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How initial price history influences expectation formation in multi-asset experimental markets: An exploratory case study

Aleš Kresta[1] Michaela Sedláková[2]

Abstract

We present an exploratory study on expectation formation in a controlled experimental setting. Participants predicted the prices of three risky assets, with their key information being the initial price history. Our research investigates the impact of the initial price history on overall price dynamics and the participants' coordination. We provide tentative evidence highlighting several key points. Firstly, a stable initial price history reduces asset price volatility. Secondly, the correlation between assets during the initial price history is crucial for price dynamics. Notably, two assets exhibited strong negative dependence, which significantly influenced participants' expectations. It is important to note that this dependence persisted in subsequent price evolution. In general, the initial price history played a pivotal role in shaping participants' expectations. Given the exploratory nature of this study, we acknowledge that these findings are preliminary and should be interpreted with caution. We also point to ways for future research to validate our initial findings.

Keywords

- experimental economics
- expectations
- asset pricing

JEL codes: C92, D84, G12, G41

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Introduction

Expectations play a crucial role in shaping economic behaviour, influencing decision-making, and driving market outcomes. Throughout history, there have been many examples of speculative asset markets, where assets are traded at prices substantially higher than their fundamental value. Notable recent examples include the dotcom bubble of the late 1990s, the US housing market bubble in the early 2000s, and the bitcoin surge in 2017, followed by a dramatic collapse in 2018. Traders often purchase assets they consider overpriced with the expectation that their prices will continue to rise, therein aiming to profit from the anticipated capital gains. For instance, Barberis et al. (2018) suggest that trend extrapolation is a key factor in explaining bubbles in the stock, housing, and commodity markets. Gaining a deeper understanding of how expectations are formed can markedly enhance our understanding of financial market behaviour.

One way to study expectations is through the analysis of survey data. Case et al. (2012) demonstrate that homebuyers' expectations about future changes in house prices are strongly influenced by past trends. Essentially, buyers expect that recent patterns of price appreciation will continue. Greenwood and Shleifer (2014) provide survey evidence showing that investors' expectations of stock market returns are heavily influenced by past performance, highlighting strong extrapolation, particularly during the dotcom bubble. Overall, these studies emphasise the role of trend extrapolation in shaping market expectations and contributing to the formation of bubbles. However, survey data research faces challenges in measuring expectation rules, as the underlying economic fundamentals and the information available to forecasters cannot be controlled.

Alternatively, expectations and bubble formation can be studied in an experimental setting. In Learning-to-Forecast (LtF) experiments, participants act as financial forecasters and are repeatedly asked to predict the price of an asset. The predictions made by participants are used to determine optimal trading decisions, with the resulting market price emerging from the aggregation of these forecasts. Once all individual predictions are collected, the market price is calculated using a computer algorithm, and this process is repeated over many consecutive periods. Participants are financially rewarded based on the accuracy of their forecasts, giving them a strong incentive to predict prices as precisely as possible. This setup allows researchers to collect valuable data on how participants form expectations and how these influence market dynamics.

In many previous LtF experiments with positive expectation feedback systems, the formation of price bubbles has been a common phenomenon. Hommes et al. (2008) investigated expectation formation in a stationary asset pricing experiment, where the rational expectations of the fundamental price was constant. Despite this, significant price bubbles often occurred in most of their experiments, sometimes 16 times in excess of the fundamental value. Another example is the study by Bao et al. (2020), which examined bubble formation in larger groups. Their results showed that prices exceeded the fundamental value by up to 15 times. These bubbles were primarily driven by positive expectation feedback, with participants generally highly coordinated and following a common prediction strategy. While these studies provide valuable insights, they primarily focus on markets with a single asset. Experiments involving multiple assets could offer deeper insights into how expectations and market dynamics evolve in more complex environments.

In this paper, we investigate bubble formation and the impact of initial price history in a multi-asset market using the Learning-to-Forecast experiment. The experimental framework builds on Anufriev et al. (2022), where participants were provided with the initial price history of a risky asset. Our experiment expands the investment options to include three distinct risky assets, each with a different initial price history. In doing so, we address a gap in the current literature, which predominantly examines single-asset markets. The controlled experimental environment enables us to observe and analyse the dynamics of expectation formation and market behaviour in a more realistic, multi-asset setting.

Our main experimental results are as follows. We conducted six experiments, which provide valuable insights and serve as case studies to explore the impact of initial price history on asset price dynamics in a multi-asset market. Firstly, we observed the formation of bubbles even in a multi-asset market setting. Secondly, assets with a stable initial price history exhibited lower volatility, suggesting that initial price history is crucial for predicting future price fluctuations. Additionally, strong negative asset dependence, evident in the initial price history, persisted in subsequent price movements, highlighting its pivotal role in price dynamics. These findings underscore the importance of initial price history in shaping subsequent market behaviour.

The remainder of the paper is organised as follows: Section 1 reviews the literature, Section 2 presents the experimental design, and Section 3 outlines the hypotheses. The results are presented in Sections 4 and 5. In Section 6, we discuss the limitations and possible extensions. The final Section offers conclusions.

1. Literature review

Since the influential works of Muth (1961) and Lucas (1972), the rational expectations (RE) hypothesis has been the standard framework for modelling expectation formation. The core idea behind rational expectations is that individuals make decisions based on all available information, and their expectations are, on average, correct. However, the limitations of the rational agent paradigm are well documented, as it unrealistically assumes perfect knowledge of the economy. More critically, RE models often conflict with empirical data. Many studies show that expectations frequently deviate from rational expectations, tending to be extrapolative or influenced by various biases (e.g., Bacchetta et al., 2009; Coibion et al., 2018; Greenwood & Shleifer, 2014; Vissing-Jorgensen, 2003). Additionally, these models are often inconsistent with behaviour observed in laboratory experiments involving human subjects.

As a result, a shift occurred towards an alternative behavioural perspective, where agents exhibit bounded rationality and incorporate elements of psychology into their decision-making processes. An influential contribution to this view comes from the work of Tversky and Kahneman (1974), which laid the groundwork for understanding how psychological factors influence judgment and behaviour. Within the broader framework of behavioural finance, various psychology-based trading and behavioural modes have been identified, including positive feedback, trend extrapolation, noise trading, overconfidence, and overreaction. Another alternative theory is the concept of adaptive expectations, in which boundedly rational agents adjust their expectations about the future based on past experiences. For a detailed overview, see Sargent (1993) and Evans and Honkapohja (2001). A complementary approach to understanding expectations involves heuristic models, such as those with heterogeneous expectations developed by Brock and Hommes (1997, 1998) and Anufriev et al. (2019). In these models, agents do not always rely on strict rationality; instead, they employ simple heuristics to form their expectations.

Bubbles in asset markets have been extensively studied in various experimental settings. A seminal study by Smith et al. (1988) conducted a laboratory experiment in a double auction market, where participants traded a hypothetical asset that paid uncertain dividends over 15 periods. In this market, participants differed only in terms of their stock holdings and cash endowments, with no information asymmetry present. Despite the absence of these imbalances, bubbles emerged in most of the experiments, with asset prices diverging significantly from their intrinsic values. Since Smith et al. (1988), numerous follow-up studies have reinforced these findings. For comprehensive reviews, see Palan (2013) or Nuzzo and Morone (2017). Overall, these experiments demonstrate that market bubbles can arise even under simple conditions, a result that has been consistently corroborated by subsequent research.

Several studies have explored the dynamics of multiple asset trading in double auction environments. For instance, Fisher and Kelly (2000) studied foreign exchange markets, examining the impact of asset correlation on pricing. Their results showed only minor deviations in pricing, suggesting that subjects traded to eliminate arbitrage opportunities. Chan et al. (2013) extended this work by exploring how differentiating characteristics, such as maturity length and dividend processes, affect asset prices, and found that differentiation helps mitigate bubbles. For an overview of market experiments with multiple assets, see Duffy et al. (2022). These studies collectively highlight the importance of asset correlation and market structure in understanding price dynamics and bubble formation in multi-asset markets.

Learning-to-forecast (LtF) experiments are used to study expectation formation in various economic settings. This approach was first introduced by Marimon et al. (1993), who examined the existence and robustness of price volatility in experimental overlapping generation economies. LtF experiments are often focused on asset pricing, where participants take on the role of professional forecasters (Hommes et al., 2005, 2008). More recently, these experiments have expanded into the field of monetary economics. For example, LtF experiments have been used to study the effects of central bank communications on economic expectations (Kryvtsov & Petersen, 2021) and expectation formation in situations where nominal interest rates are close to zero (Arifovic & Petersen, 2017; Hommes et al., 2019). Hommes (2011) presents a review of LtF experiments in different economic settings and a comprehensive review can also be found in Bao et al. (2021).

LtF experimental markets may exhibit either negative or positive feedback. In a market with positive (negative) expectation feedback, a higher average expectation of future prices results in a higher (lower) realised market price. Heemeijer et al. (2009) demonstrate that the type of expectation feedback alone leads to significantly different behaviour in aggregate prices. They find that with negative expectation feedback, prices converge rapidly to the fundamental value, whereas positive expectation feedback results in large fluctuations and persistent deviations from the fundamental value. Similar results are reported by Bao et al. (2012), who investigate the behaviour of realised prices in positive and negative feedback systems following unanticipated changes in the fundamental price. Colasante et al. (2019) also find comparable effects. A general conclusion from the LtF literature is that participants are more likely to learn the rational expectations equilibrium in markets characterised by negative feedback systems.

Our paper also examines the impact of initial price history on market behaviour, a topic that has been explored by only a few papers. Hennequin (2021) conducted a two-stage experiment where one participant and five robots created either a stable or bubbly market in the first stage, followed by a second stage where only humans participated. The experiment found that initial market conditions extensively influenced later price dynamics, with the occurrence and emergence of bubbles being typical for groups that experienced large fluctuations in the first stage. Anufriev et al. (2022) explored the effect of investment horizon on asset price volatility. Participants were shown a price history with either stable or volatile development. Unlike Hennequin's experiment, participants in this study only observed past developments. Their results showed that stable historical prices led to lower volatility, regardless of the investment horizon. Both studies highlight the importance of initial conditions and historical stability in determining future market behaviour, which is a theme also relevant to our research.

There are also other related papers that investigate how the price paths of stocks influence investor behaviour and market dynamics. Grosshans and Zeisberger (2018) demonstrate that investor satisfaction and risk preferences are significantly influenced by the price path through which returns are achieved, highlighting the importance of the sequence of returns in shaping investor behaviour. Borsboom and Zeisberger (2020) analyse various price path characteristics and their influence on risk perception, return beliefs, and investment propensity, revealing that salient features such as highs, lows, and crashes are the most influential drivers of perceived risk. Together, these studies underscore the pivotal role of historical price paths and individual perceptions in shaping market dynamics and investor behaviour, suggesting that both initial conditions and psychological factors are key determinants of asset prices.

In our study, we also explore the effect of correlation in a multi-asset market. Recent experimental studies in the banking sector have provided valuable insights into the dynamics of contagion and the role of correlations in influencing participant behaviour. Chakravarty et al. (2014) demonstrated that even when banks' liquidity levels are independent, depositor behaviour at one bank can still influence behaviour at another bank due to panic-based contagions. Similarly, König-Kersting et al. (2022) explored the impact of disclosure about bank fundamentals on depositor behaviour, finding that while transparency can enhance stability for strong banks, it may have adverse effects on weaker banks, especially when there are interbank linkages. These findings underscore the importance of initial correlations and information dissemination in shaping participant expectations and subsequent behaviour.

2. Experimental design

In this section, the experimental design is introduced. Six experiments were conducted at the VSB—Technical University of Ostrava during October and November 2022 and April and May 2023. A total of 75 students from the Faculty of Economics participated in these experiments, with the group sizes ranging from 9 to 17 students. The aim was to run sessions with groups of approximately 15 participants, due to the maximum number of 20 computers available. To avoid cancelling a session because of insufficient participants, the group size was flexible. A session would start if 8 or more participants arrived on time. Six sessions were held, with the following attendance: 11, 9, 15, 9, 13, and 17 participants in sessions EXP1–EXP6. No sessions were cancelled. The experiments took place in a computer classroom, where all participants operated within the same market throughout the entire experiment. At the beginning of each session, participants received detailed instructions, including printed copies (see Appendix A), and were familiarised with their task. No communication was allowed between participants during the experiment. After completing the experiment, students filled out a questionnaire and received payment based on their ranking.[3] The payment amounts ranged from 50 to 700 CZK (roughly from 2 to 28 EUR) and the ranking was determined by their average prediction error.

The experimental design is based on the typical LtF experimental set-up and the present value model of asset pricing is used, see Brock and Hommes (1998) and Hommes (2011) for an overview. In this model, mean-variance investors divide their wealth into risk-free and risky assets. The gross return of a risk-free asset is $R = 1 + r > 1$ and all risky assets pay an IID dividend with mean $\bar{y}$ each period. The market-clearing price $p_{t,a}$ of asset a in time period t is defined according to Anufriev et al. (2022) as follows:

$$p_{t,a} = p_a^f + \frac{1}{(1+r)}\left(\bar{p}_{t+1,a}^e - p_a^f - \varepsilon_{t,a}\right) \tag{1}$$

---

[3] We selected tournament selection to incentivise participants effectively. Tournament incentives, where compensation is tied to the rank obtained within a group rather than absolute performance, are common in financial markets. Fund managers, for example, are often evaluated based on their performance relative to peers or benchmarks, with new fund inflows typically concentrated in the most successful funds (see, e.g., Chevalier & Ellison, 1997). Furthermore, recognising the potential risks of setting incentives too low, which would demotivate the participants to continue in the experiment once they found this out, we decided to use tournament selection. For instance, in Anufriev et al. (2022) and Bao et al. (2020), the researchers had to increase show-up fees *ex-post* due to low payoffs. We believe that this approach strikes a balance between introducing competition and maintaining appropriate participant motivation.

where p_a^f is fundamental value of particular asset a, r is discount factor, $\bar{p}^e_{t+1,a}$ is average expectations about price of asset a in the period $t + 1$, and $\varepsilon_{t,a}$ is a small random outside supply of the asset from noise traders.

It is obvious from equation that the market price $p_{t,a}$ is a weighted average of the fundamental value and average expectations for the period $t + 1$. If an increase in price is expected in the future, it increases the demand in the current period as well as the current price. This is called *positive expectations feedback*. The rational equilibrium is given by the fundamental value of the asset.

Participants are introduced to the experiment in the following manner: Participants play the role of a financial forecaster for a pension fund that needs to optimally invest a large amount of money for one period. The pension fund has several investment options: risk-free asset and three risky assets. The instructions explicitly state that the risky assets are not correlated in the long term.[4] In the case of risk-free asset, the money is invested in a government bond which pays a fixed interest rate of 5%. Alternatively, a pension fund can allocate funds to shares of indefinitely lived risky assets. These risky assets are associated with uncertainty about future prices and dividends. The dividends are independently and identically distributed with a mean of \$10 per period. Since participants know the numerical values of the interest rate and dividends, they have sufficient information to potentially determine the fundamental value of risky assets. For comparability and simple visualisation during the experiment, all assets share the same fundamental value of \$200.

The participants' task is explained as making a prediction of future asset prices, based on which the pension fund will make investment decisions. The instructions do not specify the exact pricing equation in accordance with the standard practice of LtF experiments. However, some characteristics of the market are described. For instance, a higher price forecast leads to an increased demand for assets, and several funds influence total demand. As in Anufriev et al. (2022), participants receive an asset price history at the beginning of the experiment (see Figure 1) and we focus on the impact of initial price history on expectation formation. However, our research examines this effect in a multi-asset market. With the increased number of risky assets, participants can compare price developments of all assets in the market.

[4] As previously mentioned, instructions were read aloud and clarified with examples to explain the meaning of long-term asset uncorrelation. Furthermore, all participants were from the Faculty of Economics and had completed relevant courses on correlation, including the distinction between the long run and short run. Given their academic background, it is reasonable to assume that participants understood this distinction. However, to ensure comprehension and address any potential misunderstandings, future research could incorporate a quiz where participants must answer questions concerning the correlation between assets.

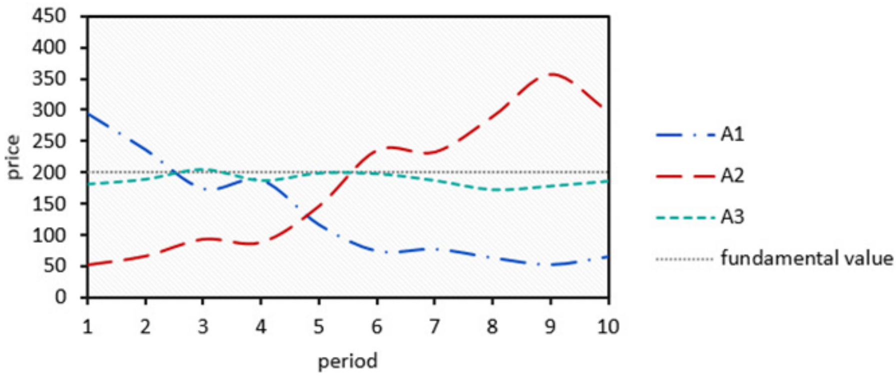
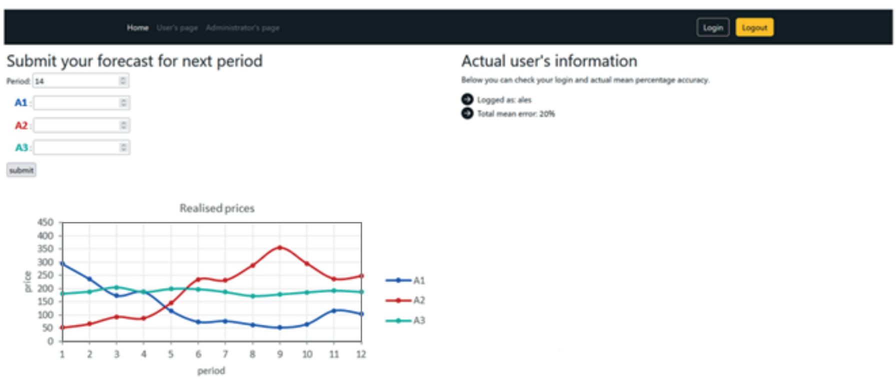


Figure 1. Initial price history for all risky assets

Source: own work.

During the experiment, the participant's available information for the price prediction of the period $t + 1$ in period t consists of:

- past realised prices up to period $t - 1$,
- participant's previous price predictions up to period t,
- participant's total average error as well as average errors for particular assets.



	Realised prices			Your forecasts			Your forecasting errors			
Period	**A1**	**A2**	**A3**	**A1F**	**A2F**	**A3F**	**A1E**	**A2E**	**A3E**	**Total**
13				115	230	190				
12	117	238	192	72	285	190	38%	20%	1%	20%
11	105	248	187							
10	65	296	186							
9	52	356	178							
8	63	289	172							
7	77	232	187							
6	74	235	198							
5	116	146	199							
4	188	88	187							
3	174	93	205							
2	237	66	189							
1	295	52	181							

Figure 2. Screenshot of the experimental interface

Source: own work.

Once all predictions from all participants for period $t + 1$ were received,[5] the realised price of assets for the current period t was determined according to equation and this was repeated for all 50 consecutive periods. An example of the experimental screen during the experiment is presented in Figure 2.

3. Hypotheses

In our experiment, the rational expectations equilibrium is represented by the fundamental value of assets. However, previous experiments have shown that asset prices often deviate from this fundamental value, leading to the formation of price bubbles and crashes. These price discrepancies arise because participants' individual forecasts, though not visible to one another, tend to be highly coordinated within the same group. The alignment of individual forecasts within a group causes asset prices to diverge from their fundamental value, challenging the applicability of the rational expectations equilibrium as an explanation for observed price dynamics.

We focus on the effect of initial price history on asset price dynamics in a multi-asset market. Previous experiments, with the exception of Hennequin (2021) and Anufriev et al. (2022), typically do not provide participants with information about asset prices. In these experiments, price dynamics in the early periods often influence the behaviour observed in later periods. This path dependency suggests that initial price movements play a critical role in shaping future market behaviour (see Anufriev & Hommes, 2012). Therefore, we hypothesise that the initial price history of assets will significantly influence subsequent price dynamics, and we formulate the following hypothesis.

Hypothesis 1: The A3 asset, characterised by stable development during the initial price history, exhibits a lower level of volatility compared to other assets in the market.

Although the instructions state that the individual assets are independent of each other in the long run, closer inspection of the initial price history reveals some remarkable characteristics. Figure 1 shows that assets A1 and A2 exhibit a clear negative correlation during the initial price history. No other noticeable dependence in the provided initial price history is evident from the

[5] All participant predictions had to be obtained in order to calculate realised asset prices, ensuring no missing values in the dataset. Predictions could only be positive numbers, and no upper limit was set. To eliminate any possible typos, participants had to confirm their predictions twice. First, participants saved their predictions in the editable textbox. Then, they had to confirm them again (in non-editable textbox) or go back and make changes if necessary.

further comparison of assets. This raises the question of whether this negative correlation influenced participants' expectations. From a behavioural perspective, participants may anticipate that a drop in one asset's price will lead to a rise in the other, reinforcing the observed price dynamics. We use this observation to formulate the following hypothesis.

Hypothesis 2: During the initial price history, there is a negative relationship between the realised prices of assets A1 and A2. This negative dependence between their prices continues to influence participants' expectations and subsequently impacts further price evolution.

As already mentioned, besides the strong negative dependence of assets A1 and A2 during the initial price history, no notable strong dependence is evident from the comparison of the other assets. We can expect that this pattern will influence participant expectations. Then, the following hypothesis can be formulated.

Hypothesis 3: Given the no correlation observed during the initial price history between asset A3 and asset A1 (or A2) we can expect that this pattern will influence participant expectations. Consequently, the realised prices of these assets will not exhibit strong dependence.

From previous LtF experiments, it is clear that participants' predictions are usually highly coordinated, see, for example, Hommes et al. (2005, 2008) or Heemeijer et al. (2009). In Hennequin (2021), heterogeneity in expectations is higher when more subjects have experienced bubbles before. Here, we expect that the stable price history also impacts the higher coordination of participants. A stable price history reduces uncertainty, leading to more homogeneous expectations among participants. The hypothesis is as follows.

Hypothesis 4: The stable initial price history of asset A3 leads to less heterogeneity in predictions compared to other assets.

While we utilise statistical tests to analyse our data and support our hypotheses, it is crucial to understand their role within the exploratory framework of this study. These tests provide valuable insights and preliminary evidence, but their results should be interpreted with caution and viewed as initial indicators that highlight potential relationships, rather than definitive proof. We emphasise the need for future research to address these findings through more rigorous, pre-registered studies.

4. Overall market dynamics

In this section, we discuss the results of the six multi-asset experimental markets. The evolution of the market prices for all experiments is shown in Figure 3 and descriptive statistics of the markets are part of Appendix B. We identify two distinct qualitative market behaviours:

1. markets where all assets are stable or present small fluctuations around the fundamental value, with the overall average relative absolute deviation for the whole market not exceeding 20%: EXP1, EXP2, EXP3,
2. markets where some assets exhibit moderately large bubbles, with peaks at 1.5–2 times the fundamental value: EXP4[6], EXP5, EXP6.

We will maintain this distinction in the following analyses.

In comparison to the results from previous LtF experiments, we did not observe large price bubbles. For example, in Hommes et al. (2008), the realised price exceeded the fundamental value 16 times in most of their experiments and in Hommes et al. (2021), price exceeded the fundamental value 10 times. One possible explanation for the absence of large price bubbles in our experiments could be the effect of negative short-term correlation**.** This correlation may have dampened price deviations from the fundamental value, as an extreme rise in the price of one asset would lead to an extreme fall in the price of another asset, potentially even causing it to drop to zero. Appendix B shows the relative absolute deviation (RAD)[7] and the relative deviation (RD) from the fundamental value. Most assets in our experimental markets are under-priced. The experiment EXP2 is unique in that the RAD and RD values are almost identical. This means that in this experimental market, the realised price of each asset is always above or below the fundamental value.

We start the discussion of the experimental results for stable markets, which have a relatively low standard deviation in comparison with the group of moderately large bubble markets, see Figure 3. In the market EXP1, it can

[6] In EXP4, we obtained predictions for 40 periods instead of the full 50, which was due to technical issues. Despite this shorter dataset, we believe the experiment remains valuable, as the 40 periods still provide a sufficient amount of data for analysis.

[7] Stöckl et al. (2010) proposed two measures that are standardly used to analyse LtF data—relative absolute deviation (RAD) and relative deviation (RD). RAD is straightforward to understand, as it is a measure of the mispricing level and is calculated as follows, $RAD_{t,a} = \left| p_{t,a} - p_a^f \right| \Big/ p_a^f$. For instance, a value of 0.15 indicates that the price deviates by 15% from the market's fundamental value. By averaging over all periods, we obtain the total level of mispricing for a given asset in the market. The second measure is a relative deviation (RD), $RD_{t,a} = \left(p_{t,a} - p_a^f \right) \Big/ p_a^f$. In this case, positive and negative deviations are compensated. A value of 0.15 (respectively –0.15) implies that the asset is overvalued (undervalued) by 15% during the experiment.

be observed that all assets maintain a very stable development around the fundamental value. In the case of EXP2, it is possible to notice an atypical price evolution, since there are no fluctuations around the fundamental value. All assets have a stable development above or below the fundamental value compared to the other sessions. In EXP3, it can be seen that all assets first show stable oscillations around the fundamental value, which are followed by more pronounced deviations from the 35th period onwards.

The effect of the initial price history on price volatility in stable markets is more difficult to assess from Figure 3. A better insight into the resulting data is provided by visualisation in box plots, as seen in Figure 4. To examine the effect of initial price history, one can focus on comparing the interquartile range (IQR) of asset A3 with a stable initial price history and assets A1 and A2. We can note that in most cases of stable markets, the IQR of asset A3 is narrower compared to the others. However, the exception is EXP1, where asset A1 exhibits a narrower interquartile range than asset A3. Based on these results, it can be assumed that the initial price history of the asset has an impact on asset price volatility.

We will now explore experimental results for markets that exhibit moderately large bubbles. In the case of EXP4, there is relatively stable development during the first predicted periods for all three assets. Nevertheless, from the 25th period, notable deviations from the fundamental value become apparent for assets A1 and A2, although the amplitude of bubbles decreases. In contrast, asset A3 continues to exhibit stationary behaviour. In EXP5, substantial deviations from the fundamental value are also evident. However, the amplitude of these deviations gradually decreases, and all assets eventually converge toward their fundamental value. Notably, asset A3 exhibits considerably less volatility compared to the other assets. In relation to EXP6, we observe pronounced bubbles, and it is interesting to note that the development can be characterised as divergent, with the amplitudes increasing. From these results, it is already possible to assume that the asset A3, which is characterised by a stable initial price history, exhibits a lower level of volatility. A similar conclusion can be drawn from the box plot, where asset A3 exhibits a considerably narrower interquartile range.

To validate our hypothesis, we conducted a Wilcoxon paired sign-rank test based on RAD and IQR. For both measures, we calculated the average value over a 50-period span. We then compared asset A3, which has a stable historical development, to assets A1 and A2, which exhibit more volatile initial price histories. The alternative hypothesis for this test is that asset A3 has a lower volatility measure compared to asset A1 or asset A2, respectively. First, we performed the paired-rank test on RAD. Based on the results, we rejected the null hypothesis at the 5% significance level, with p-values of 0.016 for both A1 and A2 compared to A3. Similarly, for the IQR test, we obtained the same results, indicating that the effect of initial price history on asset price volatil-

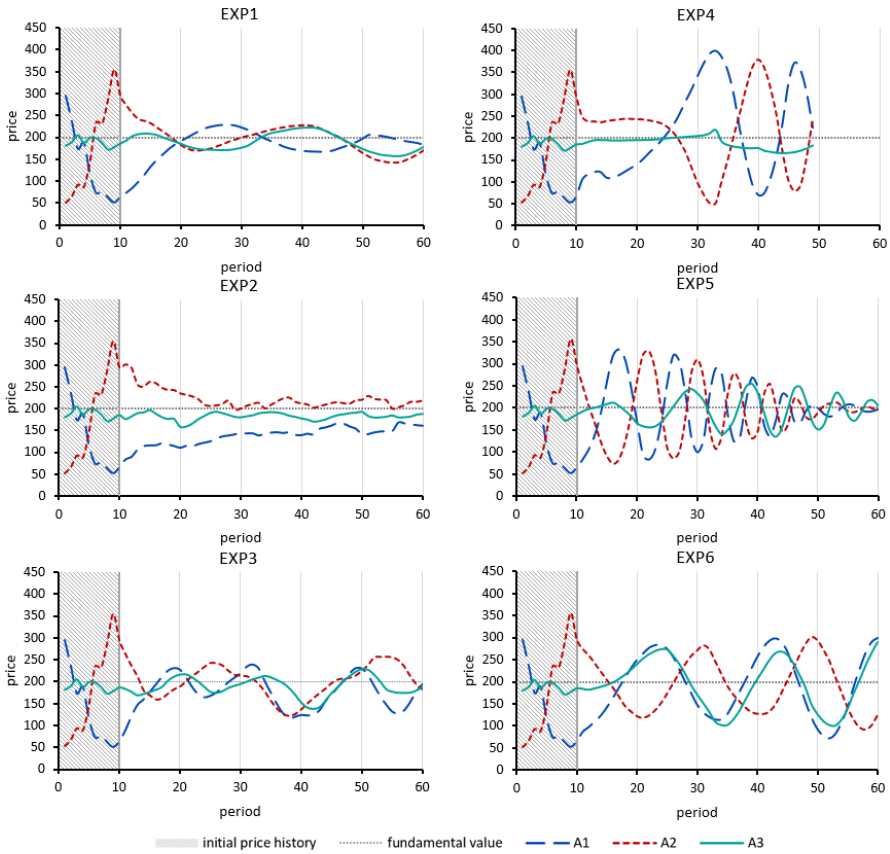


Figure 3. Price dynamics in all sessions for all three assets

Note: Left – stable markets, right – markets with moderately large bubbles. The highlighted period from 1 to 10 represents the initial price history.

Source: own work.

ity was statistically significant at the 5% level, with p-values of 0.031 for A1 and 0.016 for A2 compared to A3.

Result 1: Based on the discussion and statistical tests, it can be concluded that the initial price history of an asset has an impact on the asset price volatility. Asset A3, with its stable initial price history, exhibits lower volatility compared to other assets in the market. This suggests that the stability of prices during the initial history plays a crucial role in determining subsequent asset price fluctuations.

The focus will now turn to an investigation of the asset correlation. From Figure 5, it appears that the realised prices of assets A1 and A2 are negatively correlated in almost all cases. This dependence is most evident in markets

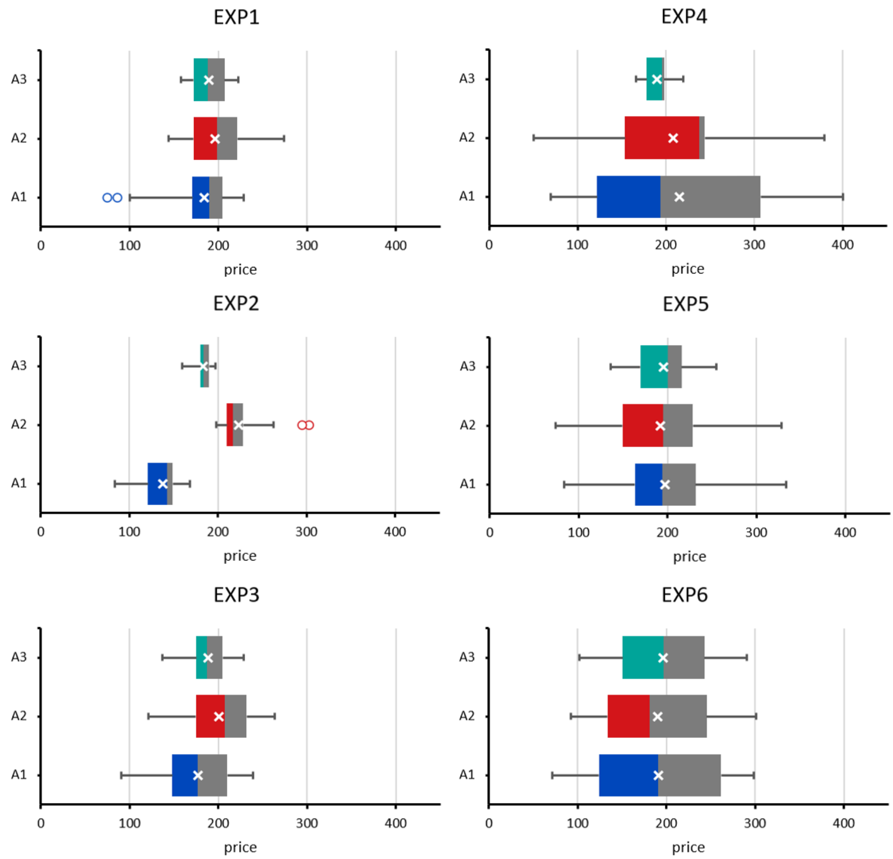


Figure 4. Box plots for all three risky assets in all sessions

Note: Left – stable markets, right – markets with moderately large bubbles.

Source: own work.

with moderately large bubbles, where the peak of a bubble in one asset is associated with the lowest point of decline in another asset after the bubble burst. The only exception is EXP3, where a negative dependence is first evident until the 30th period, after which assets A1 and A2 show a positive dependence. Towards the end of this experiment, the assets again exhibit negative dependence. Overall, these observations indicate that the negative historical dependence of assets A1 and A2 had a substantial impact on the subsequent price dynamics.

To corroborate this impression, we verify this relationship using Spearman's rank correlation coefficient. The Spearman's rho and the p-values are reported in Figure 5. From the results, it is apparent that assets A1 and A2 show a statistically significant negative correlation in 5 out of 6 experiments. A strong negative correlation is evident in markets with moderately large bubbles. The results for stable markets clearly show a moderately strong negative correlation in the case of EXP1 and EXP2, as indicated by the correlation coefficient values. Only in EXP3 is a zero correlation obtained, as these assets do not show a monotonic dependence.

To further investigate the overall dependence in all experiments, we tested the obtained correlation coefficients between A1 and A2 by means of a one-tailed signed rank test. The alternative hypothesis posits that the correlations were less than zero. The test result indicates a p-value of 0.031, which is statistically significant at the 5% level. This provides evidence to reject the null hypothesis and conclude that there is a statistically significant negative dependence between assets A1 and A2 in the experiments. Based on this result and the correlogram, we conclude that the evidence supports Hypothesis 2.

Result 2: The strong negative dependence of assets A1 and A2, which was evident in the initial price history, was maintained in the subsequent price development. Therefore, although the participants were instructed as to there being no correlation in the long run, strong asset dependence during the initial price history plays a crucial role in the subsequent price dynamics.

We can now continue with the analysis of the correlogram (Figure 5) and focus on the dependence of asset A3 with asset A1 or A2, where the initial price history showed no clear dependence between these pairs. The comparison reveals that these assets exhibit mainly very weak dependence (6 out of 12 cases) or moderate dependence (2 out of 12 cases). However, a strong degree of dependence is evident in four experimental cases. In the case of EXP1, a strong negative dependence is evident between assets A1 and A3 (rho –0.704) and conversely, a strong positive dependence is evident for assets A2 and A3 (rho 0.902), whose development has been almost identical since the 20th period. Furthermore, in the experimental markets EXP3 and EXP6, there is a strong positive dependence for assets A1 and A3.

Building on the correlogram analysis, we expanded our investigation to compare all correlation coefficients of asset A1 (and A2, respectively) with A3 using a Wilcoxon signed-rank test. The alternative hypothesis assumes that the correlations were non-zero. The p-value for the A1 and A3 comparison is 0.219, and for A2 and A3 0.844. In both cases, we failed to reject the null hypothesis, indicating no significant dependence between the pairs. These results align with the correlogram analysis, reinforcing the conclusion that a notable correlation is not common among these asset pairs.

Result 3: Based on the correlogram analysis presented here, it is evident that while there are instances of strong dependence between the realised prices of asset A3 with assets A1 or A2, the overall trend across

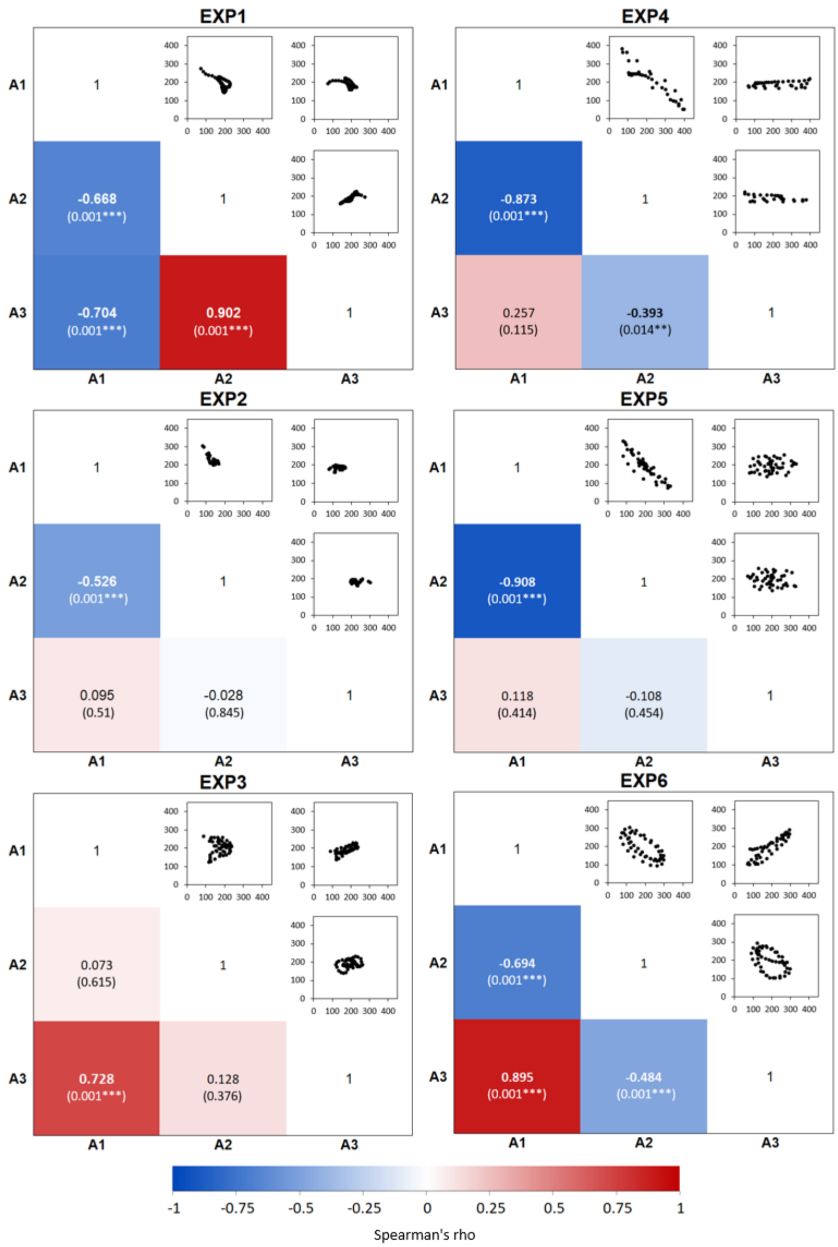


Figure 5. Correlogram representing the matrices of Spearman's order correlation coefficients between the assets for all experiments

Note: A positive correlation is marked in red and a negative correlation in blue. The left triangles represent correlation coefficients along with corresponding p-values, where *, ** and *** denote asset comparisons when the null hypothesis of no correlation is rejected at the 10%, 5% or 1% significance level, respectively. In the right triangles, scatter plots illustrate the relationships between the compared assets.

Source: own work.

all markets indicates a predominant pattern of weak to moderate dependence. The results of the statistical testing show that overall there is no statistically significant correlation between the compared assets This suggests that Hypothesis 3 holds true, with the independence of assets during initial price history influencing market participants' expectations of asset prices to some extent.

5. Coordination of expectations

From previous LtF experiments, it is clear that participants' predictions are usually highly coordinated. Therefore, we now turn to the question of whether participants' predictions are coordinated even in a multi-asset market, or if heterogeneous expectations prevail.

To study the time-varying coordination of expectations, the coefficient of variation (CV) of individual predictions is calculated as the ratio of the standard deviation and the mean of forecasted prices for each period. A low (high) CV value indicates a high (low) degree of coordination of participants' predictions. Figure 6 shows the coefficient of variation along with the realised price of a particular asset for one stable market (left) and one market with moderately large bubbles (right). The CV plots for the remaining experiments are included in Appendix C. Based on the figures for all markets, it can be assessed that for roughly the first 10 forecast periods, there is usually a higher degree of heterogeneity in the participants' predictions. This is likely due to participants trying to learn how to predict asset prices accurately.

In stable markets, in most experiments the first predicted periods are accompanied by an enhanced degree of heterogeneity, which usually stabilises very quickly (see left panel for EXP3 in Figure 6). Participants learn to coordinate their expectations in the first periods of the experiment and the realised asset prices do not exhibit substantial deviations from the fundamental value. In stable markets, except for the first periods, there are no large fluctuations in the value of the coefficient of variation, which reaches a maximum value of 0.30.

We now move on to an assessment of forecast coordination in markets with moderately large bubbles (see the right panels for EXP4 in Figure 6). The coefficient of variation in forecasts indicates a substantially higher degree of heterogeneity among participants in comparison to stable markets. The graphical data distinctly shows that heterogeneity peaks at the moment when the bubble bursts and reaches its lowest point. There appears to be a consistent pattern of heightened coordination during the ascent of asset prices, which is subsequently followed by increased discoordination after a precipitous de-

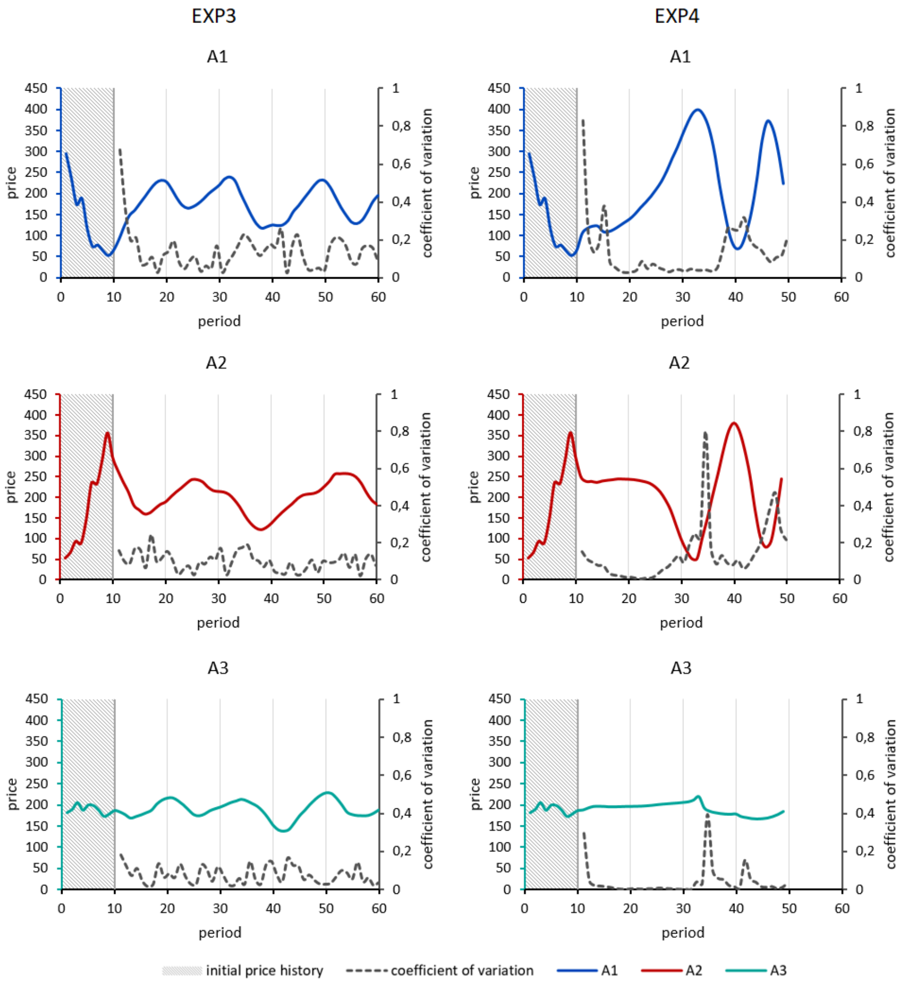


Figure 6. Coefficient of variation for forecasts along with the realised prices: EXP3 and EXP4

Note: Realised market prices (left scale) and coefficient of variation of individual forecasts (right scale) for example of stable market EXP3 (left) and market with moderately large bubbles EXP4 (right).

Source: own work.

cline. This phenomenon may be attributed to divergent expectations among participants, with some anticipating a continued decrease in prices while others expect a rebound.

We now focus on investigating the effect of initial price history on the coordination of participants. A noteworthy observation emerges from the coefficient of variation plots in Figure 6, where asset A3 exhibits a higher degree of coordination within the market in both cases. This suggests that the initial price history may influence the coordination of participants' forecasts and that the stable initial price history of asset A3 appears to lead to less heterogeneity in predictions compared to other assets.

The effect of initial price history on participants' coordination was tested using a Wilcoxon paired sign-rank test based on the CV. Previous observations indicate that the first prediction periods are naturally associated with a higher degree of heterogeneity, as participants are more likely to learn to predict correctly during these times. Therefore, the testing approach involved calculating the average CV value, excluding the first ten prediction periods. We then compared asset A3, which has a stable historical development, to assets A1 and A2, which exhibit more volatile initial price histories. The alternative hypothesis for this test is that asset A3 has a lower CV value compared to asset A1 or asset A2. The p-value for the comparison with asset A1 is 0.047, and for A2, it is 0.016. Both test results are statistically significant at the 5% level, suggesting that there is evidence to reject the null hypothesis. We conclude that a stable initial price history can potentially lead to higher coordination among participants.

Result 4: The graphical analysis and test results indicated that asset A3, with its stable price history, exhibited lower CV values compared to the more volatile assets A1 and A2. This finding suggests that a stable initial price history may enhance coordination among participants.

6. Limitations

This exploratory study has several limitations that should be acknowledged. Firstly, the relatively small sample size may limit the generalisability of the findings. Future research should consider using a larger sample size to validate these initial results and employ more robust analytical techniques, such as regression analysis, to fully model relationships. The exploratory nature of the study means that the findings should be interpreted with caution. Although the statistical tests provided preliminary evidence, their results should be viewed as initial indicators rather than as definitive proof. This underscores the need for future research to address these findings through more rigorous pre-registered studies.

Secondly, there is also the possibility that participants may not have fully understood the distinction between short-term and long-term correlation. As instructions were read aloud and clarified with examples to explain the meaning of long-term asset uncorrelation, and as all participants were from the Faculty of Economics, with relevant course on correlation, including the distinction between the long and short run, it is reasonable to assume that participants understood this distinction. However, to ensure comprehension and address any potential misunderstandings, future research could incorporate a quiz where participants must answer questions on the correlation between assets.

Thirdly, in our experiment, we operate under the assumption that assets in the market are uncorrelated in the long run, meaning the asset pricing model assumes zero asset correlation. However, this assumption may not fully capture the complexities of real-world markets. In reality, assets can exhibit varying degrees of correlation over different time periods due to factors such as economic cycles, market sentiment, and external shocks. Therefore, while our model provides valuable insights, it is important to consider these limitations and the potential need for more sophisticated models that account for asset correlations.

Thus, a promising extension of our research would be to conduct a LtF experiment with multiple assets, but with an asset pricing model that incorporates correlations. Previous studies, such as those by Duffy and Jenkins (2018) and Assenza et al. (2013), have examined interdependent variables within a new Keynesian framework, highlighting the importance of such interactions. By including correlations, we could explore how the presence of correlated assets influences the forecasting behaviour of participants and market outcomes. It would be interesting to investigate whether varying degrees of correlation impact market volatility and coordination among participants. Such an experiment could yield valuable insights into the role of asset correlations in shaping market behaviour. Furthermore, future studies should consider using two assets instead of three to simplify the experimental design while still providing meaningful insights into market dynamics and participant behaviour.

Conclusions

In this paper, we applied the Learning-to-Forecast (LtF) experiment as an exploratory case study to investigate the effect of the initial price history on asset price dynamics in multi-asset markets. Our main results are as follows. An asset with a stable initial price history exhibited lower volatility, suggesting that an initial price history was crucial for future price fluctuations. Subsequently, despite explicit instructions indicating an absence of long-term dependencies among assets, the pronounced short-term negative dependence apparent in the initial price history persisted in the ensuing price development. Therefore, strong asset dependence during the initial price history plays a pivotal role in subsequent price dynamics. Finally, in most experiments, the stable price history of the asset prices led to greater coordination of the participants compared to other assets on the market.

To the best of our knowledge, our study is the first to conduct a LtF experiment involving multiple assets. While previous LtF asset pricing experiments have typically focused on predicting the price of a single risky asset over many consecutive periods, our research extended this framework to markets with three risky assets that are uncorrelated in the long term. This innovative approach allowed us to investigate whether participants' expectations were influenced by the performance of other assets in the market, providing a more comprehensive understanding of market dynamics. By incorporating multiple assets, our study offers valuable insights into the interplay between different assets and how this affects forecasting behaviour. This extension not only enhances the realism of the experimental setup but also contributes to a deeper understanding of how market participants form expectations in a more complex and interconnected market environment.

In comparison to the results from previous Learning-to-Forecast experiments, we did not observe large price bubbles. In our multi-asset experiment, we observed markets where some assets exhibited only moderately large bubbles, with peaks at 2 times the fundamental value. Many LtF experiments with positive expectation feedback are typically characterised by persistent deviations more than 10 times from the fundamental value, as seen in studies by Hommes et al. (2008), Bao et al. (2020), and Hommes et al. (2021). One potential explanation for the absence of large price bubbles in our experiments is the multi-asset market and the presence of a short-term negative correlation. This dynamic may have mitigated extreme price deviations from the fundamental value. Future research should investigate this aspect further to understand its impact on market dynamics and participant behaviour.

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Appendix A: Experimental instructions

Today, you will participate in an experiment where you will predict the future price of risky assets. At the end of the experiment, participants will be ranked based on the accuracy of their predictions, which will determine the size of the reward paid.

Instructions for your task

In this experiment, imagine you are a financial forecaster working for a pension fund that aims to optimally invest a large amount of funds over one period. The pension fund has four investment options: an investment in a risk-free asset and three risky assets. For the risk-free asset, the funds are deposited into a government bond, with the deposited money earning fixed and constant interest. The alternative option for the pension fund is to invest the funds in risky assets, where the risk arises from the uncertain future price of the asset and the dividends paid over the period. All risky assets are uncorrelated in the long term. In each period, the pension fund decides how much of the funds to place in the government bond and how much to invest in risky assets. For optimal investment decisions, the pension fund requires accurate predictions of the future prices.

As the financial forecaster for this pension fund, your task is to predict the price of the risky assets over the next 50 periods. Your earnings will depend on the accuracy of your predictions.

Information on the asset market

The market price of the risky asset in each period is determined by supply and demand. The supply of the risky asset is fixed throughout the experiment. The demand for the asset is primarily determined by the aggregate demand of several large investment funds operating in this market. Their managers can monitor both fundamental and technical factors, with rational actors evaluating all available information. There is also uncertain and small demand from private investors for the asset. However, the influence of these private investors on the asset price is minimal.

Information on pension fund investment strategies

The exact investment strategy of the pension fund for which you are predicting the future asset prices, as well as the investment strategies of other pension funds, are unknown. The government bond, representing the risk-free investment, provides a fixed interest rate of 5% in each period.

The owner of the risky asset receives an uncertain payment in each period; however, economic experts have calculated that this payment averages $10 per period for each asset. The market return on assets in a given period depends on these payments as well as changes in the asset price.

As the financial forecaster for the pension fund, you are asked to predict the price of all risky assets in each period. Based on your future price predictions, the pension fund will make optimal investment decisions. The higher your predicted future price, the larger the share of funds the pension fund will invest in the asset market in the current period, thus increasing its demand.

Information on the course of the experiment

At the beginning of the experiment, you will have access to the initial price history of risky assets for the preceding 10 periods, and you will provide your price prediction for the 12th period. Once all participants have recorded their predictions, the realised price of the asset for the 11th period will be revealed. Subsequently, you will need to predict the asset price for the 13th period, similar to the other participants, to determine the realised price of the asset for the 12th period, and so on. This process continues until the final period.

From this information, it follows that for predicting the price for period $(t + 1)$ at time (t), the following information is available:

- Historical prices up to period $t - 1$,
- Your previous predictions up to period t,
- Your prediction error up to period $t - 1$.

From the 12th period onwards, your prediction error, which is the difference between your predicted prices for the given period and the realised prices of the assets, will also be determined. The last period for which the prediction error will be determined is period 60.

The more accurate your asset price predictions are in each period, the higher your potential reward. The prediction error will always be automatically calculated. After the experiment, participants will be ranked based on their average prediction error, and financial rewards will be paid according to the following table.

Ranking	Financial reward (CZK)
1.	700
2.	550
3.	450
4.	350
5.	250
6.	150
7.	100
8.	100
9.	100
...	50

Additional information

- After the experiment, you will be asked to complete a questionnaire. All data will be processed anonymously. Please provide accurate information.
- During the experiment, any communication with other participants is prohibited. Additionally, the use of phones, tablets, or other devices is not allowed. Violation of the experiment rules may result in exclusion without any reward.
- If you have any questions or encounter any issues during the experiment, please raise your hand, and the experiment organiser will assist you.

Appendix B: Descriptive statistics

Table B1. Descriptive statistics for realised prices of particular assets and average value for all assets in the market across all experiments

Experi-ment	Asset	Mean price	Median price	Standard deviation	IQR	RAD (%)	RD (%)
EXP1	A1	183.83	189.82	34.48	33.76	13.03	–8.08
	A2	196.13	198.48	31.83	49.59	13.36	–1.94
	A3	189.19	187.74	20.32	35.08	9.77	–5.41
	Average	*189.71*	*192.01*	*28.88*	*39.48*	*12.05*	*–5.14*
EXP2	A1	137.92	142.14	20.05	27.99	31.04	–31.04
	A2	223.23	216.31	22.04	18.27	11.65	11.61
	A3	183.19	183.54	7.99	9.43	8.40	–8.40
	Average	*181.45*	*180.66*	*16.69*	*18.56*	*17.03*	*–9.28*
EXP3	A1	176.67	176.52	39.09	62.03	18.47	–11.67
	A2	200.55	207.05	38.12	57.2	15.70	0.27
	A3	188.22	186.91	21.95	29.86	9.92	–5.89
	Average	*188.48*	*190.16*	*33.05*	*49.7*	*14.69*	*–5.76*
EXP4	A1	215.26	193.37	104.88	184.75	45.23	7.63
	A2	207.91	237.45	83.96	90	34.35	3.95
	A3	189.75	195.13	13.66	19.97	6.49	–5.13
	Average	*204.3*	*208.65*	*67.5*	*98.24*	*28.69*	*2.15*
EXP5	A1	197.3	193.59	64.59	68.27	25.10	–1.35
	A2	192.2	194.77	63.04	78.84	24.42	–3.90
	A3	195.33	199.68	31.37	46.55	13.04	–2.33
	Average	*194.94*	*196.01*	*53*	*64.55*	*20.85*	*–2.53*
EXP6	A1	190.96	190.39	72.12	137.6	31.87	–4.52
	A2	190.12	181.19	61.09	111.94	27.13	–4.94
	A3	195.98	196.5	56.94	92.17	23.88	–2.01
	Average	*192.35*	*189.36*	*63.38*	*113.9*	*27.63*	*–3.82*

Note: Stable markets – EXP1, EXP2, EXP3, markets with moderately large bubbles – EXP4, EXP5, EXP6.

Source: own work.

Appendix C: Coefficient of variation of price predictions

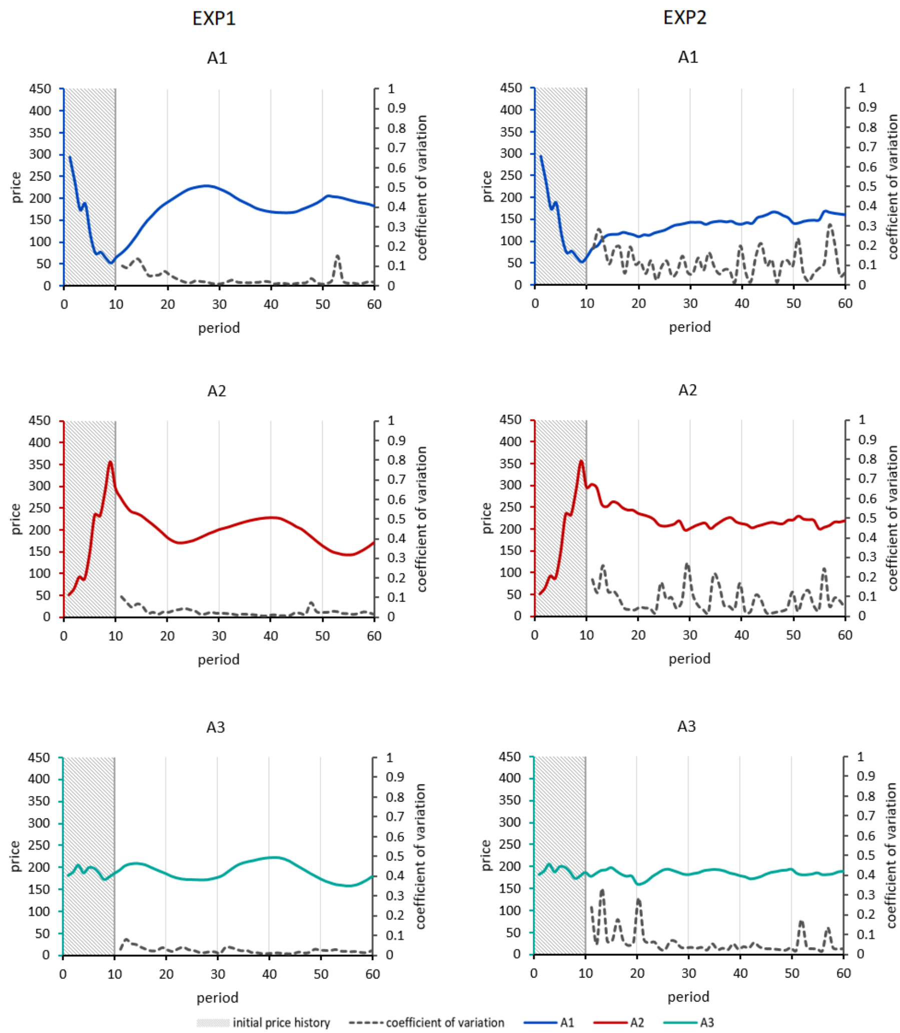

Figure C1. Realised market prices (left scale) and coefficient of variation of individual forecasts (right scale) for EXP1 (left) and EXP2 (right)

Source: own work.

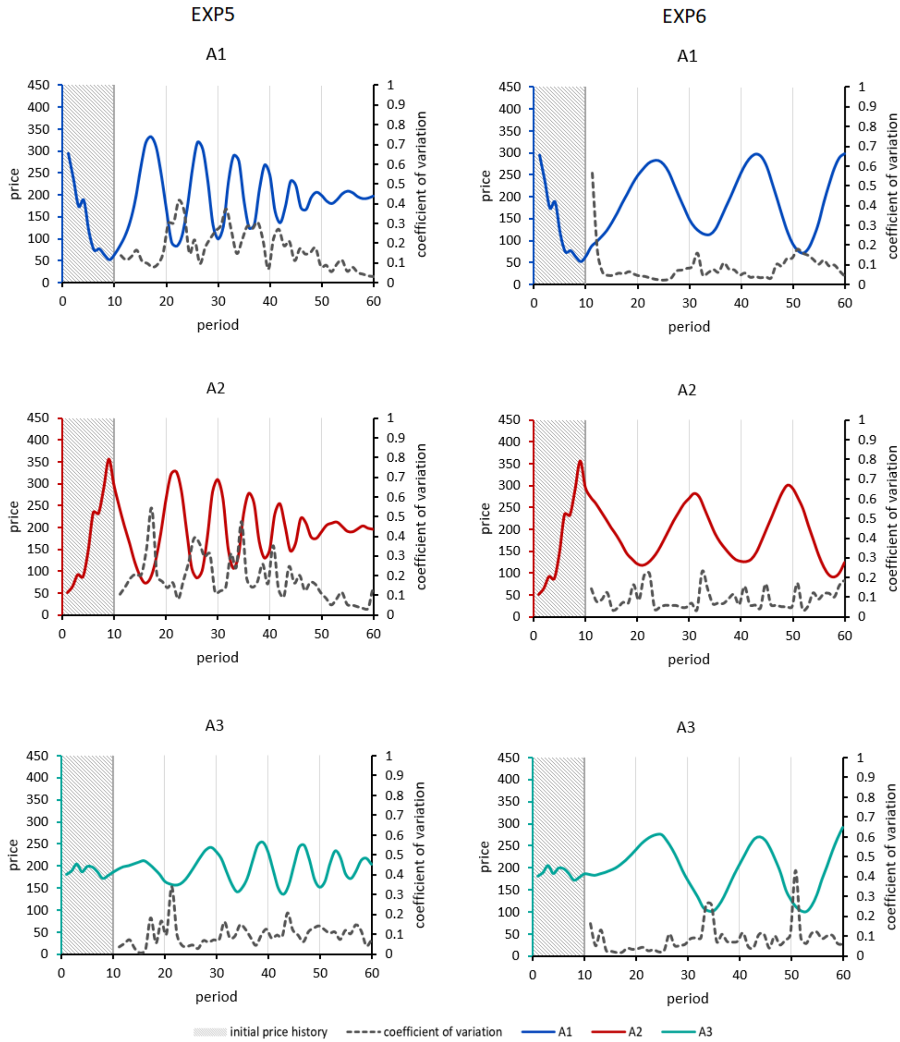

Figure C2. Realised market prices (left scale) and coefficient of variation of individual forecasts (right scale) for EXP5 (left) and EXP6 (right)

Source: own work.

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