bubbles in an experimental setting that includes both forecasting and trading, but is more complex than the classical Smith et al. (1988) design. Two distinct examples of such experimental settings are Bao et al. (2017) and Giamattei et al. (2020).

Focusing on recent personal experiences could lead to suboptimal investment decisions. Making traders aware of this bias in behavior could be a first step towards improving their decisions. Nudges in the form of presenting information about asset prices and returns in certain ways may also be helpful. For example, showing traders information over longer time horizons might mitigate their trend-extrapolating behavior. Smaller belief updates are generally associated with less active trading and higher return performance (Barber and Odean, 2000; Hoffmann

and Post, 2016). The experimental results of Gerhard et al. (2017) suggest that presenting returns over a longer horizon as a default is effective for investors with low financial literacy, who are more likely to stay in the default option. However, they observe the opposite effect for subjects who opt out of the default, indicating that the optimal way of presenting information depends on traders' characteristics. Further research is necessary to learn more about policy interventions to improve individual behavior as well as market outcomes.

My experiment provides insight in how experiences affect expectations, and when learning leads to stabilization or destabilization of markets. Asymmetric mixtures of experiences (such as markets consisting of two subjects with a stable experience and four subjects with a bubbly experience, and vice versa) could shed more light on these dynamics, and would be a valuable extension of this study.

References

- Akiyama, E., Hanaki, N., and Ishikawa, R. (2014). How do experienced traders respond to inflows of inexperienced traders? An experimental analysis. *Journal of Economic Dynamics and Control*, 45:1–18.
- Ampudia, M. and Ehrmann, M. (2017). Macroeconomic experiences and risk taking of euro area households. *European Economic Review*, 91:146–156.
- Anagol, S., Balasubramaniam, V., and Ramadorai, T. (2018). Endowment effects in the field: Evidence from India’s IPO lotteries. *Review of Economic Studies*, 85:1971–2004.
- Bao, T., Hennequin, M., Hommes, C., and Massaro, D. (2020). Coordination on bubbles in large-group asset pricing experiments. *Journal of Economic Dynamics and Control*, 110:103702.
- Bao, T., Hommes, C., and Makarewicz, T. (2017). Bubble formation and (in)efficient markets in learning-to-forecast and optimise experiments. *The Economic Journal*, 127:F581–F609.
- Barber, B. and Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance*, 55(2):773–806.
- Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2018). Extrapolation and bubbles. *Journal of Financial Economics*, 129(2):203–227.
- Brock, W. and Hommes, C. (1998). Heterogeneous beliefs and routes to chaos in a simple asset pricing model. *Journal of Economic Dynamics and Control*, 22(4):1235–1274.
- Campbell, J., Lo, A., and MacKinlay, A. (1997). *The Econometrics of Financial Markets*. Princeton University Press, Princeton.
- Chen, D., Schonger, M., and Wickens, C. (2016). oTree – An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, 9:88–97.
- Chernenko, S., Hanson, S., and Sunderam, A. (2016). Who neglects risk? Investor experience and the credit boom. *Journal of Financial Economics*, 122:248–269.
- Chiang, Y.-M., Hirshleifer, D., Qian, Y., and Sherman, A. (2011). Do investors learn from experience? Evidence from frequent IPO investors. *The Review of Financial Studies*, 24(5):1560–1580.
- Choi, J., Laibson, D., Madrian, B., and Metrick, A. (2009). Reinforcement learning and savings behavior. *Journal of Finance*, 64(6):2515–2534.
- Cordes, H. and Dierkes, M. (2017). About depression babies and red diaper babies: Do macroeconomic experiences affect everybody’s risk taking in the same way? *Journal of Behavioral and Experimental Finance*, 13:25–27.

- Cornand, C. and M'baye, C. (2016). Does inflation targeting matter? An experimental investigation. *Macroeconomic Dynamics*, pages 1–40.
- Dufwenberg, M., Lindqvist, T., and Moore, E. (2005). Bubbles and experience: An experiment. *American Economic Review*, 95(5):1731–1737.
- Fajardo, J. and Dantas, M. (2018). Understanding the impact of severe hyperinflation experience on current household investment behavior. *Journal of Behavioral and Experimental Finance*, 17:60–67.
- Gerhard, P., Hoffmann, A., and Post, T. (2017). Past performance framing and investors' belief updating: Is seeing long-term returns always associated with smaller belief updates? *Journal of Behavioral and Experimental Finance*, 15:38–51.
- Giamattei, M., Huber, J., Lambsdorff, J., Nicklisch, A., and Palan, S. (2020). Who inflates the bubble? Forecasters and traders in experimental asset markets. *Journal of Economic Dynamics and Control*, 110:103718.
- Gong, B., Lei, V., and Pan, D. (2013). Before and after: The impact of a real bubble crash on investors' trading behavior in the lab. *Journal of Economic Behavior and Organization*, 95:186–196.
- Greenwood, R. and Nagel, S. (2009). Inexperienced investors and bubbles. *Journal of Financial Economics*, 93:239–258.
- Greenwood, R. and Shleifer, A. (2014). Expectations of returns and expected returns. *The Review of Financial Studies*, 27(3):714–746.
- Haruvy, E., Lahav, Y., and Noussair, C. (2007). Traders' expectations in asset markets: Experimental evidence. *American Economic Review*, 97(5):1901–1920.
- Hennequin, M. and Hommes, C. (2019). Managing bubbles in experimental asset markets with monetary policy. CeNDEF Working Paper 2019-08, University of Amsterdam.
- Hirshleifer, D. (2001). Investor psychology and asset pricing. *The Journal of Finance*, 56(4):1533–1597.
- Hoffmann, A., Iliewa, Z., and Jaroszek, L. (2017). Wall Street crosses Memory Lane: How witnessed returns affect professionals' expected returns. Conference paper, Paris December 2017 Finance Meeting EUROFIDAI-AFFI.
- Hoffmann, A. and Post, T. (2016). How does investor confidence lead to trading? Linking investor return experiences, confidence, and investment beliefs. *Journal of Behavioral and Experimental Finance*, 12:65–78.
- Hoffmann, A. and Post, T. (2017). How return and risk experiences shape investor beliefs and preferences. *Accounting and Finance*, 57:759–788.
- Hommes, C., Kopányi-Peuker, A., and Sonnemans, J. (2018). Bubbles, crashes and information contagion in large-group asset market experiments. CeNDEF Working Paper 2018-05, University of Amsterdam.

- Hommes, C., Sonnemans, J., Tuinstra, J., and Van de Velden, H. (2005). Coordination of expectations in asset pricing experiments. *Review of Financial Studies*, 18(3):955–980.
- Hommes, C., Sonnemans, J., Tuinstra, J., and Van de Velden, H. (2008). Expectations and bubbles in asset pricing experiments. *Journal of Economic Behavior and Organization*, 67:116–133.
- Hong, J., Moinas, S., and Pouget, S. (2018). Learning in speculative bubbles: An experiment. TSE working paper n. 18-882, Toulouse School of Economics.
- Hussam, R., Porter, D., and Smith, V. (2008). Thar she blows: Can bubbles be rekindled with experienced subjects? *American Economic Review*, 98(3):924–937.
- Kaustia, M. and Knüpfer, S. (2008). Do investors overweight personal experience? Evidence from IPO subscriptions. *Journal of Finance*, 63(6):2679–2702.
- King, R. (1991). Private information acquisition in experimental markets prone to bubble and crash. *Journal of Financial Research*, 14(3):197–206.
- King, R., Smith, V., Williams, A., and Van Boening, M. (1993). The robustness of bubbles and crashes in experimental stock markets. In Day, R. and Chen, P., editors, *Nonlinear Dynamics and Evolutionary Economics*. New York, NY: Oxford University Press.
- Kirchler, M., Bonn, C., Huber, J., and Razen, M. (2015). The “inflow-effect” – Trader inflow and price efficiency. *European Economic Review*, 77:1–19.
- Kopányi-Peucker, A. and Weber, M. (2018). Experience does not eliminate bubbles: Experimental evidence. Working papers on finance no. 2018/22, University of St. Gallen.
- Kuchler, T. and Zafar, B. (2019). Personal experiences and expectations about aggregate outcomes. *Journal of Finance*, 74(5):2491–2542.
- Lejarraga, T., Woike, J., and Hertwig, R. (2016). Description and experience: How experimental investors learn about booms and busts affects their financial risk taking. *Cognition*, 157:365–383.
- Madeira, C. and Zafar, B. (2015). Heterogeneous inflation expectations and learning. *Journal of Money, Credit and Banking*, 47(5):867–896.
- Malmendier, U. and Nagel, S. (2011). Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics*, 126(1):373–416.
- Malmendier, U. and Nagel, S. (2016). Learning from inflation experiences. *Quarterly Journal of Economics*, 131(1):53–87.
- Malmendier, U., Nagel, S., and Yan, Z. (2017). The making of hawks and doves: Inflation experiences on the FOMC. NBER working paper no. 23228, National Bureau of Economic Research.

- Malmendier, U. and Steiny, S. (2017). Rent or buy? The role of lifetime experiences of macroeconomic shocks within and across countries. Working paper, University of California, Berkeley.
- Mirdamadi, M. and Petersen, L. (2019). Macroeconomic literacy and expectations. Working paper, Simon Fraser University.
- Nagel, S. (2012). Macroeconomic experiences and expectations: A perspective on the Great Recession. Paper prepared for the Academic Consultants Meeting at the Federal Reserve Board.
- Oechssler, J., Schmidt, C., and Schnedler, W. (2011). On the ingredients for bubble formation: Informed traders and communication. *Journal of Economic Dynamics and Control*, 35:1831–1851.
- Pfajfar, D. and Žakelj, B. (2016). Inflation expectations and monetary policy design: Evidence from the laboratory. *Macroeconomic Dynamics*, pages 1–41.
- Safford, A., Sundali, J., and Guerrero, F. (2018). Does experiencing a crash make all the difference? An experiment on the depression babies hypothesis. *SAGE Open*, 8(2):1–16.
- Shiller, R. (2002). Bubbles, human judgment, and expert opinion. *Financial Analysts Journal*, 58(3):18–26.
- Shleifer, A. and Summers, L. (1990). The noise trader approach to finance. *Journal of Economic Perspectives*, 4(2):19–33.
- Skeath, S. and Livingston, J. (2010). A step ahead? Experienced play in the p-beauty game. Working paper.
- Slonim, R. (2005). Competing against experienced and inexperienced players. *Experimental Economics*, 8:55–75.
- Smith, V., Suchanek, G., and Williams, A. (1988). Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica*, 56(5):1119–1151.
- Stöckl, T., Huber, J., and Kirchler, M. (2010). Bubble measures in experimental asset markets. *Experimental Economics*, 13:284–298.
- Strahilevitz, M., Odean, T., and Barber, B. (2011). Once burned, twice shy: How naive learning, counterfactuals, and regret affect the repurchase of stocks previously sold. *Journal of Marketing Research*, 56:S102–S120.
- Van Boening, M., Williams, A., and LaMaster, S. (1993). Price bubbles and crashes in experimental call markets. *Economics Letters*, 41:179–185.
- Vissing-Jorgensen, A. (2003). Perspectives on behavioral finance: Does “irrationality” disappear with wealth? Evidence from expectations and actions. *NBER Macroeconomics Annual*, 18:139–208.
- Xie, H. and Zhang, J. (2012). Bubbles and experience: An experiment with a steady inflow of new traders. Scientific publications 2012s-01, CIRANO.

Appendix

A Derivation of asset pricing equation

The asset pricing model with heterogeneous expectations is based on Campbell et al. (1997) and Brock and Hommes (1998), and is first used in an experimental setting in Hommes et al. (2005, 2008). In each period t , trader i chooses to invest in a risky asset or a risk-free asset. The wealth of trader i in period $t + 1$ is then given by

$$W_{i,t+1} = (1 + r)W_{i,t} + (p_{t+1} + y_{t+1} - (1 + r)p_t)z_{it}, \quad (4)$$

where z_{it} is the demand for the risky asset, p_t is its price, y_{t+1} is the dividend payment, and r is the risk-free interest rate. Traders calculate their optimal demand using mean-variance optimization:

$$\begin{aligned} \max_{z_{it}} \left\{ E_{it}(W_{i,t+1}) - \frac{1}{2}aV_{it}(W_{i,t+1}) \right\} = \\ \max_{z_{it}} \left\{ z_{it}E_{it}(p_{t+1} + y_{t+1} - (1 + r)p_t) - \frac{1}{2}a\sigma^2 z_{it}^2 \right\}, \end{aligned} \quad (5)$$

where a is a measure of risk aversion. Traders have heterogeneous expectations about the conditional mean of the evolution of wealth, $E_{it}(W_{i,t+1})$. It is assumed that all traders believe the conditional variance of future wealth to be constant: $V_{it}(W_{i,t+1}) = \sigma^2$. The solution of the mean-variance optimization problem is thus given by

$$z_{it} = \frac{E_{it}(p_{t+1} + y_{t+1} - (1 + r)p_t)}{a\sigma^2}. \quad (6)$$

Outside supply of the risky asset z^s is set to zero. Equilibrium between demand and supply in a market with six traders then yields

$$\sum_{i=1}^6 z_{it} = \frac{1}{a\sigma^2} \sum_{i=1}^6 E_{it}(p_{t+1} + y_{t+1} - (1 + r)p_t) = z^s = 0. \quad (7)$$

The dividend of the risky asset is i.i.d. distributed with mean \bar{y} , so $E_{it}(y_{t+1}) = \bar{y}$. Denote the prediction by trader i in period t for the price in period $t + 1$ by $E_{it}(p_{t+1}) = p_{i,t+1}^e$. Solving for the price of the risky asset p_t gives Equation (1):

$$p_t = \frac{1}{1 + r} \left[\frac{1}{6} \sum_{i=1}^6 p_{i,t+1}^e + \bar{y} \right]. \quad (8)$$

B Instructions experiment

INSTRUCTIONS PART 1

Welcome! Thank you for participating in this experiment.

The experiment is anonymous, your choices will only be linked to your table number, not to your name. You will be paid privately at the end, after all participants have finished the experiment. During the experiment you are not allowed to use your mobile phone. You are also not allowed to communicate with other participants. If you have a question at any time, raise your hand and the experimenter will come to your desk.

The main part of this experiment consists of two parts of equal length. In part 1 you will not interact with other participants, while in part 2 you will interact with other participants. You will find the instructions for part 1 on the next page; the instructions for part 2 will follow when part 1 is finished. The instructions will be available at the bottom of your screen throughout the entire experiment.

Please read the instructions for part 1 carefully.

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 and known interest rate. The alternative risky investment is an investment in a stock with uncertain return. In each time period the pension fund has to decide which fraction of its money to put on the bank account and which fraction of its money to spend on buying stocks. In order to make an optimal investment decision the pension fund needs an accurate prediction of the price of the stock. As their financial advisor, you have to predict the stock price during 36 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.

Forecasting task of the financial advisor

The only task of the financial advisors in this experiment is to forecast the stock price in each time period as accurately as possible. The stock price has to be predicted two time periods ahead. At the beginning of the experiment, you have to predict the stock price in the first two periods. It is very likely that the stock price will be between 0 and 100 in the first two periods. After all advisors have given their predictions for the first two periods, the stock price for the first period will be revealed and, based upon your forecasting error, your earnings for period 1 will be given. After that you have to give your prediction for the stock price in the third period. After all advisors have given their predictions for period 3, the stock price in the second period will be revealed and,

based upon your forecasting error, your earnings for period 2 will be given. This process continues for 36 time periods.

The available information in period t for forecasting the stock price for period $t + 1$ consists of

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

Information about the stock market

The stock price is determined by equilibrium between demand and supply of stocks. The stock price in period t will be that price for which aggregate demand equals supply. The supply of stocks is fixed during the experiment. The demand for stocks is determined by the aggregate demand of six large pension funds active. You are advising one of these pension funds. The other five pension funds make use of computer traders with a trading strategy that is based on a previous experimental stock market. Hence, you do not interact with other participants in this experiment.

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 stock receives a dividend payment in each time period. These dividend payments are uncertain and vary over time. Economic experts of the pension funds have computed that the average dividend payments are $\{\{dividend1\}\}$ euro 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 price forecast, your pension fund will make an optimal investment decision. The higher your price forecast is, 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.

Earnings

Your earnings depend on the accuracy of your predictions. The earnings shown on the computer screen will be in points. The maximum number of points you can earn in each period is 1300. The larger your prediction error, the fewer points you earn. You will earn

0 points if your prediction error is larger than 7. The earnings table below shows the number of points you earn for different prediction errors. At the end of the experiment, your total earnings in points will be converted into euros, at an exchange rate of **€1 for 2000 points (i.e. €0.65 for 1300 points)**. In addition, you will receive a fixed fee of €10 for participating in this experiment.

Earnings table									
error	points	error	points	error	points	error	points	error	points
0.1	1300	1.5	1240	2.9	1077	4.3	809	5.7	438
0.15	1299	1.55	1236	2.95	1069	4.35	798	5.75	423
0.2	1299	1.6	1232	3	1061	4.4	786	5.8	408
0.25	1298	1.65	1228	3.05	1053	4.45	775	5.85	392
0.3	1298	1.7	1223	3.1	1045	4.5	763	5.9	376
0.35	1297	1.75	1219	3.15	1037	4.55	751	5.95	361
0.4	1296	1.8	1214	3.2	1028	4.6	739	6	345
0.45	1295	1.85	1209	3.25	1020	4.65	726	6.05	329
0.5	1293	1.9	1204	3.3	1011	4.7	714	6.1	313
0.55	1292	1.95	1199	3.35	1002	4.75	701	6.15	297
0.6	1290	2	1194	3.4	993	4.8	689	6.2	280
0.65	1289	2.05	1189	3.45	984	4.85	676	6.25	264
0.7	1287	2.1	1183	3.5	975	4.9	663	6.3	247
0.75	1285	2.15	1177	3.55	966	4.95	650	6.35	230
0.8	1283	2.2	1172	3.6	956	5	637	6.4	213
0.85	1281	2.25	1166	3.65	947	5.05	623	6.45	196
0.9	1279	2.3	1160	3.7	937	5.1	610	6.5	179
0.95	1276	2.35	1153	3.75	927	5.15	596	6.55	162
1	1273	2.4	1147	3.8	917	5.2	583	6.6	144
1.05	1271	2.45	1141	3.85	907	5.25	569	6.65	127
1.1	1268	2.5	1134	3.9	896	5.3	555	6.7	109
1.15	1265	2.55	1127	3.95	886	5.35	541	6.75	91
1.2	1262	2.6	1121	4	876	5.4	526	6.8	73
1.25	1259	2.65	1114	4.05	865	5.45	512	6.85	55
1.3	1255	2.7	1107	4.1	854	5.5	497	6.9	37
1.35	1252	2.75	1099	4.15	843	5.55	483	6.95	19
1.4	1248	2.8	1092	4.2	832	5.6	468	error \geq 7	0
1.45	1244	2.85	1085	4.25	821	5.65	453		

Control questions

- Suppose in one period, your prediction for the price is 0.75 higher than the realized price. How many points do you earn in this period? (*Answer: 1285*)
- Suppose a financial advisor predicts that the stock price goes up in period 10, and goes down in period 20, and the pension fund acts according to this prediction. In which period does the pension fund increase its demand for stocks, period 9 or period 19? (*Answer: period 9*)
- In which of the following cases will the stock price go up?
 - A. When the stock price is expected to go down and the pension funds buy very

little.

B. When the stock price is expected to go up and the pension funds buy a lot.

(Answer: B)

- Which of the following statements is true?
 - A. The other five pension funds in the market are advised by other participants in this experiment, so you interact with these five participants.
 - B. The other five pension funds in the market make use of computer traders, so you do not interact with other participants in this experiment.

(Answer: B)

- Suppose by the end of the experiment you have earned 25000 points, how much is this worth in euros? *(Answer: 12.50 euro)*

INSTRUCTIONS PART 2

We will now continue with part 2 of this experiment. Please read the instructions below carefully.

The pension fund that you are advising has decided to invest in a different stock. The new stock pays an uncertain dividend, with an average dividend payment of $\{\{dividend2\}\}$ euro per time period. The alternative risk-free investment is again a bank account that pays a fixed interest rate of 5% per time period.

Your task as a financial advisor remains the same: forecast the stock price in each time period as accurately as possible for 36 time periods. The demand for stocks is again determined by the aggregate demand of six large pension funds active. However, each pension fund is now advised by a participant of this experiment. In part 1 of the experiment, all participants have advised a pension fund in a stock market with five computer traders. Other participants may have encountered the same computer traders, or different computer traders.

You can find the complete instructions, incorporating the changes for part 2, at the bottom of your screen. The instructions will be available throughout the rest of the experiment.

Control question

- In what respect is the stock market in part 2 different from part 1?
 - A. The pension fund is investing in a different stock.
 - B. All six pension funds in the market are now advised by participants in this experiment.
 - C. Both of the above.
 - D. None of the above.

(Answer: C)

C Experimental results

Table 4: Summary statistics (normalized to $p^f = 62$)

	Mean	St.dev.	Min	Max	Range	PPP	RAD	RD
PART 1								
S	58.9	8.97	39.78	77.37	37.59	15	0.12	-0.05
B	342.46	330.86	35.65	1032.18	996.52	21	4.60	4.52
PART 2								
6S	58.11	4.37	46.81	67.1	20.28	5	0.11	-0.06
Group 1	46.64	2.31	39.78	51.33	11.56	3	0.25	-0.25
Group 2	60.56	1.58	53.27	61.91	8.64	6	0.02	-0.02
Group 3	60.54	4.58	46.65	68.71	22.06	11	0.06	-0.02
Group 4	68.64	4.20	54.88	76.88	22.00	4	0.11	0.11
Group 5	58.07	5.53	43.39	70.01	26.63	5	0.08	-0.06
Group 6	59.27	9.14	40.83	79.23	38.40	6	0.12	-0.04
Group 7	48.74	2.78	42.85	52.26	9.41	3	0.21	-0.21
Group 8	62.46	4.80	52.87	76.44	23.57	4	0.05	0.01
6B	543.7	331.99	62.47	1271.7	1209.23	9	7.78	7.77
Group 1	657.32	305.28	38.79	1308.03	1269.24	8	9.63	9.60
Group 2	484.12	230.74	53.75	976.92	923.17	7	6.82	6.81
Group 3	607.01	275.34	47.24	1186.53	1139.29	6	8.80	8.79
Group 4	545.46	502.99	38.03	1518.48	1480.45	9	7.83	7.80
Group 5	274.95	152.72	48.81	723.52	674.71	21	3.45	3.43
Group 6	671.78	488.49	88.27	1759.78	1671.51	10	9.84	9.84
Group 7	541.63	410.47	62.32	1522.79	1460.48	6	7.74	7.74
Group 8	567.33	289.93	122.54	1177.56	1055.01	4	8.15	8.15
3S3B	241.38	147.37	45.56	621.04	575.48	11	2.99	2.89
Group 1	75.06	13.86	47.71	95.65	47.93	6	0.25	0.21
Group 2	443.92	296.49	53.02	1323.50	1270.48	11	6.17	6.16
Group 3	57.53	6.72	48.19	68.60	20.41	33	0.11	-0.07
Group 4	57.79	9.73	41.41	74.60	33.19	6	0.14	-0.07
Group 5	121.21	25.79	40.25	169.55	129.30	6	0.98	0.95
Group 6	609.62	362.87	52.65	1438.35	1385.70	8	8.84	8.83
Group 7	511.66	455.67	39.29	1724.06	1684.78	15	7.29	7.25
Group 8	54.22	7.83	41.98	74.03	32.06	2	0.15	-0.13

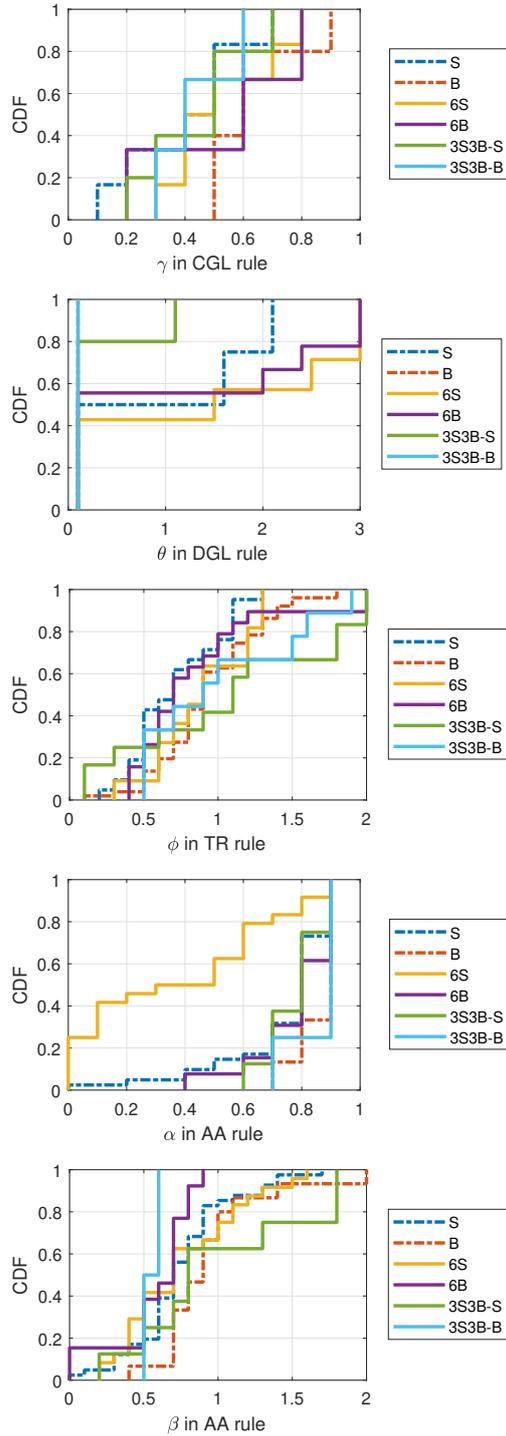
Note: To allow for comparison between markets with different fundamentals, the fundamental is normalized to $p^f = 62$ in all markets. This means that all predictions and prices are shifted downwards by six units in markets with $p^f = 68$, before the summary statistics are calculated. The statistics for part 1 are averaged over all 72 markets per experience (“S” for stable and “B” for bubbly). The statistics for part 2 are averaged over all 8 markets per treatment (shown in bold) and given for each group separately. “PPP” stands for peak price period.

Table 5: p -values of MWW tests for differences between fundamentals

	Mean	St.dev.	Min	Max	Range	PPP	RAD	RD
6S, odd vs. even groups	0.057	0.886	0.200	0.114	0.886	0.659	0.343	0.057
6B, odd vs. even groups	0.886	0.486	0.486	0.886	0.686	1.000	0.886	0.886
3S3B, odd vs. even groups	1.000	1.000	0.343	1.000	1.000	0.460	0.886	1.000

Note: Each MWW test compares the values of a given statistic in odd-numbered groups versus even-numbered groups in the three treatments. A p -value > 0.05 indicates that there is no significant difference between groups with $p^f = 68$ and groups with $p^f = 62$.

D Individual forecasting heuristics



Pairwise MWW tests for γ in CGL rule

	B	6S	6B	3S3B-S	3S3B-B
S	0.111	0.515	0.435	0.778	1.000
B		0.309	1.000	0.195	0.219
6S			1.000	0.643	0.598
6B				0.651	0.825
3S3B-S					1

Pairwise MWW tests for θ in DGL rule

	B	6S	6B	3S3B-S	3S3B-B
S	0.693	0.619	0.801	0.308	0.411
B		0.483	0.555	1.000	-
6S			0.690	0.147	0.259
6B				0.276	0.338
3S3B-S					0.752

Pairwise MWW tests for ϕ in TR rule

	B	6S	6B	3S3B-S	3S3B-B
S	0.011**	0.115	0.513	0.142	0.184
B		0.760	0.100*	0.460	0.975
6S			0.364	0.621	0.849
6B				0.370	0.520
3S3B-S					0.722

Pairwise MWW tests for α in AA rule

	B	6S	6B	3S3B-S	3S3B-B
S	0.010**	0.000**	0.582	0.966	0.156
B		0.000**	0.117	0.057*	0.951
6S			0.000**	0.003**	0.008**
6B				0.706	0.334
3S3B-S					0.245

Pairwise MWW tests for β in AA rule

	B	6S	6B	3S3B-S	3S3B-B
S	0.051*	0.827	0.15	0.347	0.087*
B		0.145	0.005**	0.871	0.010**
6S			0.431	0.274	0.487
6B				0.106	0.385
3S3B-S					0.144

Figure 11: Empirical CDFs and pairwise MWW tests of the parameter values of the CGL, DGL, TR and AA heuristics

Notes: The empirical CDFs indicate the distribution of γ , θ , ϕ , α and β for the classified heuristics. The tables present p -values of pairwise MWW tests for the parameter values. ** and * indicate significance at the 5% and 10% level, respectively. “S” and “B” represent the stable and bubbly experiences in stage 1; “6S” and “6B” contain all markets in stage 2 of those treatments, “3S3B-S” contains the stable markets (group 1, 3, 4, 5 and 8) and “3S3B-B” the bubbly markets (group 2, 6 and 7) of treatment 3S3B in stage 2.

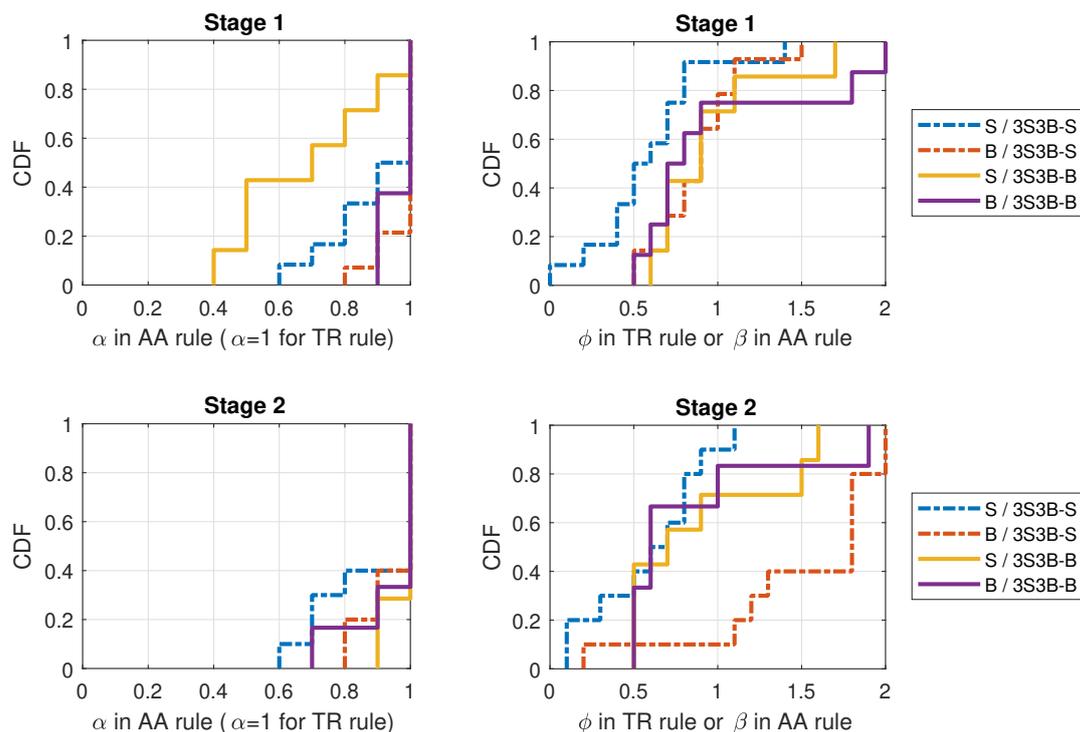
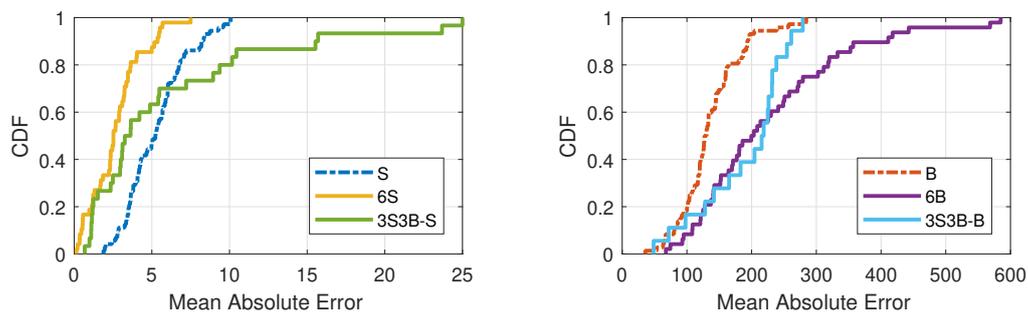


Figure 12: Empirical CDFs of the parameter values of the TR and AA heuristics in treatment 3S3B

Notes: Subjects in treatment 3S3B are divided into four groups, based on whether they have a stable (“S”) or bubbly (“B”) experience in stage 1 and whether they are part of a stable (“3S3B-S”) or bubbly (“3S3B-B”) market in stage 2. Subjects with a heuristic classified as TR or AA are included in the figures, with $\alpha = 1$ for TR heuristics. The empirical CDFs indicate the distribution of the weight parameter α (left panels) and the trend extrapolation parameter ϕ or β (right panels) of the classified TR and AA heuristics, in both stage 1 (top panels) and stage 2 (bottom panels).



(a) Stable markets

(b) Bubbly markets

Figure 13: Empirical CDFs of the mean absolute error of the classified heuristics

Notes: Panel (a) contains the stable experience, treatment 6S, and the stable markets of treatment 3S3B; panel (b) contains the bubbly experience, treatment 6B, and the bubbly markets of treatment 3S3B. Note that the scale of the horizontal axis differs for stable and bubbly markets.

Treatment 6S						Treatment 6B					
G	S	Stage 1	MAE	Stage 2	MAE	G	S	Stage 1	MAE	Stage 2	MAE
1	1	TR 0.5	8.05	DGL 0.1	0.14	1	1	TR 1.2	127.12	TR 2.0	208.65
1	2	TR 0.5	2.43	TR 0.7	0.53	1	2	TR 0.9	160.01	TR 0.5	417.82
1	3	AA (0.4, 0.3)	5.73	TR 0.8	1.71	1	3	TR 0.9	107.68	TR 0.7	74.37
1	4	AA (0.7, 0.9)	8.20	DGL 0.1	2.31	1	4	CGL 0.6	119.74	TR 0.4	120.71
1	5	AA (0.8, 0.6)	3.80	CGL 0.8	1.67	1	5	TR 0.8	94.76	TR 0.8	164.19
1	6	AA (0.8, 0.6)	4.66	CGL 0.4	1.85	1	6	AA (0.9, 0.9)	132.94	TR 1.1	171.10
2	1	AA (0.9, 0.6)	4.15	DGL 3.0	0.56	2	1	TR 1.8	123.27	TR 1.0	137.02
2	2	CGL 0.4	3.43	CGL 0.7	0.46	2	2	TR 1.1	145.10	TR 2.0	185.89
2	3	TR 0.7	3.95	TR 0.6	0.35	2	3	TR 0.8	89.73	AA (0.8, 0.8)	213.64
2	4	TR 0.5	5.42	TR 1.2	0.36	2	4	TR 0.1	117.33	DGL 0.1	140.50
2	5	TR 0.3	3.64	TR 1.3	0.22	2	5	AA (0.9, 0.8)	144.63	AA (0.8, 0.5)	203.40
2	6	AA (0.8, 1.4)	5.46	TR 0.9	0.55	2	6	TR 0.9	196.72	AA (0.9, 0.0)	442.77
3	1	AA (0.9, 0.3)	6.02	AA (0.2, 0.7)	2.52	3	1	AA (0.7, 0.7)	186.90	TR 0.6	270.99
3	2	AA (0.9, 0.7)	2.66	AA (0.5, 1.0)	2.67	3	2	TR 1.3	119.87	FUN	584.88
3	3	TR 1.1	4.29	AA (0.1, 1.5)	2.34	3	3	TR 0.8	132.91	NAI	140.81
3	4	TR 1.3	4.36	AA (0.0, 0.7)	3.24	3	4	TR 0.6	100.60	TR 0.6	169.69
3	5	DGL 1.6	2.86	AA (0.1, 0.2)	1.21	3	5	TR 1.3	116.77	TR 0.4	124.92
3	6	AA (0.8, 0.6)	2.78	AA (0.8, 0.7)	2.31	3	6	TR 0.6	82.61	TR 0.4	108.20
4	1	AA (0.8, 1.0)	4.27	AA (0.9, 0.7)	2.53	4	1	TR 1.4	195.19	AA (0.9, 0.7)	250.75
4	2	TR 1.0	5.84	AA (0.8, 0.9)	3.64	4	2	TR 1.5	144.37	AA (0.7, 0.5)	241.12
4	3	AA (0.9, 0.5)	5.90	DGL 2.5	3.36	4	3	TR 0.7	99.97	AA (0.9, 0.6)	229.93
4	4	TR 0.9	6.84	DGL 1.5	2.35	4	4	TR 1.1	130.34	AA (0.6, 0.7)	302.53
4	5	TR 1.1	5.22	TR 1.3	3.46	4	5	TR 1.4	284.51	TR 1.0	319.97
4	6	AA (0.0, 1.3)	9.30	CGL 0.3	3.18	4	6	TR 0.9	66.99	AA (0.9, 0.5)	152.44
5	1	CGL 0.7	3.65	AA (0.5, 0.2)	3.61	5	1	TR 1.1	179.93	CGL 0.8	92.89
5	2	AA (0.8, 0.4)	3.37	AA (0.6, 0.3)	2.52	5	2	TR 1.4	126.28	DGL 2.4	108.66
5	3	AA (0.9, 0.7)	5.33	AA (0.6, 1.2)	5.46	5	3	AA (0.7, 0.4)	238.93	FUN	311.30
5	4	TR 0.6	4.98	AA (0.6, 0.7)	3.09	5	4	DGL 0.1	85.91	DGL 0.1	181.12
5	5	AA (0.8, 0.7)	7.04	AA (0.3, 0.4)	4.01	5	5	AA (0.8, 1.1)	159.53	DGL 3.0	67.45
5	6	AA (0.8, 0.7)	4.18	AA (0.9, 1.0)	2.90	5	6	AA (0.8, 0.8)	284.00	AA (0.8, 0.0)	121.29
6	1	AA (0.8, 0.8)	6.74	DGL 3.0	7.50	6	1	TR 1.1	120.00	TR 1.2	142.19
6	2	AA (0.2, 0.3)	5.30	AA (0.0, 0.5)	5.52	6	2	TR 0.8	80.09	TR 0.7	94.90
6	3	AA (0.7, 0.8)	5.69	AA (0.6, 1.1)	5.00	6	3	TR 0.8	161.39	DGL 0.1	151.72
6	4	AA (0.8, 0.4)	6.50	AA (0.0, 0.4)	5.37	6	4	TR 0.5	64.57	TR 0.6	177.11
6	5	AA (0.7, 0.9)	5.24	AA (0.5, 1.1)	5.69	6	5	TR 0.3	101.67	CGL 0.2	180.75
6	6	AA (0.7, 1.3)	6.05	AA (0.1, 0.4)	5.15	6	6	CGL 0.5	148.81	CGL 0.6	568.51
7	1	AA (0.9, 0.9)	4.08	TR 0.3	0.96	7	1	AA (0.9, 0.9)	121.05	DGL 0.1	258.26
7	2	TR 1.1	3.59	TR 0.6	1.19	7	2	CGL 0.6	193.43	TR 0.9	352.68
7	3	TR 1.1	4.08	TR 1.2	2.24	7	3	TR 1.3	125.60	TR 0.5	199.42
7	4	CGL 0.5	1.88	CGL 0.5	1.31	7	4	TR 0.9	191.78	AA (0.7, 0.8)	332.75
7	5	AA (0.9, 0.8)	5.62	TR 0.9	2.66	7	5	TR 0.7	111.87	AA (0.9, 0.9)	225.77
7	6	AA (0.8, 0.9)	9.62	CGL 0.4	4.04	7	6	TR 1.3	156.99	AA (0.8, 0.7)	248.90
8	1	AA (0.9, 0.1)	3.49	AA (0.0, 0.5)	2.46	8	1	TR 0.9	133.52	DGL 2.0	279.25
8	2	AA (0.8, 0.6)	4.72	AA (0.0, 0.4)	2.94	8	2	AA (0.9, 1.4)	127.01	AA (0.4, 0.7)	356.96
8	3	AA (0.8, 0.7)	3.64	AA (0.7, 1.6)	2.89	8	3	TR 0.7	66.05	TR 0.7	127.82
8	4	DGL 2.1	6.46	AA (0.1, 1.3)	3.46	8	4	AA (0.9, 1.0)	103.99	DGL 0.1	272.76
8	5	TR 0.8	5.88	DGL 0.1	1.13	8	5	TR 0.5	257.14	FUN	411.15
8	6	AA (0.8, 0.6)	8.73	AA (0.0, 0.5)	3.23	8	6	TR 1.2	193.10	DGL 3.0	318.30

Table 6: Classified heuristics and mean absolute errors for all subjects

Notes: “G” indicates the group number in the treatment, “S” indicates the subject number in the group. The type of heuristic is followed by the parameter value(s).

Treatment 3S3B					
G	S	Stage 1	MAE	Stage 2	MAE
1	1	CGL 0.1	2.02	DGL 1.1	1.14
1	2	AA (0.9, 0.7)	3.25	AA (0.6, 0.7)	4.89
1	3	AA (0.6, 0.0)	1.96	CGL 0.5	5.42
1	4	TR 0.8	63.05	AA (0.9, 1.3)	5.48
1	5	TR 1.0	164.17	TR 1.8	7.21
1	6	TR 1.5	145.03	AA (0.8, 1.8)	15.70
2	1	AA (0.5, 1.7)	8.39	TR 1.5	71.85
2	2	DGL 0.1	10.08	TR 1.6	215.48
2	3	TR 0.7	6.73	TR 0.9	48.49
2	4	AA (0.9, 2.0)	187.24	TR 1.9	141.70
2	5	TR 0.8	92.23	CGL 0.3	97.74
2	6	TR 0.6	117.16	TR 0.5	182.93
3	1	TR 0.2	6.65	DGL 0.1	3.08
3	2	AA (0.8, 0.8)	8.19	TR 0.6	0.98
3	3	DGL 0.1	3.34	DGL 0.1	0.68
3	4	TR 0.8	109.34	TR 1.1	1.09
3	5	TR 0.5	35.61	CGL 0.7	1.18
3	6	TR 0.9	133.47	TR 1.2	1.24
4	1	AA (0.9, 0.6)	7.08	AA (0.8, 0.8)	3.63
4	2	TR 0.7	3.54	AA (0.7, 0.5)	2.49
4	3	CGL 0.5	5.69	AA (0.7, 0.8)	3.26
4	4	CGL 0.9	204.10	DGL 0.1	4.20
4	5	TR 1.1	152.24	TR 2.0	2.99
4	6	TR 0.9	103.63	AA (0.8, 1.8)	2.35
5	1	TR 0.4	5.04	TR 0.1	10.45
5	2	AA (0.8, 1.4)	10.04	TR 1.1	15.54
5	3	TR 0.5	4.22	CGL 0.2	10.17
5	4	TR 0.5	53.36	CGL 0.3	8.95
5	5	AA (0.8, 1.0)	156.88	DGL 0.1	25.00
5	6	TR 1.1	159.96	TR 2.0	23.68
6	1	AA (0.8, 0.7)	3.48	AA (0.9, 0.5)	238.27
6	2	AA (0.5, 1.1)	7.20	TR 0.7	218.70
6	3	AA (0.9, 0.6)	3.80	CGL 0.6	204.44
6	4	TR 1.8	124.28	TR 1.0	165.16
6	5	TR 0.5	80.70	AA (0.9, 0.6)	127.98
6	6	CGL 0.5	130.30	DGL 0.1	261.26
7	1	CGL 0.2	8.34	TR 0.5	226.23
7	2	AA (0.7, 0.9)	4.97	AA (0.9, 0.5)	224.98
7	3	AA (0.4, 0.9)	6.03	CGL 0.4	279.06
7	4	AA (0.9, 0.9)	126.09	TR 0.5	231.52
7	5	TR 0.7	138.44	DGL 0.1	231.92
7	6	AA (0.9, 0.7)	119.41	AA (0.7, 0.6)	254.55
8	1	TR 0.5	6.02	TR 0.3	1.52
8	2	AA (0.7, 0.8)	6.27	TR 0.9	3.11
8	3	TR 0.4	2.81	TR 0.1	1.10
8	4	AA (0.9, 0.7)	143.39	CGL 0.5	9.37
8	5	TR 0.9	184.22	TR 1.8	2.95
8	6	AA (0.9, 0.7)	131.40	AA (0.9, 0.2)	3.65

Table 6: Classified heuristics and mean absolute errors for all subjects (continued)
Notes: “G” indicates the group number in the treatment, “S” indicates the subject number in the group. The type of heuristic is followed by the parameter value(s).