ISSN (Print) 0473-453X
Discussion Paper No. 1213
ISSN (Online) 2435-0982

AN EXPERIMENT ON A DYNAMIC BEAUTY CONTEST GAME

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September 2023

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An Experiment on a Dynamic Beauty Contest Game*

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September 11, 2023

Abstract

We present and conduct a novel experiment on a dynamic beauty contest game motivated by the canonical New-Keynesian model. Participants continuously provide forecasts for prices spanning multiple future periods. These forecasts determine the price for the current period and participants' payoffs. Our findings are threefold. First, the observed prices in the experiment deviate more from the rational expectations equilibrium prices under strategic complementarity than under strategic substitution. Second, participants' expectations respond to announcements of future shocks on average. Finally, participants employ heuristics in their forecasting; however, the choice of heuristic varies with the degree of strategic complementarity.

Keywords: Expectation formation, Learning-to-forecast experiment

JEL Code: C92, D84, E70

*We thank Elena Asparouhova, Te Bao, John Duffy, Charles Noussair, Yoshiyasu Ono, Lube Petersen, Marc Willinger, and the participants at 2023 CEFM workshop (Nagasaki), AP-ESA 2023 (Seoul), EF 2023 (Sofia), and 2023 ESA world meeting (Lyon) for their comments and helpful discussion. This research has benefited from the financial support of (a) the Joint Usage/Research Center (JJURC), the Institute of Social and Economic Research (ISER), and Osaka University, and (b) Grants-in-aid for Scientific Research Nos. 18K19954, 20H05631, and 23H00055 from the Japan Society for the Promotion of Science. The design of the experiment reported in this paper was approved by the IRB of ISER (#20221102) in November 2022. The experiment is preregistered at aspredicted.org (#128898), which is available at https://aspredicted.org/ix6th.pdf. We thank Yuka Tamura and Yuta Shimodaira for their help in preparing software for the experiment, and Yuki Hamada, Hiroko Shibata, Saori Shikibu, and Satsuki Yamada for their support in conducting the experiment.

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1 Introduction

The assumption that individuals form rational expectations is pervasive and often taken for granted in macroeconomic modeling. Over the last five decades, a substantial body of macro and experimental economics literature has evaluated the rational expectations equilibrium (REE) hypothesis. One notable finding from the macroeconomics literature is that models with the strong form of rational expectations can lead to counterintuitive implications, such as the forward-guidance puzzle. Consequently, researchers have become increasingly skeptical of this hypothesis, proposing alternative frameworks (for example, Angeletos and Lian, 2018; Farhi and Werning, 2019; García-Schmidt and Woodford, 2019).

Another finding emerges from the literature on experimental economics. This literature finds that the results of numerous experiments are inconsistent with the strong form of rational expectations (see, among others, Hommes et al., 2005; Heemeijer et al., 2009; Bao et al., 2017). In these experiments, individual decisions depend on participants' expectation about what other participants do, and the market outcome (e.g., prices) is an aggregation of these individual behaviors. Markets can exhibit an expectational feedback effect. Past events can shape individual expectations which, in turn, affect the current aggregate market outcome. The results of these experiments differ substantially from those predicted by the rational expectations hypothesis. Instead, they can be better explained by models with backward-looking expectation formation (see, for example, Anufriev and Hommes, 2012; Evans et al., 2021).

Notably, most of these existing experiments are essentially static: participants only need to forecast what others do today, not tomorrow. The outcome is thus only a function of today's behaviors (see Bao et al., 2021, for a survey).[1] As a result,

[1]This approach stands in stark contrast to survey-based studies on expectation formation, which elicit expectations of the same future periods multiple times and study their evolution (see, e.g.,

it is difficult to provide useful insights for macroeconomists who study expectation formation in a dynamic environment. In a typical macroeconomic model and more generally a dynamic game, individuals forecast not only today's actions of others, but also their actions tomorrow, the day after, and beyond. The static framework does not enable us to analyze how these series of expectations change in such a dynamic situation, for example, in response to news about future shocks.

We contribute to the literature by filling this gap. We propose and conduct an experiment using a dynamic beauty contest game motivated by the canonical New-Keynesian model.[2] In our model, there are many firms, and each firm faces a linear demand curve. The demand decreases as the firm increases its price and increases as other firms increase their prices. Firms choose their prices for maximizing their profit given the prices of others. A static REE price is a fixed point of this process. Now we introduce a friction that prevents them from choosing this static optimal price. We assume that they can only choose their prices with a probability $1-\theta$. This friction compels them to factor in dynamic considerations. Specifically, firms need to make their forecasts of both today's and future prices. So, expectations of today's and future prices affect individual decisions. The market has an additional dynamic feedback effect since expectations of future prices directly affect today's outcome.

Following the literature, we transform the model into a dynamic version of the "learning-to-forecast" experiments, (Marimon and Sunder, 1993). In these experiments, participants only need to make their forecasts, eliminating the need to choose their optimal prices. This formulation excludes possible mistakes by participants when they choose their optimal prices (Bao et al., 2013), and allows us to focus on how expectations are formed.

Coibion et al., 2018).

[2]The core part of the New-Keynesian model is based on firms' maximization problem formulated by Calvo (1983).

We undertake a 3 by 2 between-subjects experimental design. Our first focus is on games that feature strategic complementarity, as well as weak and strong substitution. Furthermore, during the course of the experiment, we introduce two upward shifts in the demand curve, which we simply refer to as "shocks." Our second focus is on when these shocks occur unexpectedly, as well as on cases where shocks are announced to participants two periods in advance.

Using this experimental framework, we begin by testing two hypotheses. In the first hypothesis, we investigate the effect of the strategic environment (Hanaki et al., 2019). That is, we test whether observed prices deviate more from the REE prices under strategic complementarity than under strategic substitution. This hypothesis test is mainly to confirm existing results of past learning-to-forecast experiments within our new experimental framework.[3] In the second hypothesis, we examine how forward-looking expectation formation is. Specifically, we assess whether participants adjust their expectations for future prices in response to announcements of future shocks in environments where prices move along the REE in periods before the announcement. Our proposed framework uniquely facilitates the testing of this latter hypothesis, a feat unachievable with existing experimental designs. We show that our experimental results validate the two hypotheses.

We then proceed to analyze how participants form their expectation in our dynamic beauty contest game. We uncover various facts. First, as observed in static

[3]The existing learning-to-forecast experiments, such as Heemeijer et al. (2009); Bao et al. (2017), demonstrate that, on one hand, prices deviate substantially from those expected under REE when there is a strong positive feedback between expectations and prices (i.e., when β is positive and close to one), and on the other hand, prices converge quickly to REE prices when there is a negative feedback between the two (i.e., when β is negative and its absolute value is less than one). Recently, however, Evans et al. (2022) and Anufriev et al. (2022) demonstrated that eliciting forecasts for a longer horizon stabilizes the price dynamics under strategic complementarity, although not to the extent that prices converge to REE prices. While the frameworks of Evans et al. (2022) and Anufriev et al. (2022) are different from ours, we would like to investigate whether the effect of a strategic environment is observed in our framework.

experiments, a sizable fraction of participants has naive expectations. In other words, they anticipate that today's and future prices will mirror the price observed yesterday. Interestingly, the fraction of naive forecasts declines sharply following the shocks or their announcement, pointing to an increase in "eductive" reasoning. Second, participants revise their predictions when they observe a discrepancy between their past expectations and realized prices, but they do so sluggishly. For example, even if yesterday's price prediction was higher than the price that was realized, they do not excessively lower their price forecast. Finally, only in the case of strategic complementarity do participants also factor in the past inflation rate when shaping their expectations. In the case of strategic complementarity, prices are more likely to follow a nonstationary process or deviate from REE prices. Therefore, it is optimal for participants to incorporate inflation rate information in their predictions. In contrast, under strategic substitutes, realized prices tend to be closer to the steady-state REE prices, motivating participants to base their predictions solely on the market price *level*, not its change.

From these findings, we draw the following conclusions. There is not a single, universally correct model for expectation formation. Factors such as economic conditions, the presence of shocks, or their announcements seem to prompt participants to adaptively choose their predictive models. Similarly, participants are not purely backward-looking or forward-looking. Some participants only form forward-looking expectations when the shocks or their announcement occur. The studies most closely aligned with our paper's conclusions are those by authors Anufriev and Hommes (2012) and Evans et al. (2021). In these models, participants endogenously choose a prediction model that enhances the accuracy of their forecasts.

To the best of our knowledge, only Colassante et al. (2020) and Evans et al. (2022) elicit forecasts for multiple future periods in the framework of learning-to-forecast experiments.[4] Although Colassante et al. (2020) elicit a series of forecasts for multiple future periods, unlike our framework, the forecasts beyond that for the next period do not determine the market outcome. Evans et al. (2022) is based on Lucas' asset pricing model (Lucas, 1978) and forecasts for multiple future periods determine the next period price just as in our framework. However, their main focus is to study whether longer-horizon forecasts stabilize prices, and not to investigate how expectations respond to the arrival of new pieces of information.

The rest of the paper is organized as follows. Section 2 presents a model of a dynamic beauty contest based on Calvo (1983). The design of the experiment as well as its procedure are presented in Section 3. Section 4 shows the REE as the benchmark. The results of the experiment are summarized in Section 5 including a discussion of implications for modeling expectation formation. Section 6 concludes.

2 A Model of a Dynamic Beauty Contest

We introduce our economic model, which serves as a basis for our experiment design. Suppose that there is a continuum of firms that have monopolistic power uniformly distributed over $[0, 1]$. Let p_i denote the price chosen by individual firm i. For notational simplicity, we drop subscript i. The demand function for an individual firm is

$$D\left(p; P\right) \equiv \left[a - bp + cP\right]^{+}, \tag{1}$$

where P is the aggregate price index given by

$$P = \int_0^1 p_i di.$$

[4] There are several papers that elicit forecasts for multiple future periods in the asset market experiments pioneered by Smith et al. (1988). In these experiments, participants do not only forecast future prices, but actually trade the asset; see, e.g., Haruvy et al. (2007) and Akiyama et al. (2014, 2017).

We assume that $a > 0$, $b > 0$, and $c \in \mathbb{R}$. We impose the following condition on b and c :

$$-\infty < c \leq 2b.$$

If this assumption is violated, then the statically optimal price in an equilibrium becomes infinite. Note that parameter c can be positive or negative, which governs the degree of strategic interaction between the firms. The firms have an identical linear technology function, and the unit cost of production is denoted by κ.

Firm i maximizes the present value of its profit at each period, but is subject to a pricing friction. The friction prevents the firms from changing its price at every period, and only allows the firm to do so with probability $1 - \theta$. We assume that if a firm cannot change its prices T consecutive times, then the firm can change the price next time with probability 1. The maximization problem at period t is

$$\max_{p_t} \quad \sum_{s=0}^{T} \theta^s \pi_{t+s}, \tag{2}$$

where

$$\pi_{t+s} = p_t D\left(p_t; P_{t+s}\right) - \kappa D\left(p_t; P_{t+s}\right)$$

The demand function is given by equation (1). At every period, firm i can re-optimize its price with probability $1 - \theta$. The continuation payoffs in the events are not a function of p_t. These continuation payoffs do not appear in objective function (2). It is important to emphasize here that firms have perfect foresight (rational expectation) over the future aggregate price indexes, $\left(P_{t+s}\right)_{s=0}^{\infty}$.

We establish the following proposition:

Proposition 1. *The optimal price for firms that can reset their prices at period t is* *given by*

$$p_t = \sum_{s=0}^{T} \frac{\theta^s}{\sum_{s=0}^{T} \theta^s} \left(\alpha + \beta P_{t+s}\right), \tag{3}$$

where

$$\alpha = \frac{1}{2}\left(\kappa + \frac{a}{b}\right) \quad \beta = \frac{1}{2}\frac{c}{b}.$$

Moreover, the law of motion of the aggregate price index is

$$P_t = (1-\theta)\, p_t + \theta P_{t-1}. \tag{4}$$

Proof. Taking the first-order conditions of maximization problem (2), we obtain equation (3). To derive equation (4), recall that the aggregate price index is given by the average of individual prices (2) and that only fraction $1-\theta$ of firms can reset their prices. Because they are randomly chosen, the average price among firms that cannot reset their price today is P_{t-1}. Firms that can reset their prices choose the same price level given by equation (3). So average price P_t satisfies equation (4). □

It is important to note that $\alpha + \beta P_t$ represents the optimal price at period t, provided that the firms are not subject to any pricing friction. This essentially means that the optimal price constitutes a weighted average of static optimal prices. Equation (3) elucidates the dynamic thought process within firms: the optimal price, p_t, depends on current actions by others, as well as future actions, encapsulated in $\mathbf{P} = (P_{t+s})_{s=0}^{T}$. In other words, the best response function, given by (3), embodies dynamic feedback mechanisms. The price index today is influenced by future price indexes. This is the primary reason why this model is frequently described as a dynamic beauty contest model.

In contrast, when firms can fully adjust their prices ($\theta = 0$), the dynamic component of the decision-making process is eliminated: each firm's focus shifts solely to predicting the present-day actions of the other firms. The experiment we propose, inspired by this economic model, stands apart from existing models because it necessitates that participants anticipate not only the actions of others at period t, but also at periods $t+1, \cdots, t+T$.

3 Experimental Design

3.1 Setup

In our experimental setup, we employ a cohort of six participants.[5] These participants indexed by i engage in the game over a series of periods. As each period commences, the participants put forward their price forecasts for five subsequent periods, including the current one.[6] This implies that in the first period, participants submit their price forecasts for periods 1 through 5. Subsequently, in the second period, forecasts are given for periods 2 through 6, and this pattern continues for subsequent periods. We denote each participant's forecast submitted in period 't' for the price in period 'k' as $f^i_{t,k}$. Importantly, although not all the submitted forecasts are used for determining the payoffs of the participants ex-post, as explained below, when participants submit their forecasts at the beginning of a period, all five forecasts can determine their payoffs ex ante.

Let π^i_t denote the payoff of participant i at period t. It is determined by

$$\pi^i_t = \frac{100}{|F^i_t - P_t| + 1},$$

where P_t is the realized price at period t and F^i_t denotes the payoff-relevant forecast

[5]One may consider a cohort of six to be too small for an experiment to have macroeconomic implication. However, the main results of existing learning-to-forecast experiments do not change even if conducted with larger groups of 20 to 30 participants (Bao et al., 2020) or with close to 100 participants (Hommes et al., 2021).

[6]All the forecasts must be integers.

of participant i at period t.[7] The payoff-relevant forecast F_t^i at the first period $t = 1$, the set of forecasts submitted at period $t = 1$ is the set of payoff-relevant forecasts, and $F_1^i = f_{1,1}^i$. From period 2 and onward, the sets of payoff-relevant forecasts are determined as follows. With probability $1 - \theta = 1/2$, the newly submitted set of forecasts in that period becomes payoff-relevant. In this case, the payoff-relevant forecast F_2^i is the forecast of period $t = 2$ price submitted at period $t = 2$, $F_2^i = f_{2,2}^i$. With probability $\theta = 1/2$, however, the payoff-relevant set of forecasts remains the same as before. Thus, the forecast of period $t = 2$ submitted at period $t = 1$ is payoff-relevant, and $F_2^i = f_{1,2}^i$. The payoff-relevant sets of forecasts for $t = 3$ and onward are determined in the same manner. When a set of forecasts has been payoff-relevant for five consecutive periods, then with probability one, the new set of forecasts submitted in the next period becomes payoff-relevant.[8]

This adjustment process is motivated by the dynamic beauty contest model in Section 2. Namely, $1 - \theta$ in the model, which is the probability of firms being given an opportunity to re-optimize their prices in period t, is translated into the probability of the new set of forecasts becoming payoff-relevant for participants. And the horizon over which firms optimize, T, in the model is equivalent to the number of future periods, in addition to the current one, over which our participants forecast in each period (in the case of our experiment, $T = 4$). We set the payoffs so that the equilibrium path of the Nash equilibrium (subgame perfect Nash equilibrium) corresponds to the REE of the dynamic beauty contest game in Section 2.

To give a concrete example, consider hypothetical sets of forecasts submitted by

[7] π_t^i is rounded to the nearest integer value.

[8] This is because, in such cases, the set of forecasts that has been payoff-relevant does not contain the forecast for the next period. For example, if the set of forecasts submitted in period 1 $(f_{1,1}^i, f_{1,2}^i, f_{1,3}^i, f_{1,4}^i, f_{1,5}^i)$ has been payoff-relevant for five consecutive periods, i.e., between periods 1 to 5, then as it does not contain a forecast for period 6 price, we need to make the new set of forecasts submitted in period 6 payoff-relevant.

Table 1: Submitted Forecasts

Period\Forecast Period	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	$t=6$	$t=7$	$t=8$	F_t^i
$t=1$	**10**	**11**	12	12	12				**10**
$t=2$		~~12~~	~~11~~	~~12~~	~~13~~	~~13~~			**11**
$t=3$			**9**	10	11	10	10		**9**
$t=4$				**13**	12	12	10	10	**13**

a participant shown in Table 1. Each entry represents a submitted forecast. For example, at period $t = 1$, the participant submits her forecasts of the prices of period $t = 1$ to 5 as follows:

$$\left(f_{1,1}^i, f_{1,2}^i, f_{1,3}^i, f_{1,4}^i, f_{1,5}^i\right) = (10, 11, 12, 12, 12)\,.$$

At the initial period ($t = 1$), the set of forecasts just submitted becomes payoff-relevant. Thus, $F_1^i = 10$. Suppose that at period $t = 2$, the new set of forecasts does not become payoff-relevant. So, F_2^i is determined based on the forecasts submitted at period $t = 1$. That is, $F_2^i = 11$. At periods $t = 3$ and $t = 4$, as the new set of forecasts becomes payoff-relevant, $F_3^i = 9$ and $F_4^i = 13$.

Now we move on to explain how the price at period t, P_t, is determined. Motivated by the model in Section 2, the market price is given by

$$P_t = \frac{1}{6}\sum_{i=1}^{6} p_t^i, \tag{5}$$

where

$$p_t^i = \begin{cases} \sum_{j=0}^{4} \frac{\theta^j}{\sum_{l=0}^{4}\theta^l}\left(\alpha + \beta f_{t,t+j}^i\right) & \text{if forecasts submitted in period } t \\ & \text{becomes payoff-relevant for } i \\ p_{t-1}^i & \text{otherwise} \end{cases} \tag{6}$$

where α and β are the parameters of the model, and $\theta = 1/2$.[9]

[9] P_t is rounded to the nearest integer in our experiment because forecasts submitted by partici-

During games, we introduce two shocks to α, which captures the size of the demand. The first shock occurs in period 14, and the second shock occurs in period 29. We choose α so that the initial steady-state REE price is 65, and it becomes 85 and 110 after the first and the second shocks, respectively.

In the theoretical framework presented in Section 2, the game continues indefinitely. In our experiment, we assume that the game ends with probability $\gamma = 0.05$ at the end of each period. Otherwise, the game continues to the next period.[10] Accordingly, participants are rewarded based on the sum of points they earn from the beginning until the end of the game.

However, implementing such a probabilistic termination rule in a laboratory experiment is problematic because the game can end after only a few periods, thereby not allowing us to study the evolution of the forecasts in response to shocks, or the game may not end during the time for which participants are recruited. To circumvent the former problem, we employ the block random termination method Fréchette and Yuksel (2017) commonly used in the experiments of indefinitely repeated games.

Under the method, participants are asked to play the game in a block of B periods. Only at the end of the block are the participants informed of whether the game has already ended during the block just completed. If the game has done so, they gain the sum of π_t^i up to that period. If the game has not ended, the game continues for another block of B periods. For example, if the game has actually ended in period $\tau < B$, they are rewarded based on $\sum_{t=1}^{\tau} \pi_t^i$. They are also well informed, the game can continue beyond B periods, and if that is the case, they play the game for at least another B periods. In our experiment, we set $B = 20$. Therefore, participants are

pants are constrained to be integers.

[10]Introducing positive termination probability changes the optimization problem and the optimal solution shown in equations (2) and (3), so that equation (6) used in the experiment is different from the REE of the model with a positive termination probability. But because the quantitative impacts of this difference are small, we ignore them. See Appendix A.

informed that they are going to play the game for at least 20 periods.

Furthermore, because the duration of a game may vary across groups, participants are informed that this multiperiod game can be repeated several times if all the groups finish playing a game within 30 minutes from the start of the first game. When a new game starts, new groups of six participants are randomly formed (and thus, everyone in the same experimental session has to wait until all the groups in the same session finish a game before starting a new one). If the game is repeated several times, one of them will be selected randomly and participants are paid according to the points they earn in the chosen game.

For example, if the last group to finish the first game does so in 15 minutes since its start, the second game will be played. If the last group to finish the second game does so at 35 minutes since the start of the first game, the experiment ends. In this case, because the game has been repeated twice, either the first or the second game is selected randomly, and the participants are paid based on their earning in the selected game. Note that it is also possible that the first game ends 30 minutes after its start. If this is the case, only one game is played during the experiment, and the participants are paid according to the points they earned in this game.

3.2 Treatments

In our 3 by 2 between-participants experiment, we focus on modulating two primary aspects of the games. The first aspect is the degree of strategic interaction. We consider the games with $\beta \in \{0.9, -0.9, -1.8\}$. That is, the games exhibit strategic complementarity (positive feedback) or substitution (negative feedback).[11] As we

[11] Because participants are only allowed to submit integer forecasts, there might be multiple equilibria for cases of strong strategic complementarity. It turns out that when $\beta = 0.9$, there are multiple equilibria. However, the set of equilibria is not huge and this multiplicity does not affect the results of the paper. Therefore, we do not address this issue explicitly.

vary β, we adjust α so that the REE prices at period $t = 1$ are kept the same. We also explicitly consider a strong substitution case, $\beta = -1.8$, because some of the expectation formation models allow this kind of eductive instability, (e.g., García-Schmidt and Woodford, 2019).

The second aspect is the anticipation of the shocks to α. We consider games with and without pre-announcement of shocks. In the treatment without pre-announcement, participants are informed of the new value of α only at the occurrence of the shock, that is, in period 14 for the first shock and in period 29 for the second shock. In the treatments with pre-announcement, participants are informed of the new value of α at period 12 for the first shock, and at period 27 for the second shock. Thus, we can study the adjustment of participants' forecasts, say for period 14 price, before and after the pre-announcement. See Appendix C for the screen shots. In every treatment, the current values of α and β are presented clearly on their screens.

3.3 Procedures

We use oTree (Chen et al., 2016), an open-source platform for web-based interactive tasks, to conduct the experiments online. Participation is from where they are, and not from our physical experimental laboratory.[12] The final rewards are paid through Amazon Gift Cards (e-mail version).

Participants are students at Osaka University. They are recruited using ORSEE (Greiner, 2015). An English translation of the instruction slides as well as examples of the decision screens are provided in Appendix C.

In carrying out our experiment, following Duffy and Puzzello (2014) and Duffy and Puzzello (2022), we have used predetermined sequences of random numbers to determine the number of periods for each game. The predetermined number of periods

[12] See Appendix B for details regarding how we have conducted our online experiment.

was between 33 and 36 in each game. This allowed us to control the duration of the experiment across sessions and also to limit variation in participants' take home pay due to variation in the number of periods within a game. We did, however, withhold this information from our participants. The first game lasted more than 30 minutes in all the experimental sessions, and as a result, only one game was played in all these sessions.

4 Rational Expectations Hypotheses

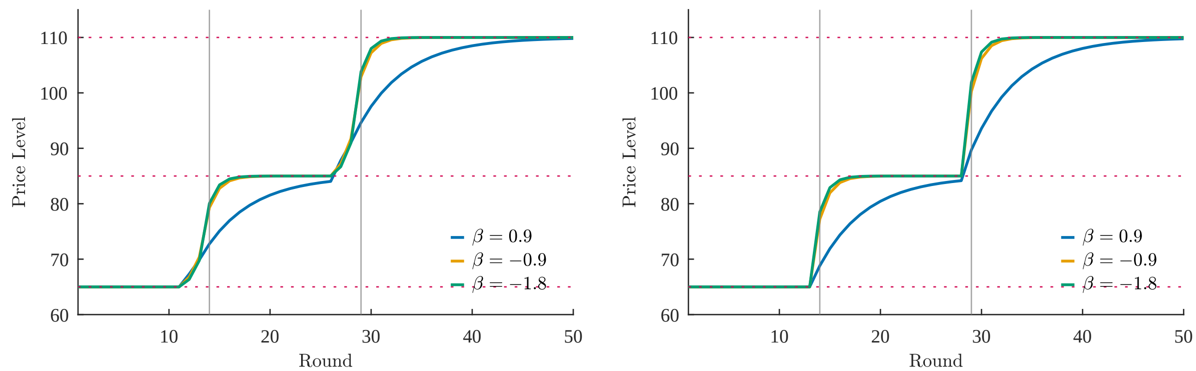
We take rational expectations as our benchmark. Given the initial conditions (p_{-1}, P_{-1}), REE prices (p_t, P_t) solve the following equations uniquely:

$$P_t = (1-\theta)\, p_t + \theta P_{t-1} \tag{7}$$

$$p_t = \sum_{k=t}^{T-t-1} \frac{\theta^{k-t}}{\sum_{s=0}^{T} \theta^s} \left(\alpha_{t,k} + \beta P_{t+k}\right), \tag{8}$$

where $\alpha_{t,k}$ is the expected value of α at period k from a period t perspective. When the shocks are not announced, $\alpha_{t,k} = \alpha_{t,t}$ for all k and t. Equation (7) describes the law of motion of P_t under no sampling uncertainty and the individual price p_t is chosen given the actual realization of the future prices. Figure 1a demonstrates the REE price sequence $(P_t)_t$ when the shocks are pre-announced, and Figure 1b depicts the price sequence when the shocks are not pre-announced.

These figures are intuitively understood. When the game demonstrates strategic complementarity ($\beta > 0$), the transition to new steady-state equilibrium prices is slower, a feature resulting from Calvo pricing friction. Participants acknowledge that others might not be capable of swiftly adjusting their prices due to pricing friction. As individual optimal prices are positively correlated with the pricing actions of others, they prefer to avoid rapid price adjustments.



(a) With Announcement

(b) Without Announcement

Figure 1: Price Dynamics under Rational Expectations

On the contrary, when the game displays strategic substitution ($\beta < 0$), the operative mechanism is reversed. Given that some participants fail to adjust their prices, the prevailing price becomes too low. This low price motivates individuals to post higher prices. Thus, the transition to the new steady-state equilibrium price is faster.

We compare the price dynamics implied by the REE with the realized price sequences of our experiments. In particular, we test the following two hypotheses: (1) price deviations from the REE are larger under strategic complementarity than under strategic substitution; and (2) participants respond to the announcement of the shocks.

5 Results of the Experiment

We conducted our experiments in April and May 2023. There was a total of 294 participants in the experiments.[13] Each experiment lasted for 90 minutes on average,

[13]However, in one session with announcement of the future shock with $\beta = 0.9$, one participant decided to leave the experiment while answering the comprehension quiz. The experimenter has substituted this participant, and thus, the experiment could continue. We have dropped the data of this group from the analyses. But because we did the same treatment in which 30 participants

Table 2: Number of Groups per Treatment

Treatments	$\beta = 0.9$	$\beta = -0.9$	$\beta = -1.8$
With Announcement	8	8^a	8
Without Announcement	8	8	7^b

Notes: Row "With Announcement" represents the results where the shocks were pre-announced while row "Without Announcement" shows the results where the shocks were not pre-announced. *a*: One group stopped at $t = 33$ due to a technical problem. *b*: One group stopped at t=39 due to a technical problem.

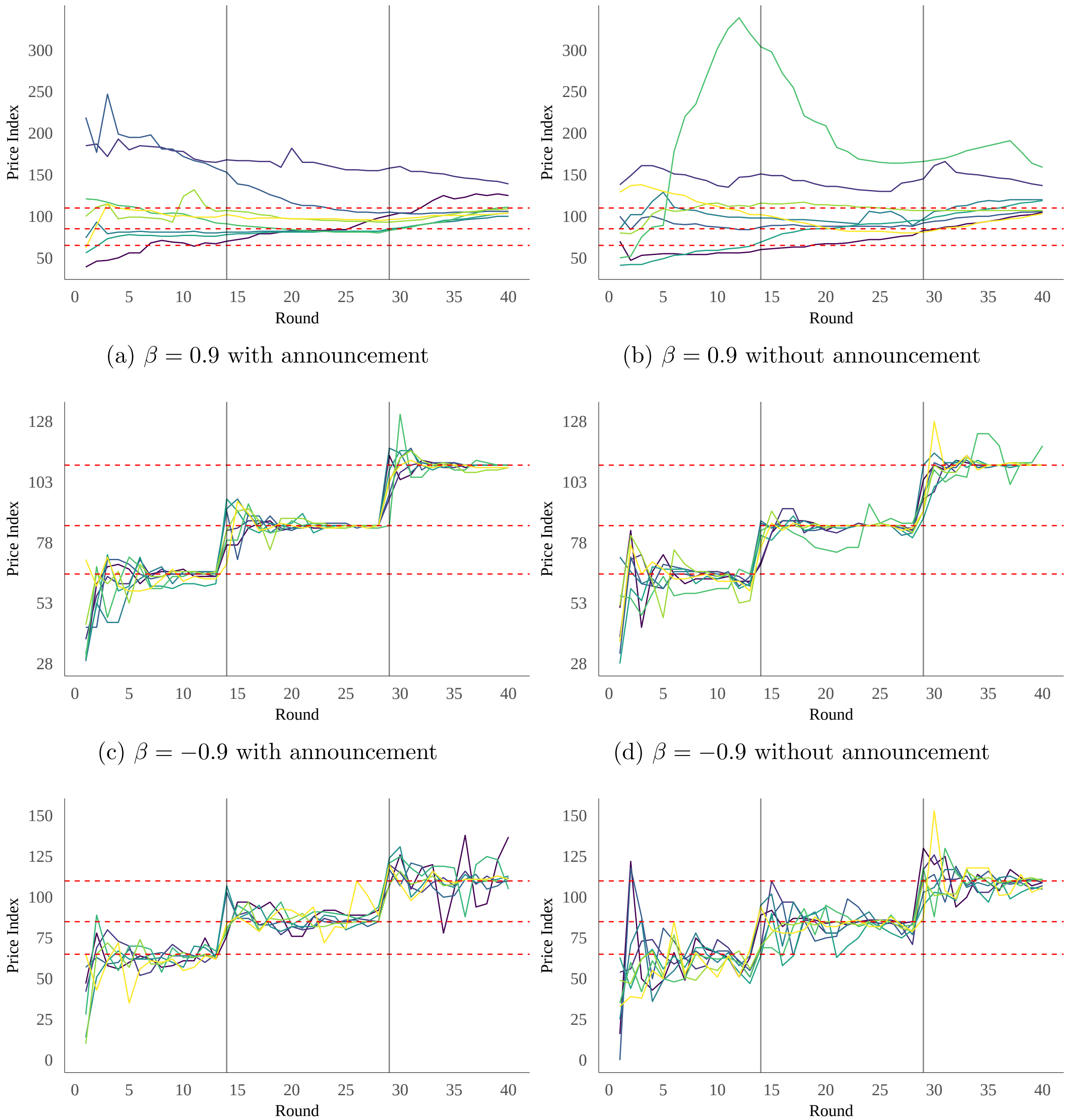
and participants earned 2482 JPY (approximately 18 USD based on the exchange rate at the time) including the show-up fee of 500 JPY on average.[14] The average payment varied across the value of β. It was lowest in the treatments with $\beta = -1.8$ (1778 JPY) followed by 2806 JPY and 2844 JPY in treatments with $\beta = -0.9$ and $\beta = 0.9$, respectively. Table 2 summarizes the number of groups per treatment.

5.1 Effect of the Degree of Strategic Interaction

Figure 2 shows the dynamics of prices observed in each treatment. One line corresponds to a group in each panel. As one can observe, regardless of the existence of the announcement, the prices follow the REE quite closely when $\beta = -0.9$ but they deviate greatly from the REE when $\beta = 0.9$. These findings are very similar to the results from the existing learning-to-forecast experiment such as those of Heemeijer

showed up, we have a total of eight groups for this treatment. Furthermore, in one session without announcement of the shock and $\beta = -1.8$, one of the participants lost his/her internet connection around period 11 and switched to a different mode of connection. As a result, an error occurred and the experiment could not continue for this group. In addition, in the same session, an error occurred for a group in period 40. Thus, we only have data for seven groups for this treatment, with one group missing the price and forecasts submitted in period 40. Finally, in the treatment with announcement of the shocks and $\beta = -0.9$, one group encountered a technical problem and the experiment stopped in period 33. Thus, while we have data for eight groups for this treatment, one lacks the data from period 34 onward.

[14]Exchange rate between the points earned during the experiment and JPY was 1 point = 2 JPY.



(a) $\beta = 0.9$ with announcement (b) $\beta = 0.9$ without announcement

(c) $\beta = -0.9$ with announcement (d) $\beta = -0.9$ without announcement

(e) $\beta = -1.8$ with announcement (f) $\beta = -1.8$ without announcement

Figure 2: Realized Price Dynamics

Notes: The red dashed lines represent the steady-state levels of the aggregated prices.

et al. (2009) and Bao et al. (2012). Accordingly, with $\beta = 0.9$, the price dynamics do not at all resemble those presented in the previous section.

When $\beta = -1.8$, the prices are close to the REE prices but fluctuate around them. These fluctuations are also in sharp contrast to the rational expectations outcome presented in Figure 1.

Now, let us quantify the degree of deviation from the REE prices. We compute the relative absolute deviation, RAD, and the relative deviation, RD, proposed by Stöckl et al. (2010). For group g, RAD_g and RD_g are defined as follows:

$$RAD_g = \frac{1}{K}\sum_t \frac{\left|P_{g,t} - P_t^{\mathrm{REE}}\right|}{P_t^{\mathrm{REE}}}$$
$$RD_g = \frac{1}{K}\sum_t \frac{P_{g,t} - P_t^{\mathrm{REE}}}{P_t^{\mathrm{REE}}}$$

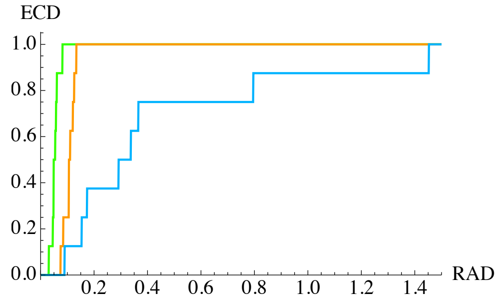
where $P_{g,t}$ is the realized period t price for group g and P_t^{REE} is the REE price in period t. K is the total number of periods (40 except for the two groups that faced a technical problem).

Figure 3 shows the empirical cumulative distribution (ECD) of RAD (top) and RD (bottom) in the treatments with (left) and without (right) announcement. In each panel, the distributions for the three values of β are shown. The top panels show that, regardless of the existence of announcement, RADs are positive for the three values of β,[15] suggesting that observed prices are significantly different from those under REE. Furthermore, the observed RADs are largest under $\beta = 0.9$, followed by $\beta = -1, 8$, and then $\beta = -0.9$ regardless of the existence of the announcement. The differences between the three treatments are statistically significant for both with and without announcement.[16] Therefore, the deviations of the observed prices from the

[15] They are all significantly different from zero at the 5% level according to the signed-rank test. $P - values$ are 0.018 $\beta = -1.8$ without announcement and 0.012 for all the other five treatments.

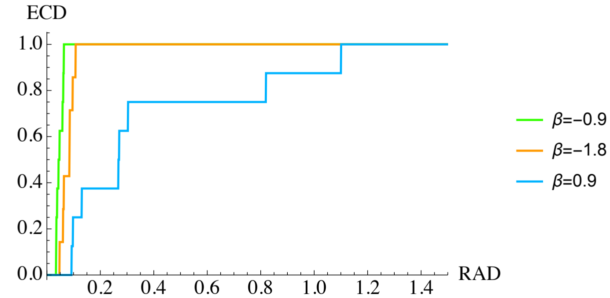
[16] $P < 0.05$ based on the Kruskal–Wallis (KW) test for both with and without announcement. For pairwise comparisons, p-values based on the Mann–Whitney (MW) test (two-tailed) are 0.0002

(a) RAD (With announcement)



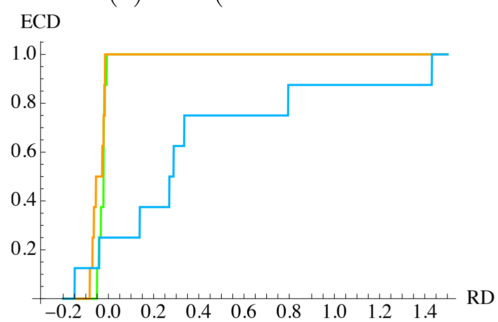
$p = 0.0001$

(b) RAD (Without announcement)



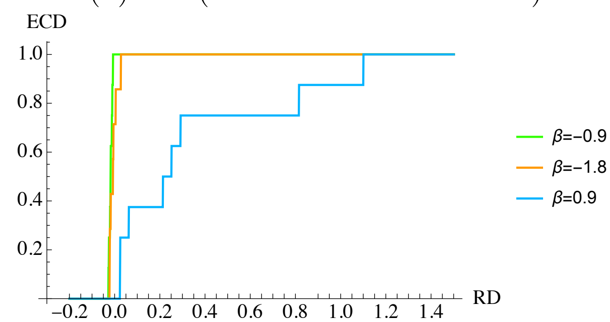
$p = 0.0002$

(c) RD (With announcement)



$p = 0.0437$

(d) RD (Without announcement)



$p = 0.0005$

Figure 3: Distribution of RAD (top) and RD (bottom)

Note: P-values of Kruskal–Wallis (KW) test are reported.

REE are smaller under strategic substitution than under strategic complementarity, and furthermore, they are smaller under "weak" substitution ($\beta = -0.9$) than under "strong" substitution ($\beta = -1.8$).

The bottom panels show, however, that while RDs are larger under strategic complementarity than under strategic substitution as in the case of RADs, there is no longer a statistically significant difference between $\beta = -0.9$ and $\beta = -1.8$.[17]

($\beta = 0.9$ vs $\beta = -0.9$), 0.0022 ($\beta = 0.9$ vs $\beta = -1.8$), and 0.0093 ($\beta = -0.9$ vs $\beta = -1.8$) without announcement, and 0.0002 ($\beta = 0.9$ vs $\beta = -0.9$), 0.0047 ($\beta = 0.9$ vs $\beta = -1.8$), and 0.0003 ($\beta = -0.9$ vs $\beta = -1.8$) with announcement.

[17]For pairwise comparisons, p-values based on the MW test (two-tailed) are 0.0002 ($\beta = 0.9$ vs $\beta = -0.9$), 0.0012 ($\beta = 0.9$ vs $\beta = -1.8$), and 0.1520 ($\beta = -0.9$ vs $\beta = -1.8$) without announcement, and 0.0650 ($\beta = 0.9$ vs $\beta = -0.9$), 0.0379 ($\beta = 0.9$ vs $\beta = -1.8$), and 0.2345 ($\beta = -0.9$ vs $\beta = -1.8$) with announcement.

Note that because RD takes the direction of the deviation from REE into account, it becomes close to zero when the prices fluctuate around REE as in the case of $\beta = -1.8$.[18]

5.2 How Forward-Looking are Expectations?

Let us now turn to the way forecasts have responded to the announcement of future shocks. To do so, we focus on the difference in the forecast adjustments at the time of shock between treatments with and without announcement. Namely, we compute the average difference in the forecast price between the period of the shock and the period just before the shock (periods 14 and 13, respectively, for the first shock and periods 29 and 28, respectively, for the second shock) submitted in the periods after the announcement (periods 12 and 13 for the first shock and periods 27 and 28 for the second shock) and those before the announcement (periods 10 and 11 for the first shock and periods 25 and 26 for the second shock). That is, for each participant i, the average forecast responses to the announcement of the first and second shocks, Δf_1^i and Δf_2^i, are defined as follows:

$$\Delta f_1^i = \frac{1}{2} \sum_{t=12}^{13} \left(f_{t,14}^i - f_{t,13}^i \right) - \frac{1}{2} \sum_{t=10}^{11} \left(f_{t,14}^i - f_{t,13}^i \right)$$

$$\Delta f_2^i = \frac{1}{2} \sum_{t=27}^{28} \left(f_{t,29}^i - f_{t,28}^i \right) - \frac{1}{2} \sum_{t=25}^{26} \left(f_{t,29}^i - f_{t,28}^i \right).$$

We compute the same measure for the participants in the treatment without announcement as for the benchmark.

Figure 4 shows the empirical cumulative distributions of Δf_1^i (left) and Δf_2^i (right)

[18] In fact, RD is not significantly different from zero for $\beta = -1.8$ without announcement (p=0.6875, signed-rank test) while it is significantly different from zero at the 5% significance level for five other treatments (p=0.0391 for $\beta = 0.9$ with announcement and 0.0078 for the remaining four treatments, signed-rank test.)

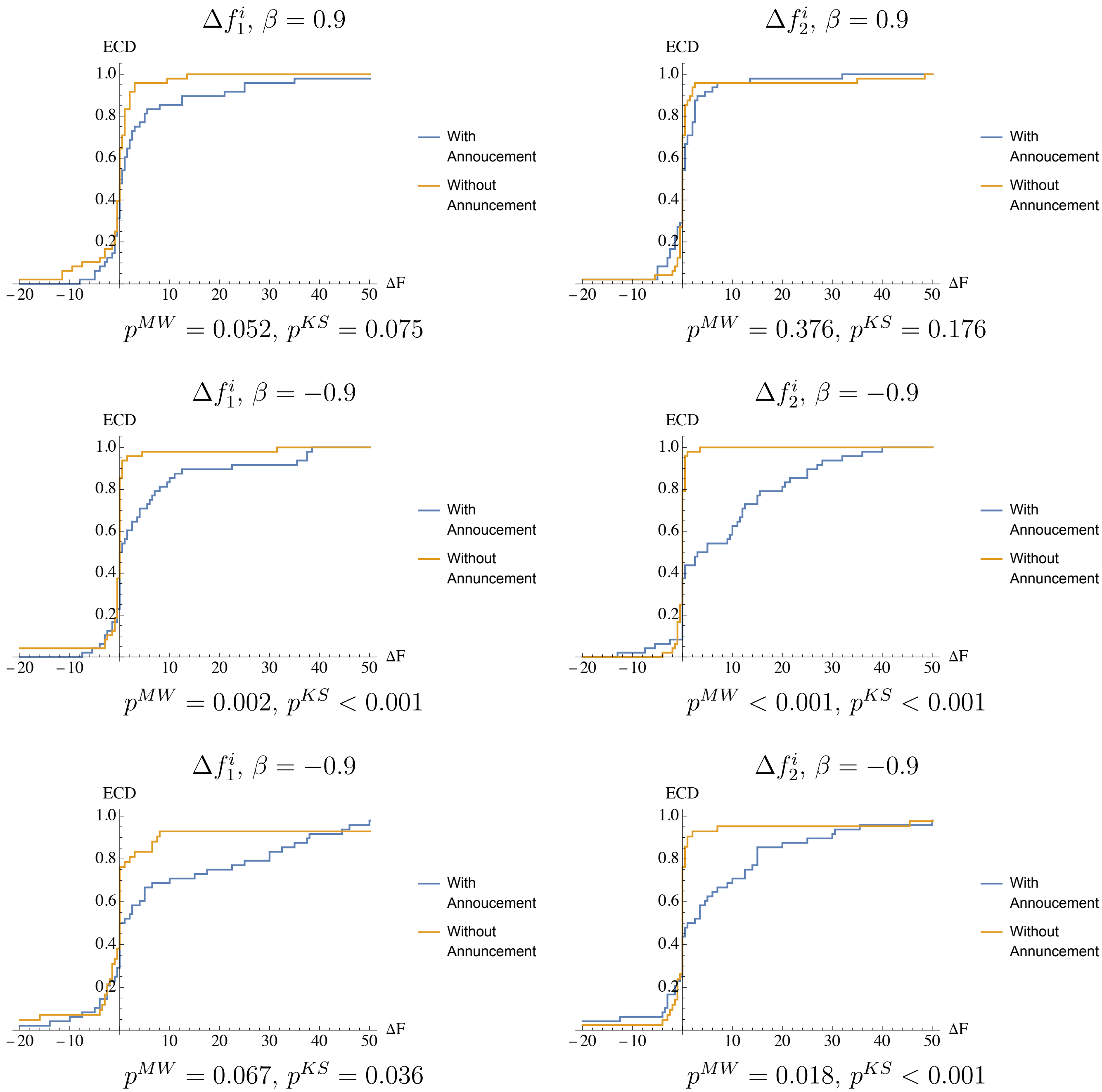


Figure 4: Distributions of Δf_1^i and Δf_2^i

with and without announcement for three values of β. P-values are from MW and Kolmogorov–Smirnov (KS) tests. We also report the distributions between treatments with and without announcement.

Figure 4 shows that, without announcement, both Δf_1^i and Δf_2^i are concentrated around zero. This is especially so for $\beta = -0.9$ for both the first and second shocks in which prices were very close to the steady-state equilibrium prices before the realization of these shocks. With announcement, however, Δf_1^i and Δf_2^i are distributed more toward positive values (except for Δf_2^i of $\beta = 0.9$), suggesting that participants adjusted their forecasts upward in response to the announcement. Except for $\beta = 0.9$, there are significant differences in Δf_1^i and Δf_2^i between treatments with and without announcement. Thus, consistent with participants having forward-looking expectations, they expect prices to go up after the announcement under strategic substitution.[19]

5.3 Expectation Formation in a Dynamic Environment

In this section, we analyze how participants form expectations in our dynamic experiments. Similar to the existing literature, we categorize price expectations into two types: naive expectations and others. In Subsection 5.3.1, we define and analyze naive expectation formation in our setting. Following that, in Subsection 5.3.2, we proceed to analyze non-naive forecasts.

[19]While Δf_2^i is significantly greater than Δf_1^i for $\beta = -0.9$ ($p^{MW} = 0.041$ and $p^{KS} = 0.034$), there is no significant difference between the two for $\beta = -1.8$ ($p^{MW} = 0.968$ and $p^{KS} = 0.760$) and $\beta = 0.9$ ($p^{MW} = 0.311$ and $p^{KS} = 0.531$).

5.3.1 Naive Expectation Formation

We commence by defining a naive expectation. We say that the forecasts of participant i at period t, $\left(f^i_{t,t+j}\right)_{j\in\mathcal{J}}$, is *naive* if for all $j \in \mathcal{J}$,

$$f^i_{t,t+j} = P_{t-1},$$

and ε-*naive* if for all $j \in \mathcal{J}$,

$$\left|f^i_{t,t+j} - P_{t-1}\right| \leq \varepsilon.$$

These definitions extend the notion of naive expectation from static to dynamic environments. For a forecast at period t to be naive, it must approximate the preceding price, P_{t-1} for all $j \in \mathcal{J}$. Therefore, if a participant anticipates today's price to mirror yesterday's, yet projects a constant future inflation rate, such forecasts are not naive.

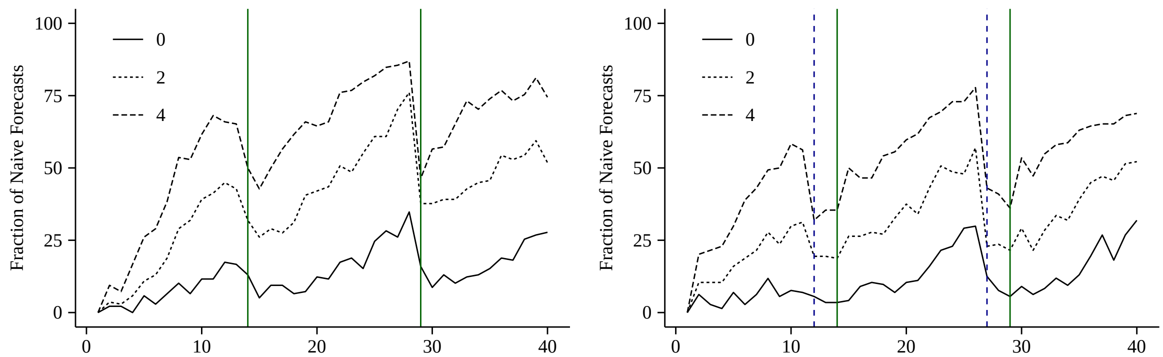
Figure 5 shows the fraction of the naive forecasts for $\varepsilon \in \{0, 2, 4\}$ in the treatment without the pre-announcements of shocks (left) and with the pre-announcements (right). In each panel, the data from three values of β are pooled. There are three points to be made about which kind of expectation formation participants will engage in. First, the number of participants forming naive expectations increases over time.[20] This is because there is a tendency for the economy to converge to steady-state REE prices. As a result, a growing number of participants form naive expectations following the shocks or announcements endogenously.

Second, despite the shocks or announcements, a significant proportion of participants remain inclined toward naive expectations. To illustrate this point, after the shocks where $\varepsilon = 4$, almost half the participants maintain roughly naive expectations (Figure 5a). Following the announcements, over 30% still exhibit naive expectations (Figure 5b).

[20] Under the REE hypothesis, the fraction of naive forecasts is zero after the realization of the shocks, and becomes 1 when the price sufficiently converges to the steady-state REE prices.

Figure 5: Fraction of Naive Forecasts for Various Cutoffs

(a) No Announcement (b) With Announcement



Notes: The solid vertical lines represent the rounds at which the shocks occurred. The dashed vertical lines in the right figure represent the rounds at which the announcements of the shocks were made. The difference in line types represents the difference in the value of ε. As indicated in the legend, a solid line represents $\varepsilon = 0$, a dotted line indicates ε being 2, and a dashed line 4.

Finally, a major chunk of participants either do not stick to, or entirely abandon naive expectation formation when faced with shocks or announcements. Instead, their expectation pattern leans more toward "eductive" tendencies, which will be elaborated on in the next section.

5.3.2 Non-Naive Expectation Formation

We now pivot to non-naive expectations, basing our analysis on experimental data that is not ε-naive with $\varepsilon = 4$. Drawing inspiration from Anufriev and Hommes (2012), we structure the forecast formation around two forecasting rules: adaptive heuristic and trend-following. If participant i adopts the adaptive rule, their belief adjustment would proceed as follows:

$$f^i_{t,t+j} = \omega f^i_{t-1,t-1} + (1-\omega) P_{t-1} = \omega \left(f^i_{t-1,t-1} - P_{t-1} \right) + P_{t-1}, \tag{9}$$

where ω is the weight assigned to the forecast at period $t-1$. When $\omega \in (0,1)$, this forecasting rule says that they only adjust their forecast gradually. When $\omega < 0$, participant i adjusts their forecast downward if the forecast at period $t-1$ is higher than the realized price at period $t-1$.

The trend-following rule says that participant i assumes that the aggregate trend will persist:

$$f^i_{t,t+j} = P_{t-1} + \chi \left(P_{t-1} - P_{t-2}\right). \tag{10}$$

Parameter χ governs the strength of the extrapolation effect. When χ is negative, then we can interpret equation (10) differently. Namely, participant i expects the short-run trend to be reversed.

We nest models (9) and (10) as follows and obtain the baseline regression specification:

$$f^i_{t,t+j} - P_{t-1} = a\Delta\alpha_t + 1_{A_t} + \gamma \underbrace{\omega \left(f^i_{t-1,t-1} - P_{t-1}\right)}_{\text{Adaptive Forecasting}} + (1-\gamma) \underbrace{\chi \left(P_{t-1} - P_{t-2}\right)}_{\text{Trend-Following Forecasting}} + \mathrm{FE}_i + \varepsilon_{t,i,j},$$

where parameter γ assigns the weight to the adaptive forecasting rule, $\Delta\alpha_t$ is the shock, and 1_{A_t} is the indicator function that is one if at period t, the announcement to a shock is made. When $\gamma = 1$, then participant i only uses the adaptive forecasting rule (9). If $\gamma = 0$, then they only use the extrapolation. By running the regression, we estimate the parameters $\gamma\omega$ and $(1-\gamma)\,\chi$. The multiplicative $\gamma\omega$ reflects the effective "weight" assigned to the adaptive forecasting rule.

The regression results for each forecast horizon j are presented in Table 3. From these regression results, four points regarding expectation formation can be discerned. First, in almost all cases, participants' expectations are influenced by the shocks. Importantly, this reaction is not just limited to expectations at the time of the shock, $f^i_{t,t}$, but also for future expectations, $f^i_{t,t+j}$. Interestingly, in the case where $\beta = 0.9$, the shocks have a greater impact on future time points than on the current time point. Such predictions also hold when participants have rational expectations. On the other hand, no such empirical patterns are observed when $\beta < 0$. This implies that participants do not necessarily have qualitatively correct dynamic price forecasts if $\beta < 0$.

Second, in many cases, participants' predictions at the time of the announcement do not significantly respond to the announcement itself. This observation is evident from the fact that the coefficients for 1_{A_t} when $j = 0$ are insignificant. However, starting from $j = 2$, there are cases where the coefficient becomes significant. Participants anticipate that other participants will not immediately respond to the announcement itself, but they anticipate that others will react when the shocks occur two periods later. This finding is consistent with that in Section 5.

Third, it is evident that participants are employing adaptive-heuristic forecasting. Across all cases, it can be interpreted that when making price predictions, participants refer to the discrepancy between their past predictions and actual prices. Notably, the coefficients do not increase as the value of j becomes larger.

The final point is that participants employ a trend-following forecasting rule only when $\beta > 0$. Also, in this case, if there was inflation in the past, they predict higher prices in the future: the coefficient at $j = 0$ is 0.5, but at $j = 4$, it is 1.2, which is significantly higher. In contrast, with $\beta < 0$, participants scarcely rely on past inflation. This stark difference is thought to arise from whether the economy is converging to the steady-state REE prices or not. When $\beta > 0$, the economy deviates from the REE prices persistently, and the realized prices move in a nonstationary manner. Therefore, forecasting prices becomes more difficult when $\beta > 0$. This would be a reason why participants also use past information to predict prices. If $\beta < 0$, the past information about prices becomes less relevant (because prices fluctuate around the steady-state REE prices.)

Our results in this section can be summarized as follows. There exists a group

Table 3: Regression Results

Panel A ($\beta = 0.9$)	Horizon $j = 0$	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$\Delta\alpha_t$	0.789	1.084**	1.212**	2.917**	3.325**
	(0.537)	(0.479)	(0.617)	(1.186)	(1.386)
1_{A_t}	1.405	2.100*	2.949**	5.060*	4.457
	(1.212)	(1.081)	(1.393)	(2.679)	(3.130)
$\gamma_j\omega_j$	0.301***	0.255***	0.197***	0.244***	0.110***
	(0.016)	(0.014)	(0.019)	(0.036)	(0.042)
$(1-\gamma_j)\chi_j$	0.518***	0.644***	0.888***	1.331***	1.249***
	(0.054)	(0.048)	(0.062)	(0.120)	(0.140)
N	3,168	3,168	3,168	3,168	3,168
R^2	0.162	0.186	0.117	0.129	0.174
Panel B ($\beta = -0.9$)	Horizon $j = 0$	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$\Delta\alpha_t$	0.250***	0.257***	0.294***	0.303***	0.248***
	(0.030)	(0.023)	(0.029)	(0.028)	(0.028)
1_{A_t}	3.553***	1.856*	4.507***	4.830***	5.364***
	(1.273)	(1.002)	(1.231)	(1.186)	(1.198)
$\gamma_j\omega_j$	0.370***	0.228***	0.265***	0.161***	0.185***
	(0.015)	(0.011)	(0.014)	(0.014)	(0.014)
$(1-\gamma_j)\chi_j$	0.213***	0.013	0.050	−0.055	−0.018
	(0.047)	(0.037)	(0.045)	(0.043)	(0.044)
N	3,120	3,120	3,120	3,120	3,120
R^2	0.244	0.212	0.201	0.128	0.116
Panel C ($\beta = -1.8$)	Horizon $j = 0$	$j = 1$	$j = 2$	$j = 3$	$j = 4$
$\Delta\alpha_t$	0.183***	0.197***	0.173***	0.207***	0.204***
	(0.032)	(0.031)	(0.038)	(0.037)	(0.041)
1_{A_t}	3.280	3.290*	7.498***	8.841***	6.550**
	(1.999)	(1.945)	(2.427)	(2.345)	(2.572)
$\gamma_j\omega_j$	0.331***	0.292***	0.303***	0.286***	0.216***
	(0.017)	(0.016)	(0.021)	(0.020)	(0.022)
$(1-\gamma_j)\chi_j$	0.015	0.005	−0.005	−0.022	−0.108**
	(0.041)	(0.040)	(0.050)	(0.048)	(0.053)
N	2,964	2,964	2,964	2,964	2,964
R^2	0.270	0.257	0.189	0.617	0.575

of participants who consistently stick to naive expectations, even when faced with dynamic and evolving scenarios. In contrast, a significant number rely on both the eductive and evolutive methods of expectation formation, as implied by Binmore (1987). Importantly, there does not exist *the* ideal model for nonrational expectations formation. The appropriate approach for modeling expectations largely hinges on prevailing economic conditions that participants face. Specific factors, such as the degree of strategic complementarity shown by β, the presence of shocks, $\Delta\alpha_t$, and their announcement, play a pivotal role in influencing these expectation formations. Thus, appropriate models should allow endogenous selection of an optimal economic forecasting model tailored to the environment that participants face. Papers consistent with our findings include Anufriev and Hommes (2012) and Evans et al. (2021). Extending this line of research would be promising.

6 Concluding Remarks

In this paper, we extend the conventional static beauty contest game to a dynamic context and conduct experiments. This dynamic model is constructed based on the Calvo (1983) pricing model commonly used in macroeconomics. Our new paradigm of "learning-to-forecast" extends the existing models and allows us to investigate how participants update their forecasts for the same future periods over time in response to the arrival of new pieces of information. The experimental results indicate that, on average, individuals react to announcements of future shocks (eductive reasoning), while a sizable fraction of participants form naive expectations even in the dynamic environment considered in our experiment. Additionally, the incorporation of trends, shocks, and their announcement into expectation formation varies depending on economic conditions. Fitting the model in which decision makers choose different forecasting models depending on the situation, as in Anufriev and Hommes (2012) and Evans et al. (2021), to our data would be a fruitful next step.

Another approach is to conduct experiments to understand how participants select the variables to use for forecasting, and under which circumstances they are more susceptible to shocks. This is important because changes in the way people form expectations can impact the dynamics of the economy and potentially cause significant fluctuations through expectational feedback loops.

To gain a deeper understanding of the above point, it might be beneficial to change the magnitude of the shocks. When a game is with strategic complementary, even a small shock is magnified, exerting a considerable influence on equilibrium prices. However, if individuals expect that others do not respond to the shock, its initial impact on the economy is tiny, and the economy will slowly transition to the new equilibrium price. This is markedly different from the case of strategic substitutes. In that case, if people expect that others do not react to the shock, it can have a bigger impact on the economy, which might explain why participants respond to the shocks in games with strategic substitutes. To explore the impact of shocks and their announcement, it is helpful to consider sufficiently large shocks in experiments of games with strategic complementarity. These remain as future research topics.

References

Akiyama, Eizo, Nobuyuki Hanaki, and Ryuichiro Ishikawa, "How do experienced traders respond to inflows of inexperienced traders? An experimental analysis," *Journal of Economic Dynamics and Control*, 2014, *45*, 1–18.

_, _, and _ , "It is not just confusion! Strategic uncertainty in an experimental asset market," *Economic Journal*, 2017, *127*, F563–F580.

Angeletos, George Marios and Chen Lian, "Forward guidance without common knowledge," *American Economic Review*, 9 2018, *108*, 2477–2512.

Anufriev, Mikhail, Aleksei Chernulich, and Jan Tuinstra, "Asset price volatility and investment horizons: An experimental investigation," *Journal of Economic Behavior and Organization*, 2022, *193*, 19–48.

_ and Cars Hommes, "Evolutionary selection of individual expectations and aggregate outcomes in asset pricing experiments," *American Economics Journal, Microeconomics*, 2012, *4* (4), 35–64.

Bao, Te, Cars Hommes, and Jiaoying Pei, "Expectation formation in finance and macroeconomics: A review of new experimental evidence," *Journal of Behavioral and Experimental Finance*, 2021, *32*, 100591.

_ , _ , and Tomasz Makarewicz, "Bubble foremation and (in)efficient markets in learning-to-forecast and -optimize experiments," *Economic Journal*, 2017, *127*, F581–F609.

_ , _ , Joep Sonnemans, and Jan Tuinstra, "Individual expectations, limited rationality and aggregate outcomes," *Journal of Economic Dynamics and Control*, 2012, *36*, 1101–1120.

_ , John Duffy, and Cars Hommes, "Learning, Forecasting, and Optimizing: An Experimental Study," *European Economic Review*, 2013, *61*, 186–204.

_ , Myrna Hennequin, Cars Hommes, and Domenico Massaro, "Coordination on bubbles in large-group asset pricing experiments," *Journal of Economic Dynamics and Control*, 2020, *110*, 103702.

Binmore, Ken, "Modeling Rational Players: Part I," *Economics and Philosophy*, 1987, *3*, 179–214.

Calvo, Guillermo A, "Staggered Prices in a Utility Maximizing Framework," *Journal of Monetary Economics*, 1983, *12*, 383–398.

Chen, Daniel L., Martin Schonger, and Chris Wicken, "oTree - An open-source platform for laboratory, online and field experiments," *Journal of Behavioral and Experimental Finance*, 2016, *9*, 88–97.

Coibion, Olivier, Yuriy Gorodnichenko, and Kamdar Saten, "How do firms form their expectations? New survey evidence," *American Economic Review*, 2018, *108* (9), 2671–2713.

Colassante, Annarita, Simone Alfarano, Eva Camacho-Cuena, and Mauro Gallegati, "Long-run expectations in a learning-to-forecast experiment: a simulation approach," *Journal of Evolutionary Economics*, 2020, *30* (75-116).

Duffy, John and Daniela Puzzello, "Experimental Evidence on the Essentiality and Neutrality of Money in a Search Model," *Research in Experimental Economics*, 2014, *17*, 259–311.

_ and _, "The Friedman Rule: Experimental Evidence," *International Economic Review*, May 2022, *63* (2), 671–698.

Evans, George W., Cars Hommes, Bruce McGough, and Isabelle Salle, "Are Long-horizon Expectations (De-) stabilizing? Theory and Experiments," *Journal of Monetary Economics*, 2022, *132*, 44–63.

_, Christopher G. Gibbs, and Bruce McGough, "A unified model of learning to forecast," mimeo, University of Oregon 2021.

Farhi, Emmanuel and Ivan Werning, "Monetary Policy, Bounded Rationality, and Incomplete Market," *American Economic Review*, 2019, *109*, 3887–3928.

Fréchette, Guillaume R. and Sevgi Yuksel, "Infinitely repeated games in the laboratory: four perspectives on discounting and random termination," *Experimental Economics*, 2017, *20*, 279–308.

García-Schmidt, Mariana and Michael Woodford, "Are Low Interest Rates Deflationary? A Paradox of Perfect-foresight Analysis," *American Economic Review*, 1 2019, *109*, 86–120.

Greiner, Ben, "An Online Recruitment System for Economic Experiments," *Journal of the Economic Science Association*, 2015, *1* (1), 114–125.

Hanaki, Nobuyuki, Yukio Koriyama, Angela Sutan, and Marc Willanger, "The strategic environment effect in beauty contest games," *Games and Economic Behavior*, 2019, *113*, 587–610.

Haruvy, Ernan, Yaron Lahav, and Charles N. Noussair, "Traders' Expectations in Asset Markets: Experimental Evidence," *American Economics Review*, December 2007, *97* (5), 1901–1920.

Heemeijer, Peter, Cars Hommes, Joep Sonnemans, and Jan Tuinstra, "Price stability and volatility in markets with positive and negative expectations feedback: An experimental investigation," *Journal of Economic Dynamics and Control*, 2009, *33*, 1052–1072.

Hommes, Cars, Anita Kopányi-Peuker, and Joep Sonnemans, "Bobbles, crashes and information contagion in large-group asset market experiments," *Experimental Economics*, 2021, *24*, 414–433.

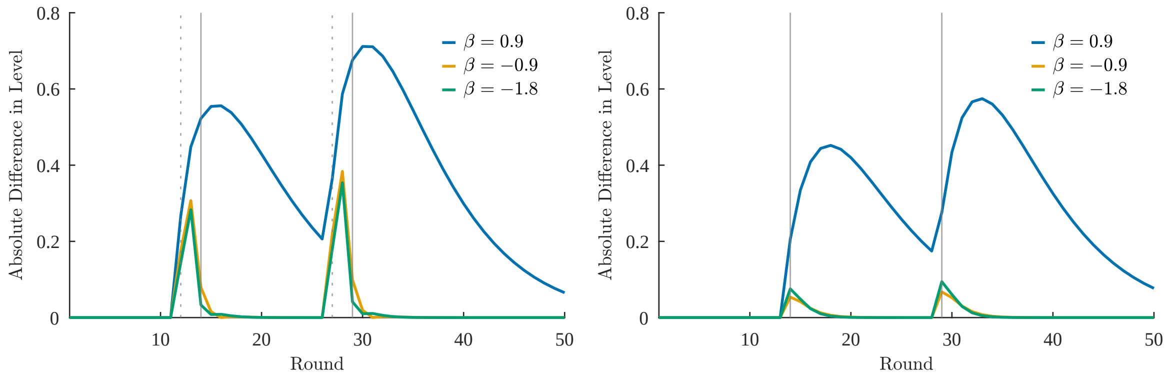
___ , **Joep Sonnemans, Jan Tuinstra, and Henk van de Velden**, "Coordination of expectations in asset pricing experiments," *Review of Financial Studies*, 2005, *18* (3), 955–980.

Lucas, Robert E., "Asset prices in an exchange economy," *Econometrica*, 1978, *46*, 1429–1445.

Marimon, Ramon and Shyam Sunder, "Indeterminacy of equilibria in a hyperinflationary world: Experimental evidence," *Econometrica*, 1993, *61* (5), 1073–1107.

Smith, Vernon L., Gerry L. Suchanek, and Arlington W. Williams, "Bubbles, Crashes, and Endogenous Expectations in Experimental Spot Asset Markets," *Econometrica*, 1988, *56* (5), 1119–1151.

Stöckl, Thomas, Jürgen Huber, and Michael Kirchler, "Bubble measures in Experimental Asset Markets," *Experimental Economics*, 2010, *13* (3), 284–298.



(a) With Announcement (b) Without Announcement

Figure 6: Comparison

A REE When $\gamma > 0$

In the paper, we ignore the impacts of termination probability, γ, on the REE prices. This is because the impacts are minor as mentioned in footnote 10. To show our claim formally, we compute the REE prices under the assumption that $\gamma = 5\%$, and compare the prices with those computed under the assumption that $\gamma = 0$.

Suppose that $\gamma > 0$. Let (p_t^γ, P_t^γ) denote the equilibrium individual price and the equilibrium price index when $\gamma > 0$. Then (p_t^γ, P_t^γ) satisfies the following equations:

$$P_t^\gamma = (1-\theta)\, p_t^\gamma + \theta P_{t-1}^\gamma \tag{11}$$

$$p_t^\gamma = \sum_{s=0}^{T} \frac{\tilde{\theta}^s}{\sum_{s=0}^{T} \tilde{\theta}^s} \left(\alpha_{t,t+s} + \beta P_{t+s}^\gamma\right), \tag{12}$$

where $\tilde{\theta} = (1-\gamma)\,\theta$. So, when firms make their decision, they take into account the fact that the economy ends with probability γ at the end of each period.

Figure 6 depicts the absolute difference between P_t^γ and P_t^0 when $\gamma = 5\%$. Note that the differences are less than one and their dynamics are virtually the same for both cases. Because of this quantitative feature, we ignore the impacts of γ on the equilibrium prices. This establishes our claim.

B Detail of the Procedure of the Online Experiment

Participants join our experiments via Zoom with their cameras and microphone turned off. The camera of the experimenter is always turned on, but her or his microphone is turned on only when necessary.

Upon connecting to a Zoom session, participants first wait in the waiting room. We let participants enter the main room one by one to check their names and to verify whether they are indeed registered for our experiments. Then, each participant is given participant ID in the form of "sub##", where ## is the two-digit number that is valid during the experiment. Once their participant ID is given, they are sent back to the waiting room until the start of the experiment. By following this procedure, we ensure anonymity.

Once ready, participants re-enter the Zoom meeting room and are given general instructions regarding the online experiment (for example, what to do, including which number to call when their internet connection fails during the experiment). Then, the prerecorded instruction video is played first. Although participants are not given a hard copy of the instruction slides, they are informed that they can go through the same set of slides after the video finishes until they finish answering the comprehension quiz. All the participants need to answer all six questions of the quiz correctly for the first game to start. As noted, participants can review the instruction slides before and while answering the quiz. While participants are asked to communicate directly with the experimenter using the chat function of Zoom when they have questions or encounter problems, they could not communicate with each other via Zoom chat.

C English Translations of the Instructions and Examples of Screenshots

English translation of the instruction slides can be found at https://osf.io/gecv8/?view_only=005886a62c3148f6afe46f0406b2887d

Figures 7 to 10 show examples of the decision screen participants faced in our experiment.

Note: The values of α and β are shown in red and with a large font in period 1 as well as when they change (in periods 14 and 29) in all the treatments (see Figure 9). In other periods, they are shown in black with a regular sized font (see Figure 10).

Figure 7: Screen (in period 1) in which participants submit their five forecasts (common to all the treatments)

Note: This is a demo screen in which the shock is introduced in period 5 (this is why the pre-announcement is made in period 3). The text in the yellow box states that "This is information regarding the future changes in the parameter values.
The values of the parameters that determine the price will be
$\alpha = xxx$ and $\beta = yyy$ from period T," where xxx, yyy, and T depend on the treatment and whether it is the first shock or the second shock. The current values of α and β are shown in black text below the announcement.

Figure 8: Screen with a pre-announcement of future shock (only for the treatments with pre-announcement)

Note: The values of α and β are shown in red with a large font when they change (in periods 14 and 29) in all the treatments.

Figure 9: Screen when the shock is realized (common to all the treatments)

Note: The values of α and β are shown in black with a regular sized font.

Figure 10: Screen for normal periods (common to all the treatments)