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April 2022

Abstract

Inspired by macroeconomic scenarios, we aim to experimentally investigate the evolution of short- and long-run expectations under different specifications of the fundamentals. We collect individual predictions for the future prices in a series of Learning to Forecast Experiments with a time-varying fundamental value. In particular, we observe how expectations evolve in markets where the fundamental value follows either a V-shaped or an inverse V-shaped pattern. These conditions are compared with markets characterized by a constant and a slightly linear increasing fundamental value. We assess whether minor but systematic variations in the fundamentals affect individual short- and long-run expectations by considering positive and negative feedback-expectation systems. Even though such variations in the fundamentals turn out not to strongly affect the way subjects form their expectations in positive feedback markets, we observe significant changes in negative feedback markets.

Keywords– Long-run expectations, Coordination, Convergence, Heterogeneous expectations, Expectations feedback, Experimental economics

JEL Classification– D03, G12, C91

1 Introduction

Expectations play a crucial role in the evolution of economic systems: expectations shape the behavior of economic aggregates, and at the same time, economic aggregates mold agents' expectations. Thus, an economy can be thought as an expectation feedback system.

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The term “rational” expectations typically labels a set of expectations that provides consistently unbiased predictions of the future behavior of the economy given the available information. Starting with the seminal paper of Muth (1961), an endless list of papers deals with the empirical validity of the rational expectations hypothesis, i.e., whether and under which conditions this benchmark is empirically relevant. Homogeneous rational expectations require agents with equal (maximal) cognitive capabilities who share the same model priors and private information. Likewise, a large number of studies consider bounded rationality as an alternative approach to rational expectations. In the pertinent literature one can find many evidences of systematic deviations from rationality that open the possibility for the emergence of a certain degree of heterogeneity in the expectations.

The unobservable nature of expectations adds a determinant layer of complexity to the formal description of how expectations are formed and how they evolve. The development of techniques and methodologies to elicit and measure agents' expectations is a very active research field. In particular, macroeconomic forecasting surveys constitute a widely employed methodology to elicit individual expectations on several macroeconomic variables like inflation, GDP, and interest rates. Despite their widespread use, the absence of economic incentives for survey respondents to reveal their expectations has raised recurrent criticisms. Nevertheless, Manski (2004, 2018) claim that surveys have proved to be a very informative source of analysis for expectation formation. Respondents usually report informative answers to questions regarding personally relevant future scenarios.

Laboratory experiments constitute a complementary methodology to surveys to study the expectations formation mechanism under different scenarios and frames. Specifically, Learning to Forecasts Experiments (LtFEs), introduced by Marimon et al. (1993), are controlled laboratory experiments used to elicit subjects' expectations in an expectation-feedback environment. Contrary to surveys, LtFEs incentivize subjects to make their predictions. Moreover, information at subjects disposal is controlled by the experimenter. LtFEs are considered a powerful and flexible experimental setting to study subjects' expectation formation under divers scenarios, including macroeconomic frameworks. Several LtFEs have been conducted to analyze expectations formation in financial markets (Hommes et al., 2005; Bao et al., 2021), real estate markets (Bao and Ding, 2016), commodity markets (Bao et al., 2013), and in stylized macroeconomic frameworks (Anufriev et al., 2013; Cornand and M'baye, 2018; Assenza et al., 2021). The external validity of the LtFEs as a decision-making tool for monetary policy has been studied by Cornand and Hubert (2020), who conclude that subjects' predictions in a LtFE are relatively comparable to inflation surveys.

In all the above-mentioned experiments, only short-run expectations have been elicited, neglecting the importance of studying the evolution of long-run expectations. Since the paper of Mankiw et al. (2003), it has been routinely recognized that the dispersion of expectations of professional forecasters contains information on the future development of the business cycle or inflation rate. Thus the degree of disagreement in expectations and its persistence over time become variables of interest from a macroeconomic point of view. Patton and Timmermann (2010) analyze the term structure of the expectations dispersion over different time horizons. They observe that the dispersion increases with the horizon and depends on the state of the economic cycle. In particular, they report that the degree of dispersion is counter-cyclical, increasing during bad states of the world. Furthermore, they observe that both the degree and the persistence of heterogeneity in expectations depend on the differences in priors and prediction models rather than on heterogeneous private information. The expectations horizon is, therefore, an essential characteristic to be considered when dealing with expectation formation. Focusing on monetary policy, an important determinant of its effectiveness is the degree of influence that central banks have on consumers' and investors' expectations in short and long horizons. The "forward guidance" communication strategy represents a perfect example of such an "expectationalist" viewpoint of modern monetary policy (Woodford, 2001).

In the last decade only a few experimental papers study the properties of long-run expectations. Haruvy et al. (2007) is the first experimental contribution that elicits the long-run expectations in a laboratory asset market with bubbles. A kind of natural experiment is conducted by Galati et al. (2011) who elicit short, medium, and long-run inflation expectations using professional forecasters from central banks, academics, and students. Colasante et al. (2018, 2019) are pioneering works in eliciting both short- and long-run expectations in LtFEs., where subjects make predictions about the price evolution for all the remaining periods. In their setting, long-run predictions do not influence directly price formation, which is solely determined by one-step ahead predictions. In this respect, this experimental setting can be considered similar to a macroeconomic survey, since subjects do not know the true generating mechanism and they have to guesstimate the evolution of macroeconomic aggregates without having a significant impact on them. They observe that short-run predictions are strongly anchored to the market price and they exhibit low volatility with respect to the long-run ones. Colasante et al. (2019) measure the so-called term structure of cross-sectional dispersion of expectations, finding an increase level of disagreement of subjects' expectations about the price evolution. These results are in line with the main finding of Patton and Timmermann (2010) about the increasing forecast disagreement across horizons. Evans et al. (2019) reach similar conclusion by considering a different theoretical framework (i.e., they consider the Lucas tree asset pricing model). Anufriev et al. (2022) implement a LtFE similar to Colasante et al. (2018) but they solely collect predictions for either one, two or three horizons. In their setting predictions determine the market price independently of the forecast horizon. They observe that the farther the horizon, the less likely the emergence of bubbles is.

This paper contributes to this literature that employs experiments to analyze the formation of expectations with time-varying fundamental value. Colasante et al. (2017) check whether an adaptive expectation scheme could provide a good description of individual one-step ahead predictions in an environment with increasing fundamental value. Noussair and Powell (2010) introduce a non-constant fundamental value (peak and valley) to understand how these different patterns may affect bubble formation in asset markets observing larger heterogeneity in recession phases (i.e., decreasing fundamental value). Bao et al. (2012) evaluate how short-run expectations behave in the presence of unexpected large shocks in the fundamental value.

The current work aims to check whether small but systematic changes in the fundamental value impact the formation of expectation. Indeed, we want to assess whether minor variations that lead to marginal effects in the short-run predictions could result in significant changes in long-run predictions. Inspired by the results of Patton and Timmerman about the dependence of the degree of expectations disagreement on the phase of the business cycle, our design studies individual predictions when the fundamental value pattern follows a V-shape or an inverse V-shape, where the turning point is an unanticipated event. We also run a baseline treatment with constant fundamental value and a treatment with a linearly increasing fundamental value. For each of the four patterns of the fundamentals, we consider positive and negative expectations feedback between one-step ahead predictions and the market price. We find that the stylised facts of LtFEs are robust against changes in the fundamentals: fast coordination of short-run expectations and slow convergence to the fundamentals in positive feedback markets; slow coordination of expectations and good convergence to the fundamentals in negative feedback markets (Heemeijer et al., 2009). Instead, the curvature of term structure depends not only on the expectation-feedback system but also on the characteristics of the pattern of the fundamentals. Interestingly, we find that the heterogeneity of expectations persists even though the short- and long-run predictions are quite homogeneous in negative feedback markets. In other words, homogeneous predictions across subjects can be an apparent effect of a rather homogeneous price history. The heterogeneity in the way subjects form their expectations emerge clearly when an unexpected event happens. How subjects form their expectations seems to be a crucial ingredient for explaining not just positive feedback markets but also negative feedback markets.

We organize the reminder of the paper is as follows. Section 2 describes the experimental design, and Section 3 develops reference conjectures to interpret the results. Section 4 presents the experimental results, followed by discussion and conclusions in Section 5.

2 Experimental Setting

2.1 Treatments

The experimental setting is based on Colasante et al. (2018) in which subjects' task is to forecast prices at different time horizons for 20 periods. We distinguish between short-run predictions, which are the subjects' one-period-ahead predictions, and long-run predictions that includes the forecasts for longer horizons. At the beginning of period t, subject i submits his/her short-run prediction for the market price at the end of period t as well as his/her long-run predictions for the price at the end of each one of the $20 - t$ remaining periods.

We implement eight treatments differing in the evolution of the fundamental value and the expectation-feedback syestem. For the Baseline treatment (B), the fundamental value is constant whereas for the other treatments it follows a time varying pattern. In the Increasing treatment (I), the fundamental value rises linearly during the 20 periods. In the Peak (P) and the Trough (T) treatments the total number of periods are divided in two phases: period 1-10 and 11-20. In Peak (Trough) treatment the fundamental value linearly increases (decreases) until period 10, while it linearly decreases (increases) afterward. For each different pattern of the fundamental value, we consider both positive and negative feedback treatments to evaluate the effect of the feedback system on expectations formation. We end up with the following eight treatments: BP (BN) baseline with positive (negative) feedback, IP (IN) increasing with positive (negative) feedback, PP (PN) peak with positive (negative) feedback, TP (TN) trough with positive (negative) feedback.

Subjects receive qualitative information about the implemented feedback system, i.e., whether there is a positive or negative relationship between subjects' one-step ahead predictions and the market price. They are informed that, in both feedback markets, the demand/supply of the asset or the good can change exogenously in each period. Subjects are shown in their screen the history of market prices and their short-run and long-run past predictions. They are also informed that the market price depends just on their one-step ahead predictions. Besides this information, they can follow their payoff relative to each period and the cumulative gains. In Appendix B.1, one can find the translated version of the instructions and the computer screen that subjects see during the experiment (Figure 10).

The experimental sessions were conducted in the Laboratory of Experimental Economics at the University Jaume I in October 2020 and April 2021. We recruited 336 students who participated in eight experimental treatments. Most subjects were at least second-year economics, business, and engineering students. Each student only participated in one session. In each session, subjects were randomly divided into 6-player markets that remained fixed throughout the session, creating independent markets. Each treatment has seven independent markets, including a total of 20 periods per market. At the beginning of the session, subjects had printed copies of the instructions on their tables. After giving the subjects time to read the instructions, the experimenter explained the instructions aloud when presenting the software. All subjects questions were addressed privately by the experimenter. Sessions were programmed with the z-Tree software (Fischbacher, 2007). Each subject earned on average 20 euros, including a show-up fee, in approximately one hour.

2.2 Expectations feedback and the fundamental value

As in Heemeijer et al. (2009), we consider positive and negative expectation feedback between predictions and the market price, which is determined exclusively by short-run predictions. Indeed, the market price is a function of the average of the six one step-ahead predictions submitted at the beginning of period t, defined as $\overline{p}_t^e = \frac{1}{6}\sum_{i=1}^{6} {}_ip_{t,t}^e$, where ${}_ip_{t,t}^e$ stands for the expected price of subject i at the beginning of period t about the market price at the end of period t.

Following Heemeijer et al. (2009), the market price in period t depends positively on the average short-run predictions as described in the following equation:

$$p_t = f + \frac{1}{1+r}\left(\overline{p}_t^e - f\right) + \varepsilon_t \ . \tag{1}$$

According to this specification, the higher the individual predictions the higher will be the realized price. For negative feedback markets, the market price in period t depends negatively on the average short-run price predictions so that, the higher the predictions, the lower the market price:

$$p_t = f - \frac{1}{1+r}\left(\overline{p}_t^e - f\right) + \varepsilon_t \ . \tag{2}$$

The fundamental value in the positive feedback system can be expressed as $f = \frac{d}{r}$, where $d = 3.25$ in the first period and $r = 0.05$ throughout all periods. The term $\varepsilon_t \sim N(0, 0.25)$ is a small iid random shock following a normal distribution with zero mean that can be interpreted as accounting for small fluctuations of supply or demand due to exogenous motives.

The fundamental value may change over time depending on the treatment. In the I treatments, the variation of the value in each period is equal to $\Delta f = 0.6$. In the P treatments, the fundamental value raises as in the I treatments up to period 10 and then decreases following the same variation, i.e., $\Delta f = 0.6$ when $1 < t \leq 10$, and $\Delta f = -0.6$ when $11 \leq t \leq 20$. Finally, in the T treatments, the

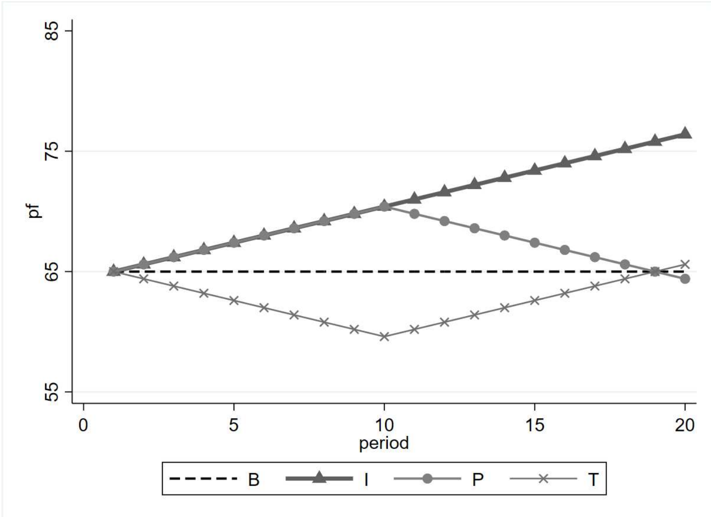


Figure 1: Time evolution of fundamental value for each treatment. B corresponds to the baseline treatment with a constant fundamental value; I refers to the increasing treatment with a linear increasing fundamental value; P corresponds to the peak treatment in which the fundamental value firstly increases and then decreases; T refers to the trough treatment in which the fundamental value falls and then rises.

fundamental value firstly increases in the first ten periods and then decreases until the end of the market, that is $\Delta f = -0.6$ when $1 < t \leq 10$, and $\Delta f = 0.6$ when $11 \leq t \leq 20$. The value $\Delta f = 0.6$ is chosen to be roughly of the same magnitude as the average of the absolute price change using the data from Colasante et al. (2019). Therefore, the systematic change of the fundamental value is hided by the price fluctuations, so that, the signal-to-noise ratio is approximately equal to 1 in both, the positive as well as the negative feedback treatments. Figure 1 summarizes the trajectories of the fundamental value in the different treatments.

2.3 Earnings

The subject's earnings per period depend on the quadratic error of her short- and long-run predictions. We employ two different payment schedules to compute her short- or long-run earnings. Subject's earnings from the short-run predictions (π^s_{it}) are computed as:

$$\pi^s_{it} = \frac{250}{1+\gamma_{i,t}} \qquad \text{with} \qquad \gamma_{i,t} = \left(\frac{{}_ip^e_{t,t} - p_t}{2}\right)^2 . \tag{3}$$

The earnings of subject i from her long-run predictions at time t is $\pi^l_{it} = \sum_{j=1}^{t-1} {}_i\pi^l_{t-j,t}$, where ${}_i\pi^l_{t-j,t}$ represents the earnings based on the prediction ${}_ip^e_{t-j,t}$ done by the subject in period t-j about the future realization of market price in period t, with $1 \leq t \leq 20 - t$. The subject's individual long-run prediction earnings are computed as:

$$ {}_i\pi^l_{t-j,t} = \frac{27}{1 + {}_i\gamma_{t-j,t}} \qquad \text{with} \qquad {}_i\gamma_{t-j,t} = \left(\frac{p_t - {}_ip^e_{t-j,t}}{7} \right)^2 \qquad 1 \leq j \leq t-1 \; . \tag{4} $$

Given the high level of uncertainty, it is a more difficult task to predict the evolution of the market price in the long-run than in the short-run. Therefore, the hyperbolic decay in the case of long-run predictions is milder than the short run prediction – note the scaling factor 7 in the quadratic term in Eq. (4) as compared to the scaling factor 2 in the quadratic term in Eq. (3). Additionally, we calibrate the parameters for both equations in order to provide similar incentives for short- as well as long-run predictions. Essentially, the value 27 in Eq. (4) is computed using the constraint $\max \sum_{t=1}^{20} \pi^l_{it} = \max \sum_{t=1}^{20} \pi^s_{it}$, for each i. In other words, if a subject would predict correctly the market price in all periods and for all horizons, she will earn the same amount of ECUs from her short- as well as long-run predictions.[1] Note that, while subjects receive immediate feedback on the forecasting errors of their short-run predictions, they experience some delay in evaluating the accuracy of their long-run predictions. So, we provide them with the Earnings Table to facilitate the evaluation of their long-run forecasting accuracy (see Table 3 in the Appendix). The individual earnings per period are $\pi_{it} = \pi^s_{it} + \pi^l_{it}$. A subject's total earnings are the sum of earnings across all periods, i.e. $\Pi_i = \sum_{t=1}^{20} \pi_{it}$.

3 Conjectures

3.1 Coordination and convergence of predictions

According to the rational expectations equilibrium, subjects should behave similarly in all treatments. Within this benchmark, the predictions of all subjects closely fluctuate around the time-varying fundamental value, independently of the horizon and the expectation feedback system, i.e., ${}_ip_{t,t+k} \approx f$, and $p_t \approx f_t$.

Previous experimental contributions have reported that the expectation feedback mechanism plays a role in the coordination of subjects' short- and long-run predictions as well as in the convergence of the market price to a constant fundamental value (Heemeijer et al., 2009; Colasante et al., 2019). In particular, Heemeijer et al. (2009) show that short-run predictions quickly coordinate in a positive feedback system, while they need more time in a negative feedback system. Regarding price convergence, they observe significant and persistent price deviations from the fundamental value in the positive feedback system, while prices quickly converge to the fundamentals in the negative feedback system. Colasante et al. (2019) extend this analysis considering the whole spectrum of expectations. They report that in the positive feedback prices and predictions (short- and long-run) slowly converge to the fundamental value. However, short- and long-run predictions widely differ in their degree of coordination. Whereas subjects' short-run predictions quickly coordinate on the market price, they strongly disagree on their predictions on the future price trajectory. This result suggests that the forecast disagreement increases with horizons. In the negative feedback treatment they report a strong connection between coordination and convergence; once the market price converges to the fundamental value, there is a simultaneous coordination of short- and long-run predictions.

[1]The number of short-run predictions is 20 and the long-run predictions are 189

Given the marginal changes in the fundamentals, we expect no significant effects in the coordination and convergence of short-run predictions compared to the results in the literature with constant fundamentals. Our conjectures are:

Conjecture 1 Short-run predictions coordinate faster in the positive feedback system than in the negative feedback system, independently of the trajectory of the fundamentals.

Conjecture 2 Market prices converge to the fundamentals slower in the positive feedback system than in the negative feedback system, regardless of the evolution of the fundamental value.

Considering the extrapolative component in the formation of expectations, we conjecture that changes in the fundamentals, even though marginal, have a significant impact in the heterogeneity of long-run predictions independently of the feedback system.

Conjecture 3 Long-run predictions exhibit higher cross-sectional standard deviation with time varying fundamentals, independently of the feedback system.

In particular, Conjecture 3 implies that after the change in the trend of the fundamentals in treatments PP, PN, TP, and TN, we should observe an increase in the dispersion of the cross-sectional standard deviation of predictions.

3.2 The term structure of cross-sectional dispersion of predictions

As a proxy for the level of disagreement among subjects, we consider the variance of their predictions at different horizons. Following the analysis of Patton and Timmermann (2010), we introduce the term structure of subjects' expectations to study the characteristics of the disagreement among subjects. Comparing the term structure among treatments allows us to identify possible candidates for the expectations formation rules and to exclude expectations rules that do not fit with the observed term structure. Additionally, collecting only short-run predictions could distort the estimation of the level of subjects' disagreement. For example, if we record just one-step ahead predictions, a small variance of short-run predictions can wrongly suggest a high level of agreement in the subjects' future view of the price evolution. Despite observing a high level of coordination of short-run predictions, detecting an increasing variance of long-run predictions with forecasting horizons allows us to conclude that they disagree on the future evolution of prices.

Following Colasante et al. (2019), we assume that subjects anchor their long-run predictions to the last realized price and linearly extrapolate the past price variations.[2] Furthermore, we introduce the principle that the longer the forecasting horizon, the longer the past price history that subjects consider to form her expectations. We assume that the extrapolation coefficient is the average of the past h price increments. The parameter h depends on the subject, i.e., ${}_ih$. Formally, the expectations formation rule for short- and long-run horizons is given by:

$$ {}_ip^e_{t,t+k} = p_{t-1} + \frac{p_{t-1} - p_{t-1-{}_ih}}{{}_ih + 1}(k+1)\,, \tag{5} $$

where k is the forecast horizon. Note that the estimated price trend can be decomposed as follows:

[2]Previous experimental contributions report that subjects tend to make their predictions by extrapolating the trend of realized prices (Barberis et al., 1998; Hirshleifer, 2001; Hommes, 2013).

$$\frac{p_{t-1} - p_{t-1-h}}{_ih + 1} = \frac{1}{_ih + 1} \sum_{j=1}^{h} [(p_{t-j} - p_{t-j-1})] \ . \tag{6}$$

Eq. (5) implies that the expected price k periods ahead is linearly proportional to the average price variations h periods in the past. In principle, k and $_ih$ do not have to be strictly proportional. We might have a subject predicting far in the future, looking at a few steps backward and vice-versa. However, if we consider the entire population, we think it is plausible that the two time scales, namely k and h, are somewhat related to each other. Given Eq. (5), we can compute the variance of subjects' expectations and, therefore, propose some benchmarks for the term structure under the positive and negative expectation feedback. In Appendix A, we develop three benchmarks: two related to the negative feedback and one to the positive feedback. Based on the idea that to forecast farther in the future subjects consider longer price history, we can show that the strong convergence of the market price to the fundamentals in the negative feedback translates into a low dispersion of the subjects' expectations. The term structure turns out to be either linearly increasing or flat. In the case of positive feedback, instead, the high volatility of prices and their poor convergence to the fundamentals lead to a quadratic term structure of variance expectations. We can quantitatively measure the shape of the term structure employing the following equation:

$$\mathrm{Var}[_ip^e_{t,t+k}] = \mathrm{Var}[_ip^e_{t,t}](k+1)^\alpha \ , \tag{7}$$

where the shape parameter α measures the level of disagreement on the future evolution of prices as a function of the forecast horizon. Given the variance of short-run predictions, $\alpha = 0$ implies that the disagreement is independent of the forecast horizon, i.e., rather homogeneous expectations. $\alpha < 0$ implies that the disagreement about future prices decreases as the forecast horizon grows until dispersion vanishes. Conversely, $\alpha > 0$ implies that disagreement increases with the forecast horizon. For values $0 < \alpha < 1$ the term structure is concave, indicating a medium forecast disagreement. When $\alpha = 1$, the scaling is linear. For values $\alpha > 1$ the term structure is convex, implying a wide forecast disagreement.

Colasante et al. (2019) compare the term structure between the two feedback systems in an experiment with constant fundamental value. They observe a high level of disagreement in positive feedback markets, reporting a value $\alpha > 1$. By contrast, the level of disagreement is lower in negative feedback markets, with an estimated range of $0 < \alpha < 1$. They argue that the faster and more stable convergence to the fundamental value in the negative feedback markets leads to a higher level of agreement among subjects on the price evolution.

Based on the term structure benchmarks, we can more precisely quantify our conjecture proposing some expected ranges for the estimated value of α for each treatment (see Table 1). In particular, in positive feedback markets, we conjecture that the term structure will be convex (note that the propose benchmark predicts $\alpha = 2$). In the negative feedback markets, we expect a concave term structure (note that the two proposed benchmarks predict either $\alpha = 0$ or $\alpha = 1$). Furthermore, our setting allows us to analyze the impact of an unanticipated change in the fundamental slope on the level of disagreement. Intuitively, we expect an increase in the value of the shape parameter after that change. The magnitude of such increment depends on the subjects' heterogeneity concerning the past history considered when forming their expectations, namely the between-subject variability of the individual parameter $_ih$. We

Table 1: Expected ranges for the shape parameter of the term structure (α) based on Conjecture 4 for each treatment. In the treatments P and T, the parameters $\underline{\alpha}$ and $\overline{\alpha}$ refer to the shape parameters for periods before and after the change of trends, respectively ($t \leq 10$ and $t > 10$).

	B	I	P		T	
Positive feedback	$\alpha > 1$	$\alpha > 1$	$\underline{\alpha} > 1$	$\overline{\alpha} > \underline{\alpha} > 1$	$\underline{\alpha} > 1$	$\overline{\alpha} > \underline{\alpha} > 1$
Negative feedback	$0 < \alpha < 1$	$0 < \alpha < 1$	$0 < \underline{\alpha} < 1$	$0 < \underline{\alpha} < \overline{\alpha} < 1$	$0 < \underline{\alpha} < 1$	$0 < \underline{\alpha} < \overline{\alpha} < 1$

conjecture that the curvature of the term structure is independent of the unexpected change in the slope of the fundamentals and depends just on the feedback system.

Conjecture 4 The curvature of the term structure depends only on the feedback system: convex for the positive feedback markets and concave for the negative feedback markets.

4 Results

4.1 Coordination and Convergence

Figures 2 and 3 plot the realized market price for each of the seven market in each treatment in positive and negative feedback system, respectively. The pattern observed are in line with previous contributions Heemeijer et al. (2009); Colasante et al. (2018): (i) prices tend to deviate from the fundamental value in positive feedback markets whereas quickly converge to the fundamentals in negative feedback markets; (ii) the rational expectation equilibrium better accounts for the behavior in negative feedback markets than in positive feedback markets; (iii) no significant differences among treatments emerge about the convergence of prices to the fundamentals.[3]

Figures 4 and 5 show the individual short-run predictions and the realized market price of one representative group per treatment in a positive and a negative feedback system, respectively.[4] In the positive feedback markets, Figure 4 shows that individual predictions coordinate around the last realized price after a few periods in all treatments. On the contrary, in negative feedback markets, short-run predictions need approximately 10 periods to coordinate, as shown in Figure 5. Despite we consider a time varying fundamental value, results in terms of coordination of short-run predictions are in line with the existing literature (see Heemeijer et al., 2009; Colasante et al., 2018). The empirical evidence shown that **Conjecture 1** and **Conjecture 2** hold.

Figures 6 and 7 show the evolution of individual long-run predictions in one representative group for each treatment for positive and negative feedback system, respectively. In positive feedback markets, a cone-shaped trajectory emerges, signalling the presence of a significant subjects' disagreement about the future evolution of prices. In those markets, the persistent and systematic deviations from fundamentals prevent the subjects to provide precise long-run predictions. We compute the standard deviation of both

[3]Following the literature, a more quantitative analysis has been performed in order to give a more firm base to the previous statements. Given that we essentially confirm known-results, it is omitted in the paper (material upon request).

[4]All the other groups show similar properties.

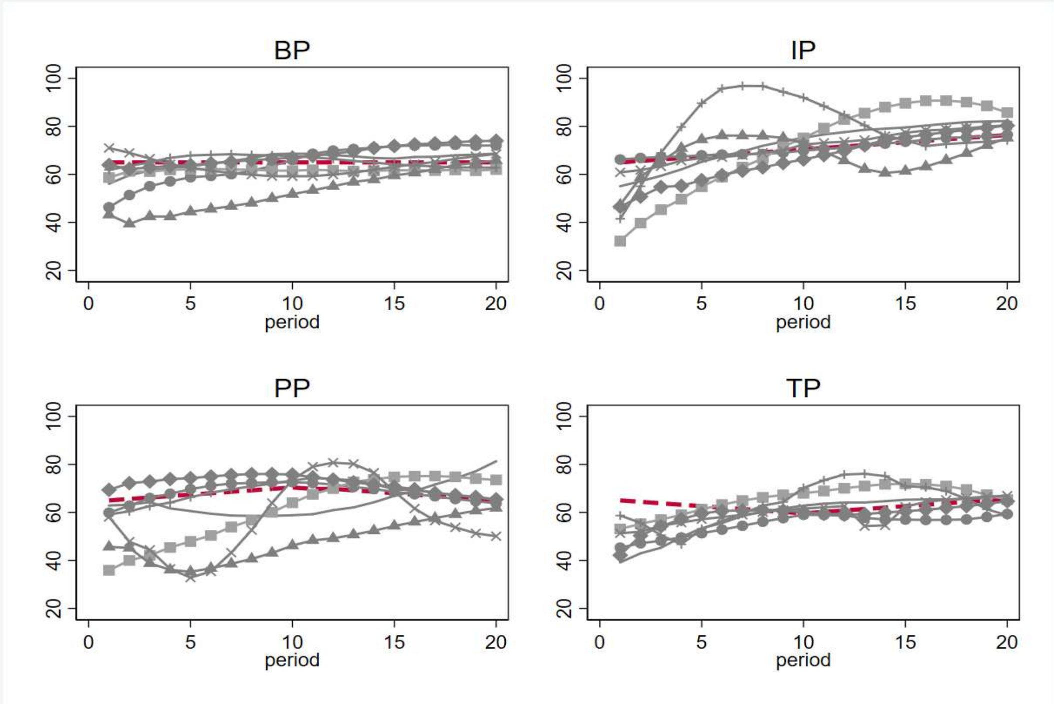


Figure 2: Market prices for each treatment in the positive feedback system. Connected lines represent the realized price of a single group and the dashed red lines represent the fundamental value. The panels display the baseline (B), the increasing (I), the trough (T) and the peak (P) treatments, in a clockwise direction.

one step-ahead and five steps-ahead predictions to measure forecast disagreement. From a glance at Figure 8, long-run predictions are systematically more heterogeneous than short-run ones. Furthermore, the dispersion in short- and long-run predictions does not show a notable increase in the proximity of the turning point of the fundamental value trajectory (i.e., period 11 in PP and TP treatments). Comparing the results of all treatments, we conclude that having introduced time varying fundamentals does not change the qualitative picture reported in Colasante et al. (2019).

Consistently with the main findings of (Colasante et al., 2019), the cone-shaped trajectory is not observed in the negative feedback markets. Indeed, subjects replicate the market price shape drawing a hog cycle pattern in the initial periods, followed by a smoother pattern close to the fundamental value in the last periods. Figure 9 gives an intuition about the volatility of predictions submitted one and five-steps ahead. In both the PN and TN treatments, the changes in the slope of the fundamental value generates a marked increase of volatility. Considering eq. (5), we interpret that the widening of the gap between the dispersion of short- and long-run predictions after the turning point in both PN and TN, depends on the heterogeneity in past information each subject takes into account to forecast the future evolution of prices (see section 4.2).

In all but IN treatments with time varying fundamentals, we observe higher dispersion in the long-run

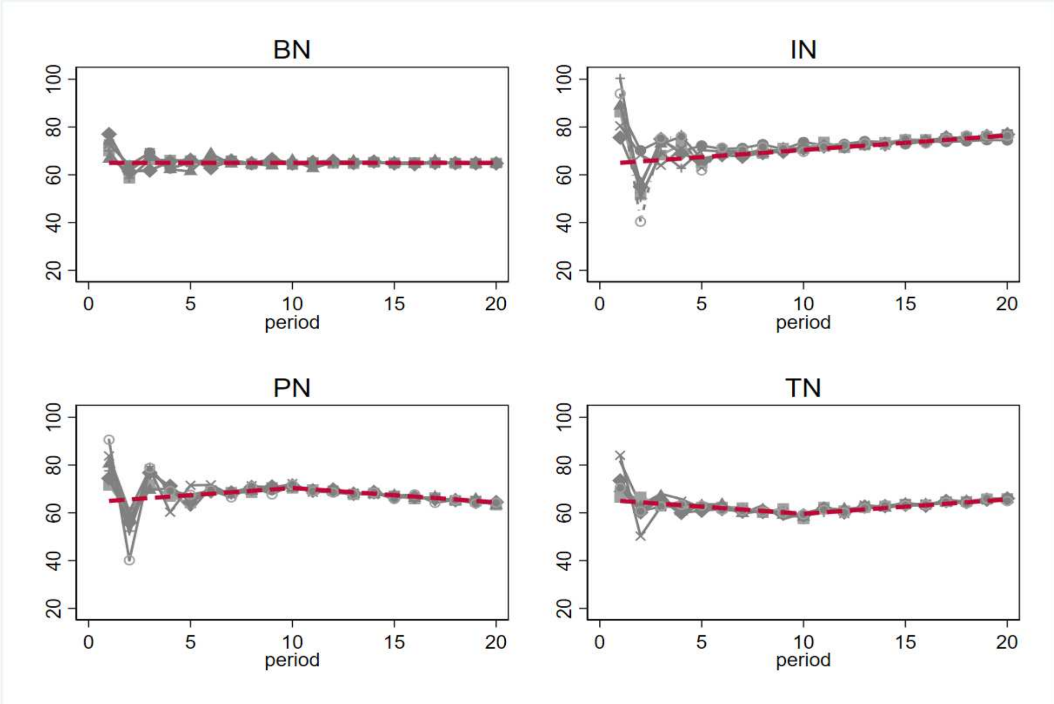


Figure 3: Time series of market prices in each treatment in the negative feedback system. Connected lines are the realized price of a single group and the dashed red lines represent the fundamental value. The panels display the baseline (B), the increasing (I), the trough (T) and the peak (P) treatments, in a clockwise direction.

predictions as compared to the short-run predictions, giving a (weak) empirical support to **Conjecture 3**.

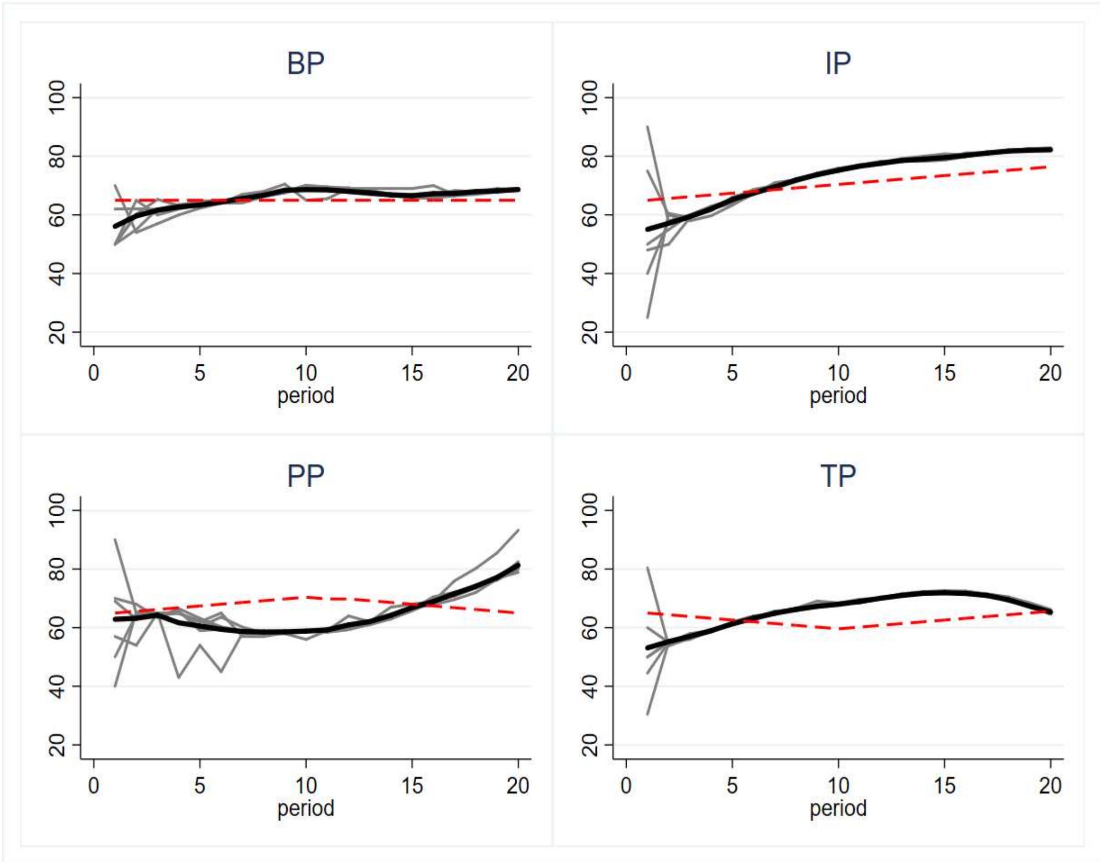


Figure 4: Realized price and individual short-run predictions of a representative group in each of the treatment with positive feedback. The black solid line represents the realized market price, the grey lines represents individual one-step ahead predictions and the dashed line represents the fundamental value. The panels display the baseline (B), the increasing (I), the trough (T) and the peak (P) treatments, in a clockwise direction.

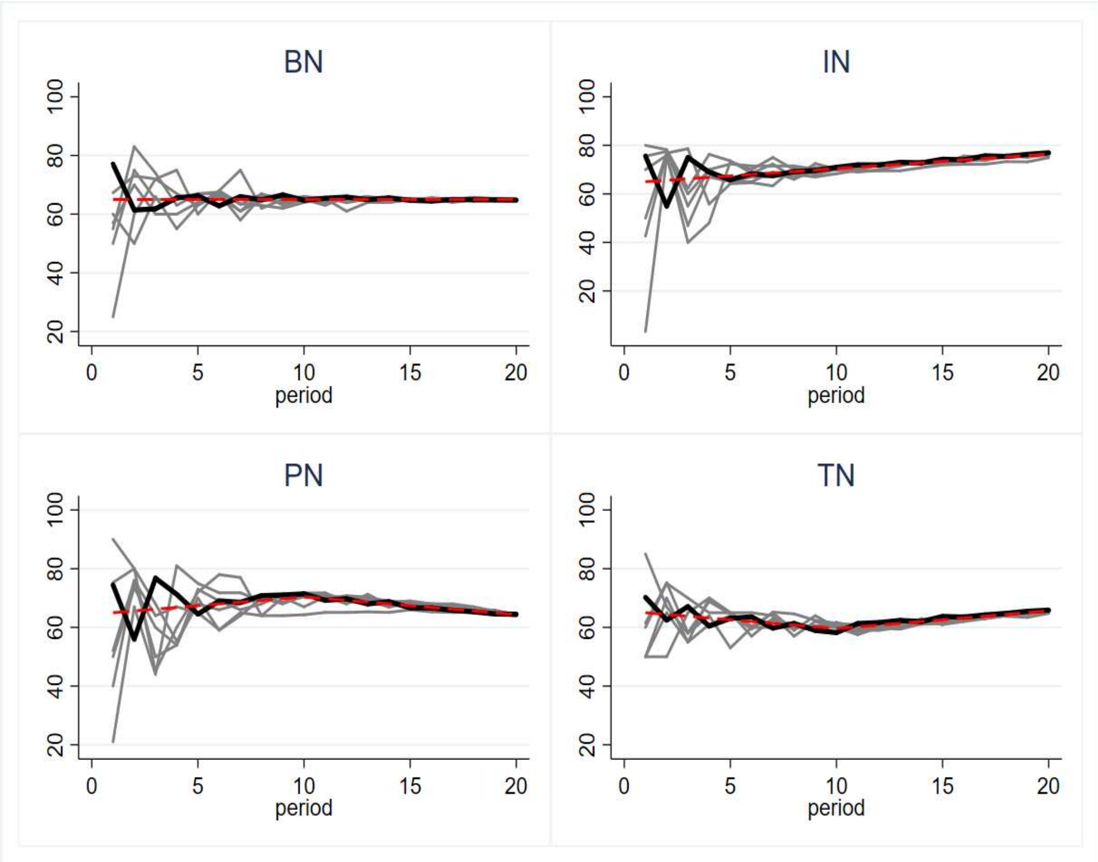
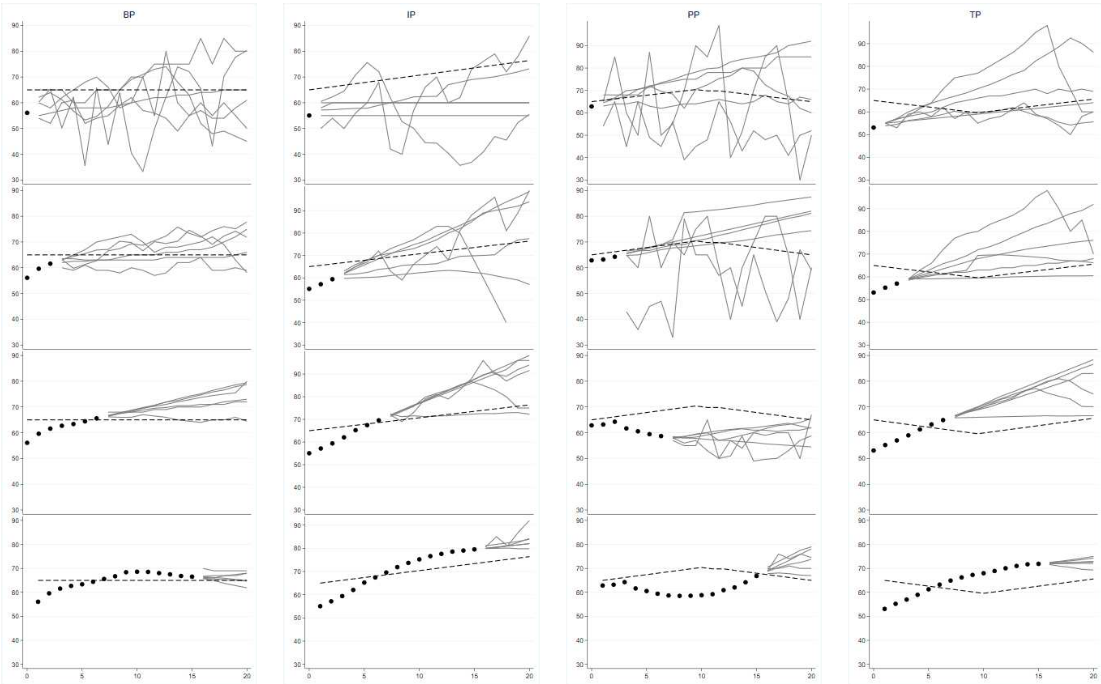
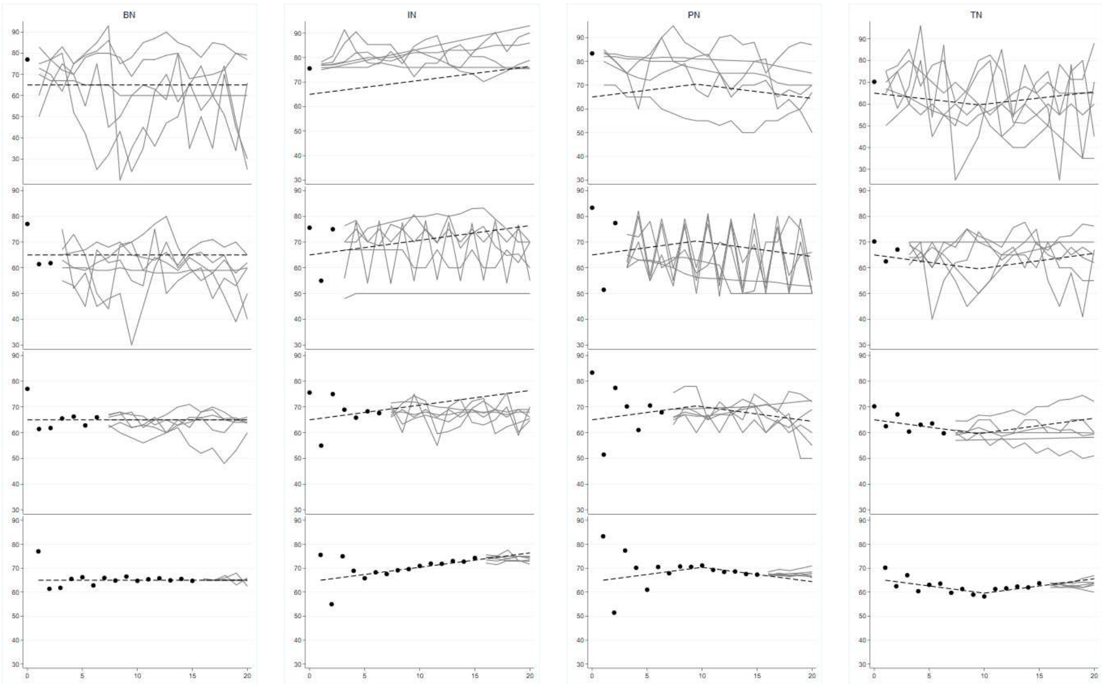


Figure 5: Realized price and individual short-run predictions of a representative group in each of the treatment with negative feedback. The black solid line represents the realized market price, the grey lines represents individual one-step ahead predictions and the dashed line represents the fundamental value. The panels display the baseline (B), the increasing (I), the trough (T) and the peak (P) treatments, in a clockwise direction.



(a) BP (b) IP (c) PP (d) TP

Figure 6: Realized price and individual long-run predictions of a representative group in each of the treatment with positive feedback. Dots represent the realized market price, the grey lines represents individual long-run predictions and the dashed line represents the fundamental value. From left to right, each column displays the baseline (B), the increasing (I), the peak (P) or the trough (T) in periods 2, 4, 8 and 16.



(a) BN (b) IN (c) PN (d) TN

Figure 7: Realized price and individual long-run predictions of a representative group in each of the treatment with negative feedback. Dots represent the realized market price, the grey lines represents individual long-run predictions and the dashed line represents the fundamental value. From left to right, each column displays either the baseline (B), the increasing (I), the peak (P) or the trough (T) in periods 2, 4, 8 and 16.

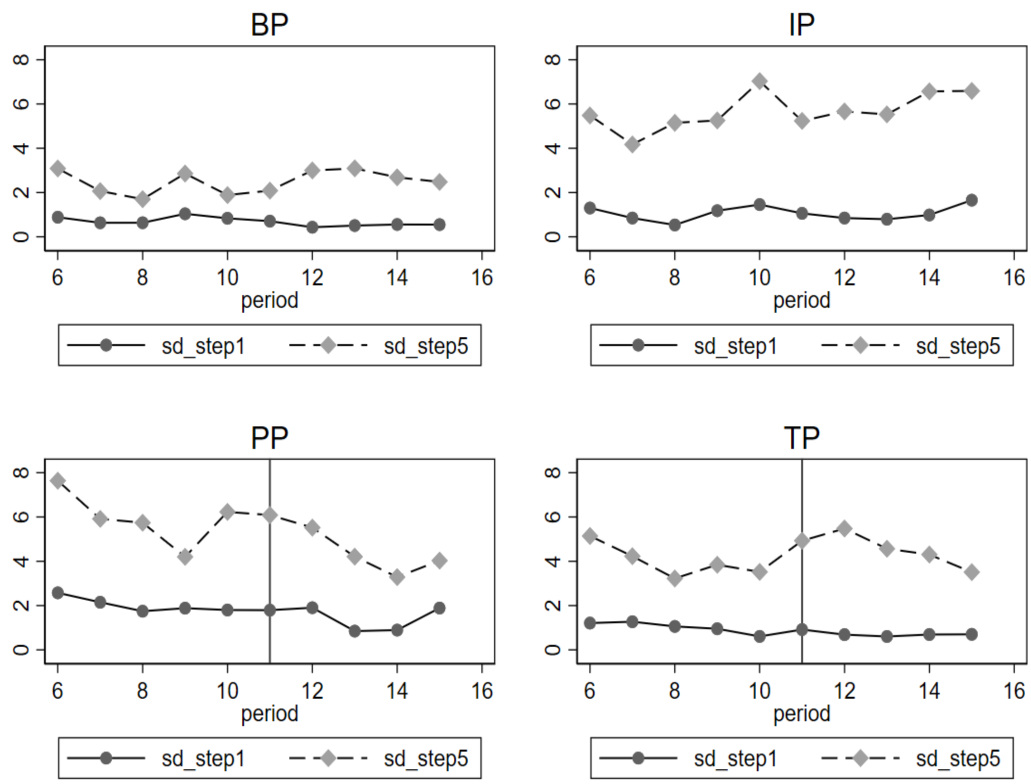


Figure 8: Standard deviation, averaged by groups, of both one (grey dashed line) and five-step (dark grey continuous line) ahead predictions for each of the treatment with positive feedback. The vertical line in bottom panels is in correspondence of period 11. The panels display the baseline (B), the increasing (I), the trough (T) and the peak (P) treatments, in a clockwise direction.

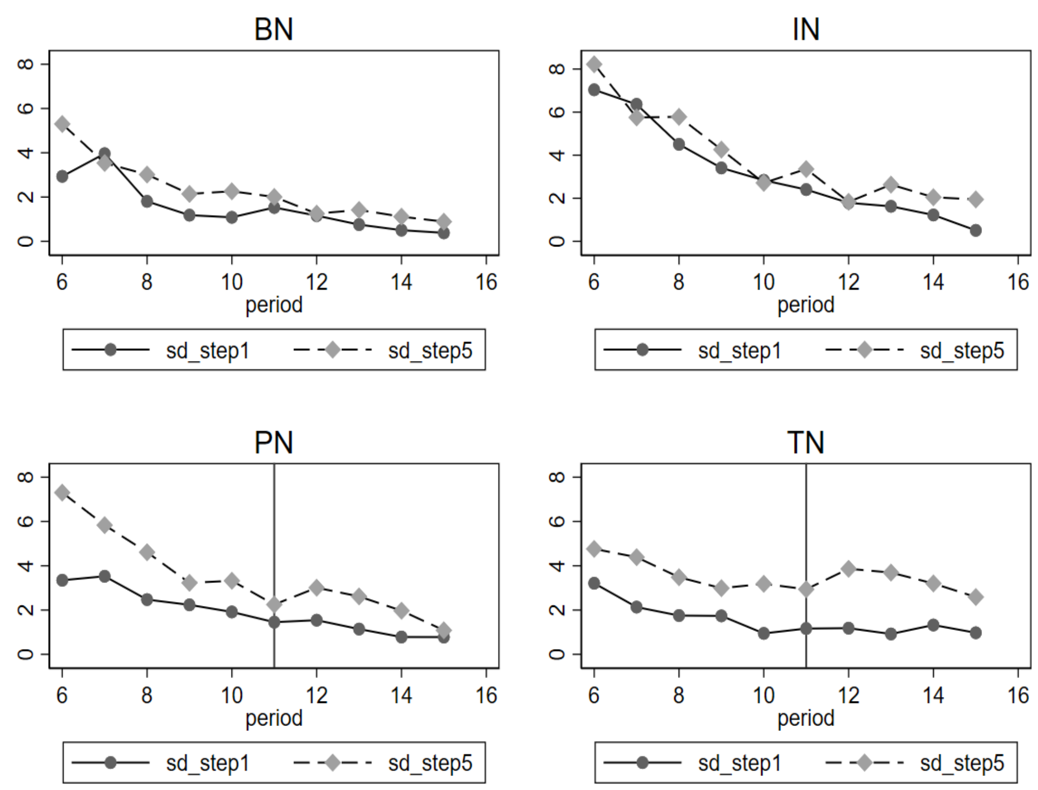


Figure 9: Standard deviation, averaged by groups, of both one (grey dashed line) and five-step (dark grey continuous line) ahead predictions for each of the treatment with negative feedback. The vertical line in bottom panels is in correspondence of period 11. The panels display the baseline (B), the increasing (I), the trough (T) and the peak (P) treatments, in a clockwise direction.

4.2 The term structure of the cross-sectional dispersion of subjects' predictions

Even though most of the contributions on LtFEs focus on short-run predictions, by collecting long-run predictions we could move forward in the analysis of the main properties of the term structure of expectations. To this aim, we estimate the value of α for all treatments using a pooled panel regression of a log-linearization of Eq. (7) with normalized variances:

$$\log\left[\frac{\langle \mathrm{Var}[{}_ip^e_{t,t+k}]\rangle_g}{\langle \mathrm{Var}[{}_ip^e_{t,t}]\rangle_g}\right] = \alpha \cdot \log(k+1)\ , \qquad (8)$$

where g denotes the average across groups of a given treatment. The estimated values of the shape parameter $\hat{\alpha}$ for the different treatments are shown in Table (2). In particular, for treatments P and T, the estimates $\hat{\alpha}$ refer to the periods before (i.e., from period 3 to period 10) and after (i.e., from period 11 to period 16) the turning point of the fundamental value.

The estimates are consistent with the expected ranges for the shape parameter based on Conjecture 4 (see Table 1) for positive feedback system. In fact, we consistently obtain a convex term structure for all the positive feedback treatments, independently of the patter of the fundamentals. Furthermore, in treatments P and T, we observe a significant increase of $\hat{\alpha}$ after the unanticipated change of slope in the fundamentals, without affecting the concavity of the term structure. Regarding the negative feedback markets, the estimates $\hat{\alpha}$ are consistent with a concave shape of the term structure. Interestingly and somewhat unexpectedly, in the negative feedback markets the change in the slope after period 10 **does affect** the concavity of the term structure. Indeed, in the PN and TN treatments the term structure after the unanticipated change in the slope of the fundamentals becomes convex, signaling a more-than-liner increasing disagreement of long-run predictions. We can conclude that our results do not support Conjecture 4, since relevant changes in the fundamentals do affect significantly the term structure, changing the sign of its curvature.

How can we interpret our results? Let us make use of the simple expectation formation rule of Eq. (5) and the corresponding benchmarks for positive and negative feedback system. The convexity of the term structure for the positive feedback system stems from the high volatility of past price changes and the heterogeneity in considering the past history when subjects for their expectations. Subjects look at different past histories when forming their expectations and, therefore, they come up with different estimates for the future price trend. The combination of high volatility and a heterogeneous inference are the two main elements for the emergence of a remarkable level of disagreement in positive feedback markets. Moreover, the unanticipated change in the slope does not have a large impact in the time evolution of prices, given the low sensitivity of the market price to marginal changes in fundamentals. The shape of the term structure, therefore, is robust against smooth changes in the fundamentals. Note that the high level of coordination of short-run predictions is not an indication of homogeneous expectations. This apparent agreement of subjects on the future development of prices is an artifact of limiting the forecast horizon to one-step ahead predictions.

The concavity of the term structure for the negative feedback system is a reflection of the rather homogeneous price history, i.e., the more clear anchoring of past price to the fundamentals leads to a homogeneous estimation of price trend among subjects. Even though subjects consider heterogeneous price histories when make the inference on the extrapolation trend, their predictions reflect the homogeneous past price fluctuations. Looking at few steps backward or considering a longer price history leads to a unbiased estimation of the future price trend across subjects and, hence, to a concave term structure (see section 9 in the appendix). Such homogeneity of expectations is again apparent, similarly to the case of positive feedback markets. In fact, the unexpected change in the slope of the fundamentals and the consequent higher fluctuations in market price changes is immediately reflected in a heterogeneous price trend extrapolation, given the heterogeneity[5] in ${}_ih$. The term structure changes its shape, reflecting the variability across subjects[6] of ${}_ih$. The shape of the term structure, therefore, is not robust against smooth changes in the fundamentals in negative feedback markets. Note that a greater homogeneity in the predictions across horizons, characterized by a concave term structure, can be a misleading indication of homogeneous expectations across subjects. In our experiment, the heterogeneity in subjects' expectations is hided by the homogeneity of price history and it emerges strongly after even a marginal change in the slope of fundamentals. We predict that, after the shock, the term structure will return to a concave shape. The relaxation time should depend on the heterogeneity of the individual parameters ${}_ih$.

Table 2: Results of the pooled panel regression from Eq. (8). Dependent variable: log of cross-sectional normalized variances of long-run predictions for a given period and forecast horizon. We include periods from 2 to 16 ($t = 2, ..., 16$) and five horizons ($h = 1, ..., 5$). Standard errors are reported in parentheses.

	B	**I**	**P** [3-10]	**P** [11-116]	**T** [3-10]	**T** [11-16]
Positive	1.42 (0.08)	1.79 (0.10)	1.14 (0.08)	1.54 (0.16)	1.20 (0.19)	0.92 (0.11)
Obs.	75	75	40	30	40	30
R^2	0.79	0.83	0.86	0.74	0.54	0.95
Negative	0.62 (0.07)	0.17 (0.10)	0.65 (0.06)	1.48 (0.19)	0.92 (0.06)	1.61 (0.11)
Obs.	75	75	40	30	40	30
R^2	0.52	0.04	0.76	0.72	0.87	0.90

5 Discussion and Conclusion

This paper evaluates the effects of time-varying fundamentals on subjects' expectations in a Learning to Forecast Experiment. We simultaneously elicit a broad spectrum of expectations by asking subjects to submit their short- and long-run predictions on the future evolution of prices. Inspired by macroeconomic scenarios, the fundamental value exhibits different patterns over time: (i) constant, (ii) linearly

[5]Let us consider as an example a subject consider just the previous price change as a proxy for the future evolution of price k steps ahead. She will submit very different predictions than a subjects considering a much longer price history.

[6]When the variability in the trend is sufficiently high, according to the determination of the positive feedback term structure benchmark in Section A, the term structure depends on the heterogeneity of ${}_ih$ across subjects and it exhibits a quadratic increase with the forecast horizon k.

increasing, (iii) a V-shaped or (iv) an inverse V-shape. Changes in the fundamentals are smaller or comparable in magnitude with the price changes (unitary signal-to-noise ratio), and they are systematic for a vast number of periods. To a large extent, the marginal changes in fundamentals do not qualitatively impact the short-run predictions, so we can study in isolation the modifications of the behavior of the subjects when forming long-run expectations.

Following the literature on macroeconomic surveys (Patton and Timmermann, 2010), we analyze in detailed the evolution of the disagreement in expectations among subjects as a function of the forecasting horizon. We find that the empirical regularities of LtFEs are robust against changes in the fundamentals: fast coordination of short-run predictions and slow convergence to the fundamental value in positive feedback markets; slower coordination of expectations and good convergence to the fundamentals in negative feedback markets. The long-run predictions are characterized by a cone-shape behavior in the positive feedback markets and smoother fluctuations around the fundamentals in the negative feedback markets. This different pattern of long-run expectations translates into a convex or concave term structure in the positive and negative feedback systems, respectively.

In order to interpret the results, we introduce an expectation formation rule based on the principle that the longer the forecasting horizon, the more extended the price history considered by the subjects to linearly extrapolate the estimated price trends. Such a backward-looking expectation formation rule, quite intuitively, and perhaps obviously, implies that the features of the long-run predictions mirror the past price behavior. However, to account for the empirical observations, we have to add the additional characteristic that the extent of the price history considered by the subjects in forming their expectations has to be quite heterogeneous across subjects. In other words, if the individual history parameter is homogeneous across the subjects (i.e., ${}_ih = h$), the expectations will be essentially homogeneous. Therefore, the contemporaneous presence of backward-looking subjects and the heterogeneous sensibility to price history are key elements to account for our experimental findings, especially if we focus the attention on the evolution in the level of disagreement. In particular, we find that, even though in the negative feedback markets the price converges to the fundamental value with a low disagreement of both short and long-run predictions described by a concave term structure, the heterogeneity in the expectations persists underneath. In fact, after an unexpected and rather marginal shock, the heterogeneity of the expectations emerges again, leading to a high level of disagreement. The homogeneity in the predictions is just an artifact of a “homogeneous” price history that leads to similar homogeneity in the predictions.

Our setting clearly demonstrates to be a useful and flexible tool in eliciting expectations, complementing macroeconomic literature based on surveys about the origin of heterogeneity in expectations. Future research will be devoted to evaluate the external validity of our setting. We will compare the properties of the short-and long-run subjects' predictions generated in the laboratory with those measured in surveys, following the methodology of Cornand and Hubert (2020).

Acknowledgments

We acknowledge the financial support of the Generalitat Valenciana under the project AICO/2021/005 and the University Jaume I under the project UJI-B2021-66.

References

M. Anufriev, T. Assenza, C. Hommes, and D. Massaro. Interest rate rules and macroeconomic stability under heterogeneous expectations. *Macroeconomic Dynamics*, 17(8):1574–1604, 2013.

M. Anufriev, A. Chernulich, and J. Tuinstra. Asset price volatility and investment horizons: An experimental investigation. *Journal of Economic Behavior & Organization*, 193:19–48, 2022.

T. Assenza, P. Heemeijer, C. H. Hommes, and D. Massaro. Managing self-organization of expectations through monetary policy: A macro experiment. *Journal of Monetary Economics*, 117:170–186, 2021.

T. Bao and L. Ding. –nonrecourse mortgage and housing price boom, bust, and rebound. *Real Estate Economics*, 44(3):584–605, 2016.

T. Bao, C. Hommes, J. Sonnemans, and J. Tuinstra. Individual expectations, limited rationality and aggregate outcomes. *Journal of Economic Dynamics and Control*, 36(8):1101–1120, 2012.

T. Bao, J. Duffy, and C. Hommes. Learning, forecasting and optimizing: An experimental study. *European Economic Review*, 61:186–204, 2013.

T. Bao, C. Hommes, and J. Pei. Expectation formation in finance and macroeconomics: A review of new experimental evidence. *Journal of Behavioral and Experimental Finance*, 32:100591, 2021.

N. Barberis, A. Shleifer, and R. Vishny. A model of investor sentiment. *Journal of Financial Economics*, 49(3):307–343, 1998.

A. Colasante, A. Palestrini, A. Russo, and M. Gallegati. Adaptive expectations versus rational expectations: Evidence from the lab. *International Journal of Forecasting*, 33(4):988–1006, 2017.

A. Colasante, S. Alfarano, E. Camacho, and M. Gallegati. Long-run expectations in a learning-to-forecast experiment. *Applied Economics Letters*, 25(10):681–687, 2018.

A. Colasante, S. Alfarano, and E. Camacho-Cuena. The term structure of cross-sectional dispersion of expectations in a learning-to-forecast experiment. *Journal of Economic Interaction and Coordination*, 14(3):491–520, 2019.

C. Cornand and P. Hubert. On the external validity of experimental inflation forecasts: A comparison with five categories of field expectations. *Journal of Economic Dynamics and Control*, 110:103746, 2020.

C. Cornand and C. K. M'baye. Does inflation targeting matter? an experimental investigation. *Macroeconomic Dynamics*, 22(2):362–401, 2018.

G. W. Evans, C. H. Hommes, B. McGough, and I. Salle. Are long-horizon expectations (de-) stabilizing? theory and experiments. Technical report, Bank of Canada Staff Working Paper, 2019.

U. Fischbacher. z-tree: Zurich toolbox for ready-made economic experiments. *Experimental economics*, 10(2):171–178, 2007.

G. Galati, R. Moessner, and P. Heemeijer. How do inflation expectations form? new insights from a high-frequency survey. *New Insights from a High-Frequency Survey (June 9, 2011)*, 2011.

E. Haruvy, Y. Lahav, and C. N. Noussair. Traders' expectations in asset markets: experimental evidence. *American Economic Review*, 97(5):1901–1920, 2007.

P. Heemeijer, C. Hommes, J. Sonnemans, and J. Tuinstra. Price stability and volatility in markets with positive and negative expectations feedback: An experimental investigation. *Journal of Economic Dynamics and Control*, 33(5):1052–1072, 2009.

D. Hirshleifer. Investor psychology and asset pricing. *The Journal of Finance*, 56(4):1533–1597, 2001.

C. Hommes. *Behavioral rationality and heterogeneous expectations in complex economic systems*. Cambridge University Press, 2013.

C. Hommes, J. Sonnemans, J. Tuinstra, and H. van de Velden. A strategy experiment in dynamic asset pricing. *Journal of Economic Dynamics and Control*, 29(4):823–843, 2005.

N. G. Mankiw, R. Reis, and J. Wolfers. Disagreement about inflation expectations. *NBER macroeconomics annual*, 18:209–248, 2003.

C. F. Manski. Measuring expectations. *Econometrica*, 72(5):1329–1376, 2004.

C. F. Manski. Survey measurement of probabilistic macroeconomic expectations: progress and promise. *NBER Macroeconomics Annual*, 32(1):411–471, 2018.

R. Marimon, S. E. Spear, and S. Sunder. Expectationally driven market volatility: an experimental study. *Journal of Economic Theory*, 61(1):74–103, 1993.

J. F. Muth. Rational expectations and the theory of price movements. *Econometrica*, pages 315–335, 1961.

C. N. Noussair and O. Powell. Peaks and valleys: Price discovery in experimental asset markets with non-monotonic fundamentals. *Journal of Economic Studies*, 2010.

A. J. Patton and A. Timmermann. Why do forecasters disagree? lessons from the term structure of cross-sectional dispersion. *Journal of Monetary Economics*, 57(7):803–820, 2010.

M. Woodford. Monetary policy in the information economy. Working Paper 8674, National Bureau of Economic Research, December 2001.

A Term structure benchmarks

This appendix describes the benchmarks for the term structure of the cross-sectional dispersion under the negative and positive feedback expectations' mechanisms. In the following, we consider that the variation of the fundamental value is constant (Treatments B and I). Let us consider the following forecasting rule:

$$ {}_ip^e_{t,t+k} = p_{t-1} + \frac{p_{t-1} - p_{t-1-{}_ih}}{{}_ih+1}(k+1) \; . \tag{9} $$

The expected value of the cross-sectional expectations as a function of the forecasting horizon is:

$$ E[{}_ip^e_{t,t+k}] = p_{t-1} + (k+1)E\left[\frac{p_{t-1} - p_{t-1-{}_ih}}{{}_ih+1}\right] \; . \tag{10} $$

A.1 Negative feedback

According to the empirical evidence, the price converges "reasonably" well to the fundamental value f in negative feedback markets. To formalize this statement, we assume that:

$$ E\left[\frac{p_{t-1} - p_{t-1-{}_ih}}{{}_ih+1}\right] = \Delta f_{t-1} + \frac{\varepsilon_{t-1}}{\sqrt{\lambda(k+1)}} \; , \tag{11} $$

where $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$. The previous equation states that the average of the subjects' estimated price variation is an unbiased estimator of the change in the fundamental value with an error inversely proportional to the forecasting horizon. In order to derive Eq. (11), we assume that the past market price increments are iid. Eq. (11) stems from the assumption that subjects tend to consider a longer price history when they forecast far in the future. Essentially, we assume that ${}_ih = {}_i\lambda \cdot k$. The variable λ in Eq. (11) is function of the parameters ${}_i\lambda$, which characterizes each subject. Given Eqs. (9) and (11), we can compute the variance of the expectations as a function of the forecasting horizon:

$$ \mathrm{Var}[{}_ip^e_{t,t+k}] = \frac{\sigma^2}{\lambda \cdot (k+1)}(k+1)^2 = \mathrm{Var}[{}_ip^e_{t,t}](k+1) \; . \tag{12} $$

This benchmark leads to a linear term structure in the forecasting horizon for the negative feedback mechanism. We can think that this benchmark is valid when subjects are coordinating around the fundamental value.

Following the previous reasoning, we can also introduce an alternative benchmark for the case of a strong alignment of the short- as well as long-run expectations, and the market price to the fundamental value. In other words, this is valid when subjects have already coordinated to the fundamental value. We can assume that:

$$ E\left[\frac{p_{t-1} - p_{t-1-{}_ih}}{{}_ih+1}\right] = \Delta f_t \; , \tag{13} $$

which is independently of ${}_ih$. When subjects are strongly coordinated around the fundamental value, the estimated trend is robust to the price history they consider. We can rewrite the expectations' formation rule as:

$$ {}_ip^e_{t,t+k} = p_{t-1} + \Delta f_t \cdot (k+1) + {}_i\eta_t \; , \tag{14} $$

where ${}_i\eta_t$ represents a small perturbation to the expectation formation rule, which is now homogeneous across subjects and is distributed as ${}_i\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$. The resulting term structure is given by:

$$ \mathrm{Var}[{}_ip^e_{t,t+k}] = \mathrm{Var}[{}_ip^e_{t,t}](k+1)^0 = \mathrm{Var}[{}_ip^e_{t,t}] \; . \tag{15} $$

This benchmark leads to a flat term structure as a function of the forecasting horizon for the negative feedback mechanism. Note that we could also include an additive noise in Eq. (9) as done in Eq. (14), without significantly changing the result given by Eq. (12).

A.2 Positive feedback

We now describe the case of the positive feedback mechanism. According to the empirical evidence from our experiment and the LtFEs literature, the price converges poorly to the fundamental value f in positive feedback markets. Instead, the market price exhibits large swings around f or even bubbles-and-crashes events. Consequently, the estimated trend is very heterogeneous across subjects, which depends on their individual choice[7] of ${}_ih$. The new benchmark expectation formation rule is:

$$ {}_ip^e_{t,t+k} = p_{t-1} + {}_im \cdot (k+1) \ , \tag{16} $$

where ${}_im$ is the individual coefficient of extrapolation. We can compute the variance of the expectations as a function of the forecasting horizon:

$$ \text{Var}[{}_ip^e_{t,t+k}] = \text{Var}[{}_im](k+1)^2 = \text{Var}[{}_ip^e_{t,t}](k+1)^2 \ , \tag{17} $$

This benchmark leads to a quadratic term structure in the forecasting horizon for the positive feedback mechanism.

[7]Note the difference with the negative feedback, where the estimated price trend is rather robust with respect to the choice of ${}_ih$ given the strong convergence to the fundamental value.

B Instructions and screenshot

B.1 Translation of the instructions

[General information]

Welcome to the Laboratory of Experimental Economics. You are participating in an experiment in which you will take decisions in a financial (goods) market.[8] The instructions are very simple but, please, read them carefully. During the whole experiment you will play with experimental currency units (ECU) and, at the end of the experiment, your final profit, which will be added to a show-up fee of 3 euros, will be converted into euro according to the following exchange rate: 1 Euro = 500 ECU. The total amount will be paid at the end of the experiment in cash.

[Only for positive feedback treatments]

You are a financial advisor to a pension fund that wants to invest an amount of money. In each period, the pension fund has to choose between investing its money in a bank account and buy a risky asset that pays dividends. To take an optimal decision, the pension fund will decide how many assets to buy based on your price prediction. The market price will be determined by the demand for the asset. If the demand for the asset increases, the price will rise.

Consider that the market price is determined by the decisions of the pension funds (you are advising one of them). Higher price predictions raise the market demand for assets. As a consequence, the market price will rise. The asset price in each period is positively affected by the advisors' predictions of the market price in that period.

The total demand is largely determined by the sum of the pension funds' demand.

[*For non-stationary treatments*] Additionally, there are exogenous shocks every period that cause fluctuations in the supply or demand.

[Only for negative feedback treatments]

You are an advisor to an import firm. In each period, the manager of the firm decides how many units of this particular product she wants to buy or to sell in the next period. To take an optimal decision, the manager needs a good prediction of the market price in the next period. The market price will be determined by the demand and supply of the product. If the demand for the product is higher than its supply, the price will rise. Conversely, if the supply of the product is higher than its demand, the price will fall.

Consider that the market price is determined by the decisions of the firms (you are advising one of them). Higher price predictions raise the quantity these firms will be willing to import of the product that will later come into the market, thereby increasing the market supply. As a consequence, the market price will fall. The price of the product in each period is negatively affected by the advisors' predictions of the market price in that period.

[8] The word "financial" refers to all markets in the positive feedback mechanism, while "goods" refers to the negative feedback markets.

The total demand and supply are largely determined by the sum of firms' demand and supply (your are advising one of them).
[*For non-stationary treatments*] Additionally, there are exogenous shocks every period that cause fluctuations in the supply or demand (e.g. transportation delay).

[General information]

Your task is to predict the price for 20 periods. In each period (t) you will predict the price for all the remaining $20 - t$ periods, i.e., in period 1 you will submit 20 predictions starting from the prediction about the price at the end of period 1, in period 2 you will submit 19 predictions, and so on. Your predictions must be between 0 and 100. In period 1 you will submit predictions without any information about the market. From period 2 onward, you will have the following information: a graph with both the time series of your past predictions and the time series of the market prices, all your past predictions, the earnings from the predictions you submit for the end of the period as well as the earning you get for the other predictions. In the graph, green dots represent the time series of your predictions for the end of the current period, while the blue dots represent the market price. In the table you can see the value for both the market price as well as of all your past predictions.

Once each subject has submitted his/her prediction for each period, the price will be computed according the demand and the supply and it will be shown at the beginning of period 2. The same mechanism will be used for subsequent periods. This means that in period 3, for example, you will see the market price for both period 1 and period 2.

Your profit will depend on the accuracy of your predictions. The smaller the error of your forecasts (the distance between your prediction and the market price in a period), the greater the profit you will get. Your benefits will be calculated at the end of each period. Regarding the predictions you submit for the end of the period, in case you predict exactly the next period price your earning will be 250 ECU and in case your prediction error will be higher than 15 your earning will less than 5 ECU. Moreover, for each predictions you submit for subsequent periods, you will receive an extra profit. This extra profit will be computed according to the following table (see Table 3):

Table 3: Payoff table for long-run predictions

Difference between the market price in period t and your predictions for period t	ECU
0	27,0
1	26,5
2	25,0
3	22,8
4	20,3
5	17,9
6	15,6
7	13,5
8	11,7
9	10,3
10	8,9
11	7,8
12	6,8
13	6,1
14	5,4
15	4,8
>15	0

B.2 The computer screen

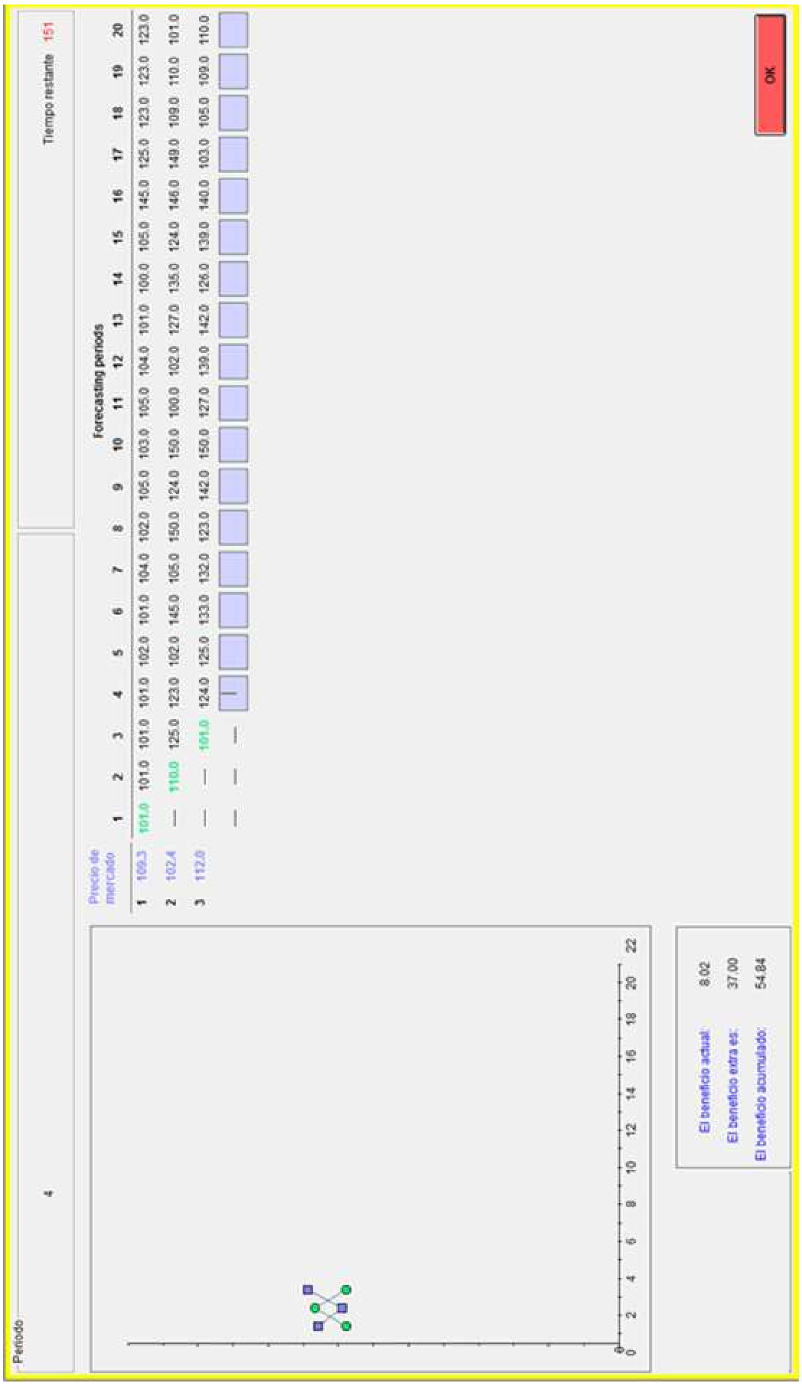


Figure 10: Screenshot of the experiment