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
Keywords: Experimental finance; Asset market experiences; Asset price bubbles; Heterogeneous expectations

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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 (Greenwood and Nagel, 2011; Chernenko et al., 2016).

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 In

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1Studies examining experience effects in stock markets are Greenwood and Nagel (2011); Malmendier and Nagel (2011); Strahilevitz et al. (2011); Nagel (2012); Chernenko et al. (2016); Cordes and Dierkes (2017); Anandia and Ehrmann (2017); Hoffmann et al. (2017); Hoffmann and Post (2017) and Vissing-Jorgensen (2003). Anagol et al. (2018); Chiang et al. (2011) and Kaustia and Knüpfer (2008) focus on IPOs. Fajardo and Dantas (2018); Malendier and Nagel (2016); Madeira and Zafar (2015) and Malmendier et al. (2017) consider inflation, Kuchler and Zafar (forthcoming) 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); Smith et al. (1988); King (1991); King et al. (1993) 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 (Dufwenberg et al., 2005; Xie and Zhang, 2012; Akiyama et al., 2014; Kirchler et al., 2015). Counterexamples of the result that experience eliminates bubbles are found by Oechssler et al. (2011); Hong et al. (2018) and Kopányi-Peuker and Weber (2018).

3Similar behavior is observed in beauty contest games: experienced players anticipate the
the market setting of Smith et al. (1988), such a trading strategy mitigates bubbles. By contrast, stationary repetition does not eliminate bubbles in an asset market learning-to-forecast experiment (LtFE): bubbles emerge even faster in the second and third repetition (Kopányi-Peuker and Weber, 2018).

To learn more about the effect of experiences in asset markets, I conduct a LtFE 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. 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 LtFEs 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 have the same experience (stable or bubbly), or an equal mix of experiences.

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.

My experiment differs from the repeated LtFE of Kopányi-Peuker and Weber (2018) in three main respects. First, I induce either a stable or a bubbly experience, such that the effect of both types can be studied. Second, I form mixed-experience choices of their inexperienced opponents and play a best response (Slonim, 2005; Skeath and Livingston, 2010).

Large bubbles driven by trend-following expectations are found in the asset market LtFEs of Hennequin and Hommes (2018); Bao et al. (2016) 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. Shleifer and Summers (1990); Hirshleifer (2001); Shiller (2002); Greenwood and Shiller (2014); Barberis et al. (2018)).

Lejarraga 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 also have an impact: subjects who personally experienced a boom in the Shanghai Stock Exchange make bigger trades.
markets in addition to same-experience markets. Third, unlike stationary repetition, the fundamental price is not the same in the two stages and subjects do not know about the experiences of others in the market.

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 LtFE

The general design of the experiment is based on the asset market LtFE 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, \( E_{it}(p_{t+1}) = p_{e_i,t+1} \), traders calculate their optimal demand for shares using myopic mean-variance optimization. The market price is determined by the equilibrium between demand and supply:

\[
p_t = \frac{1}{1 + r} \left[ \frac{1}{6} \sum_{i=1}^{6} p_{e_i,t+1} + \bar{y} \right].
\]

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 and hold more shares than cash, as opposed to subjects who experienced a crash.
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:

$$e_{it} = \max \left\{ 1300 - \frac{1300}{49} (p_t - p_{it}^e)^2, 0 \right\}.$$  \hspace{1cm} (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 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
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?

<table>
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<th>Period</th>
<th>Your Prediction</th>
<th>Market Price</th>
<th>Earnings</th>
</tr>
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<td></td>
<td></td>
</tr>
<tr>
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<td>61.81</td>
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</tr>
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<td>0.00</td>
</tr>
<tr>
<td>24</td>
<td>71.00</td>
<td>71.65</td>
<td>1288.76</td>
</tr>
</tbody>
</table>

Total Earnings (Part 1):
17533.73 points

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

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, making it a two-period-ahead prediction. After completing the two prediction stages of the experiment, subjects fill in a short questionnaire, which includes 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 LtFE. 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

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\(^6\)The markets are taken from Hennequin and Hommes (2018). 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 LtFEs.
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 $p^f = 68$).

stage 1 of this experiment.\(^7\)

Figure 2 shows the predictions of the five robots and the price pattern that they generate. In my experiment, the robots’ predictions have a total weight of $\frac{5}{6}$ in 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 LtFE, 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 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 (treat-

\[^7\]The fundamental in Hennequin and Hommes (2018) is $p^f = 60$, so all predictions are increased by either 2 or 8 units. This makes sure that the price pattern remains the same, but the stable market converges to the fundamental of $p^f = 62$ or $p^f = 68$.

\[^8\]A 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 a single typo 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.
ment 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).

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. In treatment 3S3B, the dynamics could go 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). A session lasted for about two hours in total. Earnings were on average €21.63 and ranged from €10 to €40.90.

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 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 LtFEs. 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 LtFEs 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.
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 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
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 $p_f = 62$. The upper bound on predictions is 2000.

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.

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.\footnote{Subjects 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.} 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.

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 making an effort to stabilize the price by submitting (almost) constant predictions or by submitting low predictions whenever the price goes up too quickly.\(^\text{12}\) 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

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\[^{12}\text{A number of subjects describe stabilizing strategies for stage 2 in the questionnaire, using phrases such as “trying to maintain as constant a price as possible”, “mitigating fluctuations”, and “preventing a bubble from forming by predicting a price of 1”. Some of these subjects experienced stability in stage 1, some of them experienced bubbles.}\]
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 2 in Appendix C. The fundamental is normalized to $p_f = 62$ in all markets to allow for comparison between markets with different fundamentals. 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 3 in Appendix C). Hence, the change in fundamentals does not matter for the results.

### 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):

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

For instance, a value of $\text{RAD} = 0.5$ indicates that the price differs on average 50% from the fundamental. 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 2 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.
Table 1: \(p\)-values of pairwise MWW tests for volatility and mispricing

<table>
<thead>
<tr>
<th>Pairwise MWW tests for st.dev. of prices</th>
<th>Pairwise MWW tests for RAD</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>S</td>
</tr>
<tr>
<td></td>
<td>S</td>
</tr>
<tr>
<td>6S</td>
<td>0.000**</td>
</tr>
<tr>
<td>6B</td>
<td>0.025** 0.022** 0.001**</td>
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<tr>
<td>3S3B</td>
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</table>

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).

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 sta-
The experiences of subjects also affect coordination of expectations in stage 2. To illustrate this, Figure 8 plots the standard deviation of predictions over time for treatment 6S, 6B and the stable and bubbly markets of 3S3B separately. A low standard deviation of predictions 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 coordi-
oordination in most markets as well, but there is somewhat more heterogeneity in expectations than in 6S. By contrast, coordination is completely lost in the bubbly markets of 6B and 3S3B. The large price changes make it harder to coordinate, and this in turn leads to more fluctuations in the price. However, the heterogeneity in predictions is slightly lower in the bubbly markets of 3S3B than in 6B. The differences in the average standard deviation 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 have less heterogeneity in expectations than bubbly-experience markets.

4 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. The results show that experiencing price stability or bubbles has a large effect on future market dynamics. Many subjects seem to (initially) expect the same price pattern as in the first market and play a best response in the second market. This leads to faster convergence 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.

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-Peuker and Weber (2018), and contradicts a robust finding in experiments la Smith et al. (1988). In these trading experiments, subjects buy and sell an asset for about fifteen periods in a simple market. The market setting in learning-to-forecast experiments is less transparent and has a longer time horizon, making it more difficult to learn from bubble experiences. On the other hand, 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 (Greenwood and Nagel, 2011; Chernenko et al., 2016). To some extent, my experimental results are in line with this: inexperienced subjects often have strong 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. Malmendier and Nagel (2011); Ampudia and Ehrmann (2017)). 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. (2018).

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


the Great Recession. Paper prepared for the Academic Consultants Meeting at
the Federal Reserve Board.

bubble formation: Informed traders and communication. Journal of Economic
Dynamics and Control, 35:1831–1851.

all the difference? An experiment on the depression babies hypothesis. SAGE
Open, 8(2):1–16.


p-beauty game. Working paper.

Slonim, R. (2005). Competing against experienced and inexperienced players. Ex-
perimental Economics, 8:55–75.

Smith, V., Suchanek, G., and Williams, A. (1988). Bubbles, crashes, and endoge-
nous expectations in experimental spot asset markets. Econometrica, 56(5):1119–
1151.


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.


ity” 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:

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

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 $E_{it}(p_{t+1}) = p^e_{i,t+1}$. Solving for the price of the risky asset $p_t$ gives Equation (1):

$$p_t = \frac{1}{1 + r} \left[ \frac{1}{6} \sum_{i=1}^{6} p^e_{i,t+1} + \bar{y} \right]. \quad (8)$$
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 $\{\text{dividend1}\}$ 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.

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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? \((Answer: \ 12.50 \text{ euro})\)

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 \(\{\text{dividend2}\}\) 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 2: Summary statistics (normalized to $p^f = 62$)

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<tr>
<td>Group 8</td>
<td>54.22</td>
<td>7.83</td>
<td>41.98</td>
<td>74.03</td>
<td>32.06</td>
<td>2</td>
<td>0.15</td>
<td>-0.13</td>
</tr>
</tbody>
</table>

*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 3: $p$-values of MWW tests for differences between fundamentals

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>St.dev.</th>
<th>Min</th>
<th>Max</th>
<th>Range</th>
<th>PPP</th>
<th>RAD</th>
<th>RD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>6S, odd vs. even groups</strong></td>
<td>0.057</td>
<td>0.886</td>
<td>0.200</td>
<td>0.114</td>
<td>0.886</td>
<td>0.659</td>
<td>0.343</td>
<td>0.057</td>
</tr>
<tr>
<td><strong>6B, odd vs. even groups</strong></td>
<td>0.886</td>
<td>0.486</td>
<td>0.486</td>
<td>0.886</td>
<td>0.686</td>
<td>1.000</td>
<td>0.886</td>
<td>0.886</td>
</tr>
<tr>
<td><strong>3S3B, odd vs. even groups</strong></td>
<td>1.000</td>
<td>1.000</td>
<td>0.343</td>
<td>1.000</td>
<td>1.000</td>
<td>0.460</td>
<td>0.886</td>
<td>1.000</td>
</tr>
</tbody>
</table>

*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 $p^f = 62$. 

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