MPRA
Munich Personal RePEc Archive

Heterogeneous Adaptive Expectations and Coordination in a Learning-to-Forecast Experiment

Annarita Colasante and Antonio Palestrini and Alberto Russo and Mauro Gallegati

Università Politecnica delle Marche

11. September 2015

Heterogeneous Adaptive Expectations and coordination in a Learning-to-Forecast Experiment

Annarita Colasante, Antonio Palestrini, Alberto Russo, Mauro Gallegati

Università Politecnica delle Marche

Preliminary Draft

Abstract

The present work analyzes the individual behavior in an experimental asset market in which the only task of each player is to predict the future price of an asset. To form their expectations, players see the past realization of the asset price in the market and the current information about the mean dividend and the interest rate. We investigate the mechanism of expectation formation in two different contexts: one with a constant fundamental value, and one in which the fundamental price increases over repetitions. Results show that there is heterogeneity both within and between Treatments. Considering an increasing fundamental value has no impact on the individual expectations but it increases the volatility of the market price. We investigate in depth the reasons behind the observed heterogeneity between groups in the same treatment and results show that the heterogeneity of players' expectations is the main cause of the heterogeneity in the realized price. Looking at the coordination, we find out that homogeneous expectations is not a sufficient condition to have high degree of coordination. We analyze the individual forecasting errors as a determinant of the coordination within group and results show that a positive and significant correlation between individual errors strongly influence the level of coordination.

Contents

1 Introduction

The recent financial crisis highlights the strong relation between agents expectations and the real macro and financial variables. The predominant approach in the mainstream literature is based on the *Rational Expectation Hypothesis* firstly introduced by Muth (1961) and then analyzed in depth by Lucas Jr and Prescott (1971). According to this hypothesis, agents make no systematic errors in their forecasting, taking into account the entire set of available information[1]. Experimental evidence suggests that agents form their expectation according to an adaptive rule, that is the forecast is a function of both past expectations and past realizations.

The present work is a contribution in the field of the analysis of agents' expectation in the experimental financial market. We run a Learning to Forecast Experiment (LtFE) similar to that by Hommes *et al.* (2005). In this experiment players predict the future price of an asset taking into account the past values of the realized price in the market, the time series of their own past predictions, the mean dividend and the interest rate. Usually, the interest rate and the mean dividend are assumed to be constant. Indeed, the main difference with respect to the existing literature is that we consider a treatment with an increasing fundamental price, in addition to the standard game with a constant fundamental value. Our aim is to investigate individual behavior, and in particular agents' expectations, in a market with no constant fundamental price. We choose the increasing dividend as a source of market instability to observe if players are able to capture the increasing trend. A recent contribution by Palestrini and Gallegati (2015) shows that, in a context with the value to predict follow a trend and under the hypothesis of adaptive expectations, the individual prediction will be unbiased in the case in which agents are able to estimate the value of the trend.

The growing experimental evidence which deals with the expectation formation should be grouped in two main fields: on the one hand, the approach proposed by Dwyer *et al.* (1993) in which players predict the future realization of a predefined series, i.e. an Auto Regressive process (Hey (1994)) or a random walk (Bloomfield and Hales (2002)). On the other hand, the method proposed by Marimon *et al.* (1993) in which the realized price is a function of players' forecasts. In this field, players should predict the asset price (Hommes *et al.* (2005), Hommes *et al.* (2008)) or the price of a commodity (Hommes *et al.* (2007)). The main difference between these approaches is the role of agents' expectations. Indeed, only in the LtFE there is an expectation feedback mechanism, that is individual forecasting influences the realized price. For an exhaustive review of these experiment see Assenza *et al.* (2014).

We use the Learning-to-Forecast Experiment to analyze not only the forecast ability of players but also the level of coordination in the group. Indeed, we investigate not only the individual expectations but the level of coordination in each group and the link between these variables. This means that players should forecast an endogenous price and, to do so, they must be able to infer the predictions of other participants.

This paper is organized as follows: in Section 2 we describe our experiment and the related works. In Section 3 we show the main graphical results, and in Section 4 and Section 5 we analyze in more detail the level of coordination in a group and the forecasting strategies, respectively.

[1]Muth based his analysis on three assumptions: 1) Information is scarce, and the economic system generally does not waste it. 2) The way expectation are formed depends specifically on the structure of the relevant system describing the economy. 3) A "public prediction", in the sense of Grunberg and Modigliani (1954), will have no substantial effect on the operation of the economic system (unless it is based on inside information). Muth at pg. 317 stresses, in a sense, that the rational expectation hypothesis is made only to represent heterogeneous behaviors of entrepreneurs: "It *does not* assert that the scratch work of the entrepreneurs resembles the system of equations in any way; nor does it state that predictions of entrepreneurs are perfect or that their expectations are all the same".

2 Experimental setting

The aim of this paper is to understand the mechanism of expectation formation in a financial market with a positive feedback system, that is we assume that the realized price is a function of agents' expectations. In particular, in a positive feedback system there is a positive correlation between expectations and price, i.e. the higher the forecasting, the higher the price. Financial markets are characterized by this kind of feedback, while the main feature of commodity markets is the negative correlation between predictions and real price.

The existing literature about the analysis of expectation in the lab (see for example Hommes *et al.* (2007), Hommes *et al.* (2008), Heemeijer *et al.* (2009)) assume that both the mean dividend and the interest rate are constant. The evidence from this stream of literature is that, usually, in the negative feedback system there is a convergence toward the fundamental price, i.e. the equilibrium under the Rational Expectation Hypothesis. This kind of convergence does not occur in the case of positive feedback system, but it has been shown that the coordination among players is faster than that in the negative feedback system. Moreover, Bao *et al.* (2012) analyze the impact of positive and negative shocks on the price in order to capture the reaction of players and the speed of convergence to the new equilibrium.

The main novelty of the present work is that we consider two different treatments: *Treatment 1* in which the mean dividend, and so the fundamental price, is constant over repetition ($\bar{d}$); *Treatment 2* in which the mean dividend increases over time ($\bar{d}_t$). Introducing non constant fundamental value increases the uncertainty in the market. Our focus is to investigate the impact of this sources of ambiguity on individual expectations.

We take into account the *Asset Price Model*, as in Campbell *et al.* (1997). In this model there is a single security with a dividend d_t and a price p_t, and a risk-free asset that pays a constant rate $R = 1 + r$ units per period. The dividends are an i.i.d. variable with mean $\bar{d}$, so the *fundamental price* is given by $p^f = \frac{\bar{d}}{r}$.

We run a *Learning to Forecast Experiment* similar to that proposed by Hommes *et al.* (2005). The only task of players is to predict the future price of the asset knowing the mean dividend $\bar{d}$ and the interest rate r. In particular, in the first and in the second period, participants have no information about the past price realizations and about their profit. From the third period, participants are able to see the realized price until period $t - 1$ and their own forecast. Taking into account these information they must predict the future price of the option p^e_{t+1}. In Figure 1 there is the experimental computerized screen. We consider small group of investors, i.e. 6 people, which make their predictions for 51 periods.

Participants to the experiment are divided in groups of six and they receive only qualitative information. Players know that they are advisor of a pension fund and this fund takes into account their predictions to decide how to invest their money between a risk-free asset and a risky option. They do not know the equation that determines the price but they know that the price is given by the equilibrium between demand and supply. Moreover, they know that the higher their prediction the higher the realized price will be. They are informed about the mean dividend and the interest rate. Considering these information, agents could compute, and so predict, the fundamental price.

According to Brock and Hommes (1998), the equation for determining the market price corresponds to the market clearing equilibrium. The theoretical model suggests that each myopic agent, in each period, chooses how much to invest in the risky asset according to the process of maximization of her own future expected wealth. The future wealth (W_{t+1}) depends on the interest rate (r), the demand for the risky asset (z_{it}), the price (p_t) and the dividend of the risky asset (d_t):

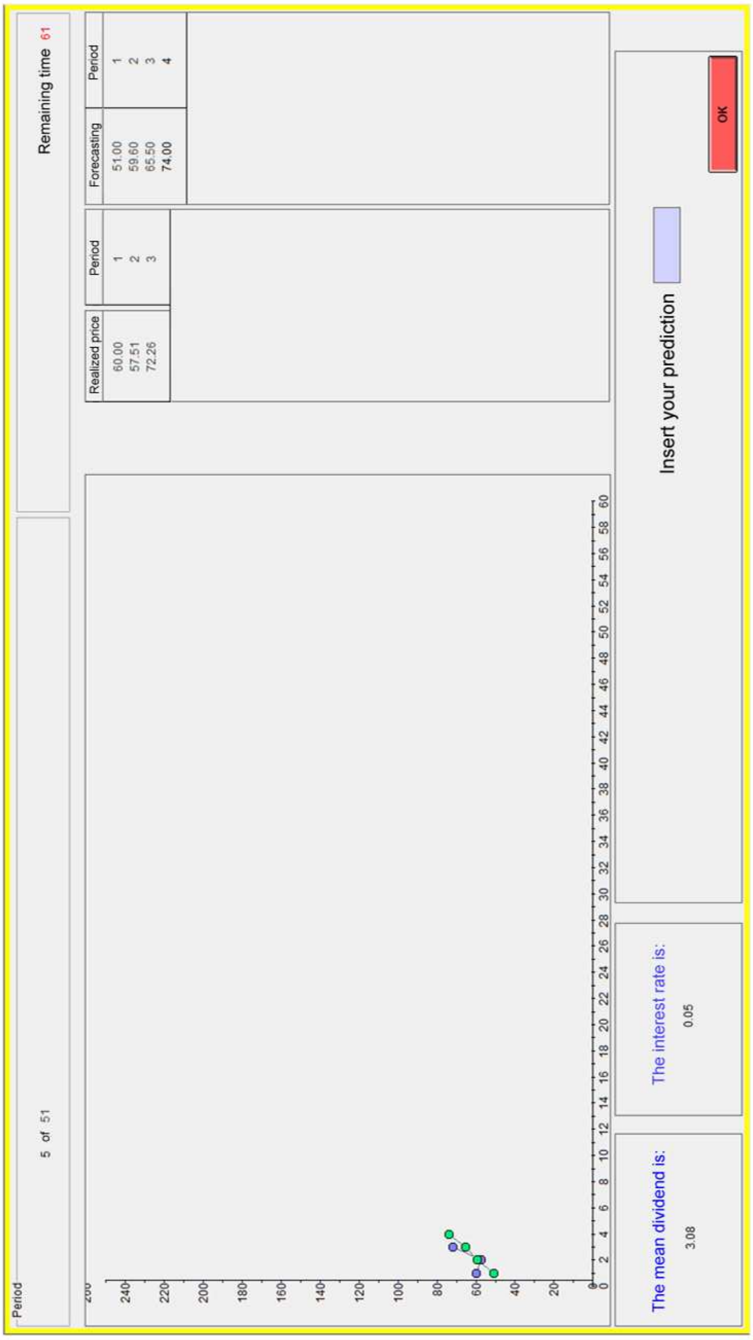


Figure 1: The screen-shot of the experiment in Treatment 1

$$W_{i,t+1} = (1+r)W_{it} + z_{it}(p_{t+1} + d_{t+1} - (1-r)p_t)$$

By equating demand, which derives, in turn, from the solution of the problem, and supply we obtain the equilibrium price given by:

$$p_t = \frac{1}{1+r}\left[\bar{p}^e_{t+1} + \bar{d}_t + \varepsilon_t\right] \tag{1}$$

where r is the interest rate, $\bar{p}^e_{t+1}$ is the average predicted price, $\bar{d}_t$ is the mean dividend and ε_t is a small normal shock.

Following the same approach in Hommes *et al.* (2005), we consider in our setting a fraction of computerized fundamentalist computer traders n_t. The equation used for the determination of price is the following :

$$p_t = \frac{1}{1+r}\left[(1-n_t)\bar{p}^e_{t+1} + n_t p^f_t + \bar{d}_t + \varepsilon_t\right] \tag{2}$$

where n_t is the share of fundamentalist robots in each period. This means that the price is a weighted average between the predicted price by each group and the fundamental price plus a small shock.

The number of robot traders[2] is a function of the absolute distance between the realized market price and the fundamental price. As in Hommes *et al.* (2005), the equation which determines the share of this trader is defined as:

$$n_t = 1 - exp\left(-\frac{1}{200}\left|p_{t-1} - p_f\right|\right) \tag{3}$$

According to Equation (3), as the price diverges from the fundamental the number of fundamentalists increases. This mechanism is useful to avoid the creation of bubbles in the market[3].

As defined in Hommes (2013), the payoff function depends on the distance between the individual prediction and the realized market price, as in Equation (4):

$$\begin{cases} \pi_{it} = \left(1 - \frac{(p_t - p^e_{it})^2}{7}\right) & if\ \left|p_t - p^e_{it}\right| < 7 \\ \\ \pi_{it} = 0 & \text{otherwise} \end{cases} \tag{4}$$

The experiment involves in total 72 participants (37 female), half of them plays in Treatment 1. In both treatments we consider $r = 5\%$, 6 players in each group and the small shock is such that $\varepsilon \sim N(0, 0.25)$. In Treatment 1 the mean dividend is constant $\bar{d}_t$ and so the fundamental price is equal to $p^f = 60$. In Treatment 2 the mean dividend increases step-by-step by 0.02, so the fundamental price ranges from 60 to 80. The experiment was conducted in October 2014 in the lab of the Faculty of Economics of the Polytechnic University of Marche using the software *z-tree* (Fischbacher (2007)). We randomly drawn 72 students in Economics from a population of 390 registered participants sending an invitation email. They were invited to show-up in the Laboratory of Faculty of Economics to participate to the experiment. Each session lasted about

[2]According to Assenza *et al.* (2014), robot fundamentalists are useful to avoid that there is an explosive increasing of the price. Moreover, since that this kind of traders assert that the deviation from the fundamental price is only temporary, the share of fundamentalists increases with the distance between the realized price and the rational equilibrium.

[3]Hommes *et al.* (2005) run the same experiment with and without the robot traders and they show that there are not significant difference between these settings. However, how bubbles in the financial markets emerge are a very interesting topic which is out of our analysis.

Table 1: Test of comparison between the realized price and the fundamental value

Treatment 1					Treatment 2				
Group	t	p-value	z	p-value	Groups	t	p-value	z	p-value
1	-14.89	< 0.01	-13.411	< 0.01	1	-41.45	< 0.01	-15.079	< 0.01
2	-28.23	< 0.01	-15.162	< 0.01	2	-17.80	< 0.01	-13.427	< 0.01
3	14.25	< 0.01	11.000	< 0.01	3	-66.20	< 0.01	-15.162	< 0.01
4	7.73	< 0.01	-6.098	< 0.01	4	-56.78	< 0.01	-15.162	< 0.01
5	27.70	< 0.01	14.225	< 0.01	5	-43.85	< 0.01	-15.162	< 0.01
6	42.19	< 0.01	14.880	< 0.01	6	-73.71	< 0.01	-15.162	< 0.01

90 minutes and participants were paid by cash at the the end of each session. During the game, prices were expressed in ECU (Experimental Monetary Currency). At the beginning of each session, we read aloud the general instruction and then players read on their screen the specific instructions. The final payment depended on the total gains earned in the game. The mean earning per player was equal to 15 Euro (the exchange rate is 1 Euro = 4 ECU), including the show-up fee[4]. In Appendix A there are a summary of the instruction and the average payment per group.

3 Aggregate behavior and emergent heterogeneity

The individual predictions divided in group are shown in Figures 2, 3, 4, 5. On the left panel we observe the realized price with respect to the fundamental value. On the right panel, we show in more detail the individual predictions[5].

The main results that emerges from the eye inspection are: *i)* there is no convergence to the rational expectation equilibrium; *ii)* in Treatment 2 agents are able to understand that the fundamental value follow an increasing trend; *iii)* there is heterogeneity both within and between Treatments.

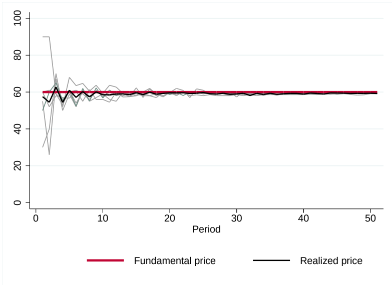
Observing the realized price in each group it is easy to see that all groups converge to a price different to the fundamental value represented by the red line.

According to Hommes (2013), in a positive feedback system we should observe no convergence to the fundamental price but high level of coordination in the group. In order to verify if the difference between the fundamental value and the realized price is statistically significant, we run a t-test and a Wilcoxon test to compare these series. Results are shown in Table 1. Both tests confirm that the realized price for each group is different from the fundamental price, i.e. none of the group converge to the rational expectation equilibrium. In Treatment 1 only Group 2 seems to converge to the fundamental price, that is players behave as if they have rational expectations and in this group there is an high level of coordination. Group 1 reaches an equilibrium close to the fundamental value but there is strong heterogeneity until period 30. Three groups (Group 3, Group 5, Group 6) show a good level of coordination from period 20, but their prediction converge to a price higher than the fundamental. Players in Group 4 coordinate slowly and, at the end, they overestimate the fundamental price[6].

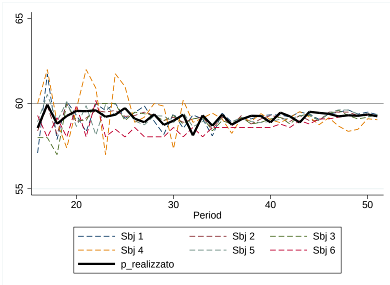
[4]We give also an extra- bonus to participants who collect perfect prediction in each period.

[5]In Figure 3, subfigure (b) and in Figure 4, subfigure (d) we omitted the extreme predictions for a better view of the individual behavior.

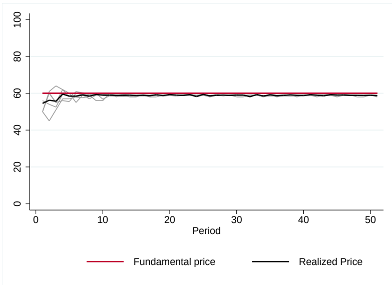
[6]One player makes strange forecasts also in the end of the game and this inconsistent behavior increases the volatility of the predicted price.



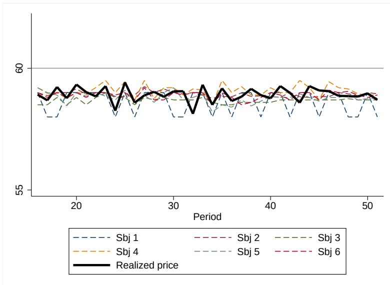
(a) Group 1



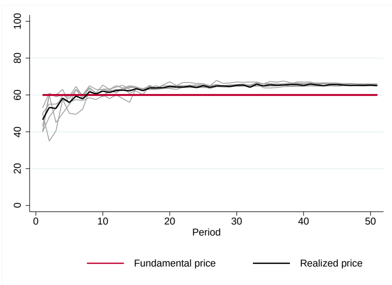
(b) Group 1



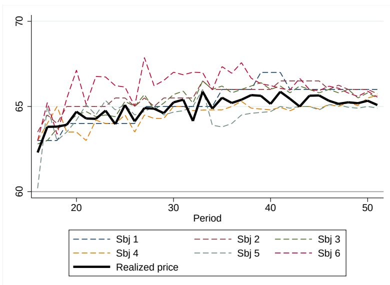
(c) Group 2



(d) Group 2

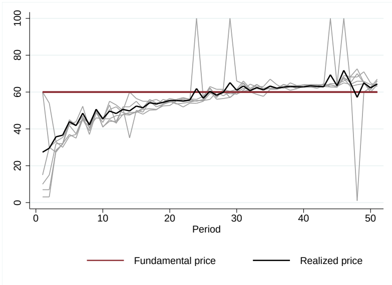


(e) Group 3

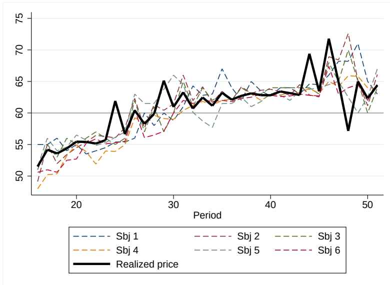


(f) Group 3

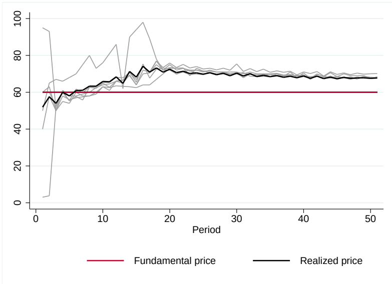
Figure 2: Individual prediction and fundamental price for each group (Treatment 1)



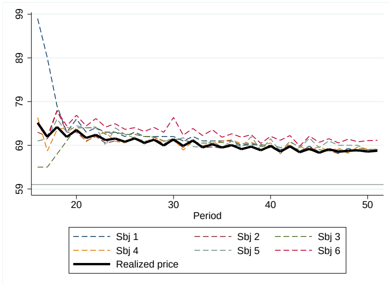
(a) Group 4



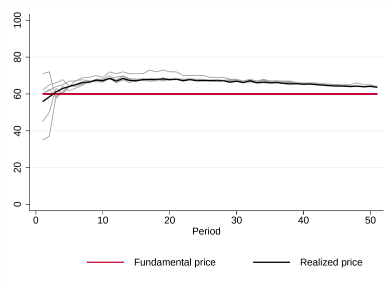
(b) Group 4



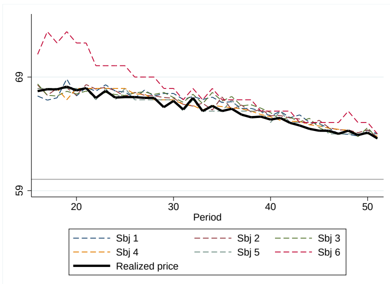
(c) Group 5



(d) Group 5

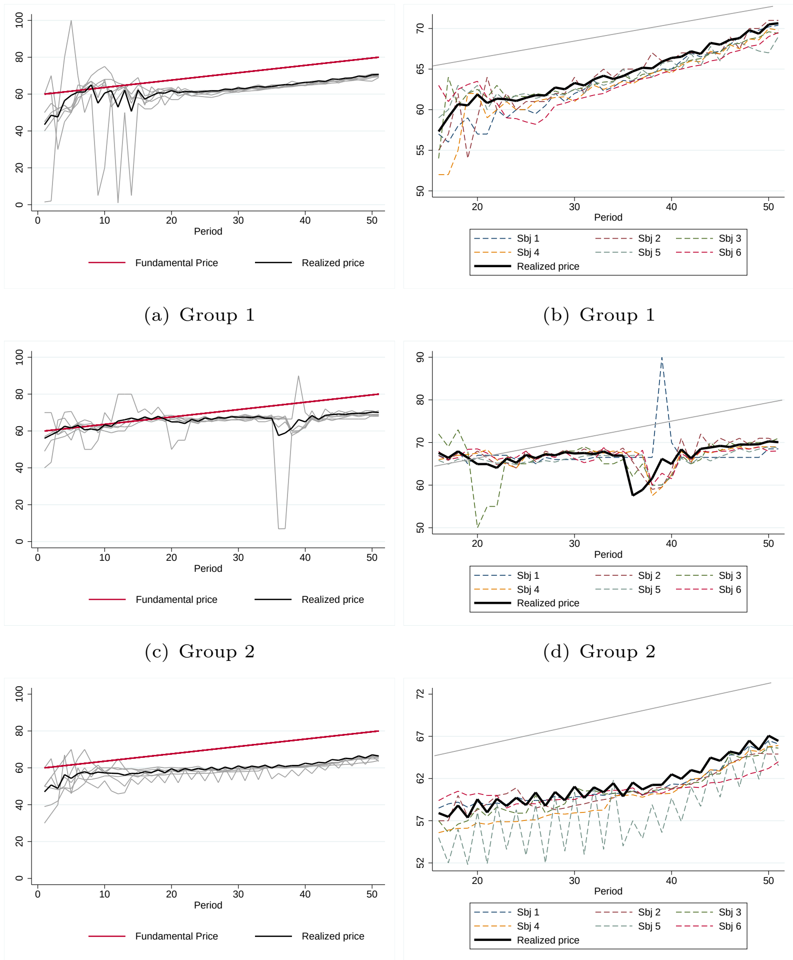


(e) Group 6



(f) Group 6

Figure 3: Individual prediction and fundamental price for each group (Treatment 1)

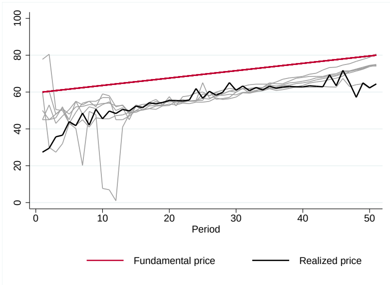


(a) Group 1 (b) Group 1

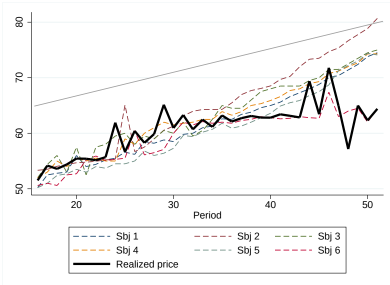
(c) Group 2 (d) Group 2

(e) Group 3 (f) Group 3

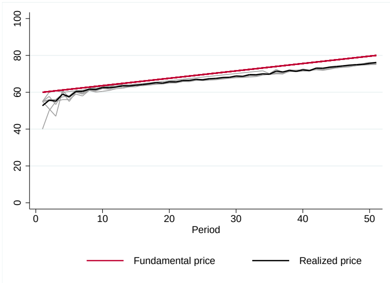
Figure 4: Individual prediction and fundamental price for each group (Treatment 2)



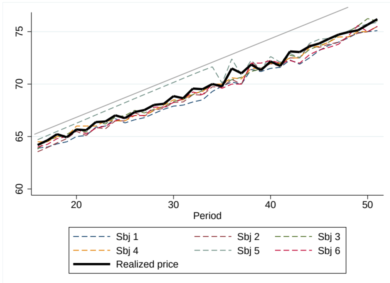
(a) Group 4



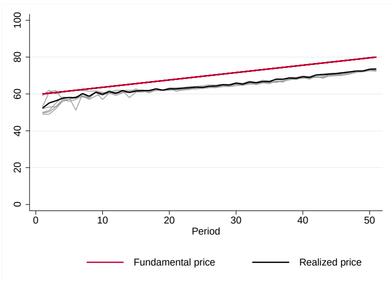
(b) Group 4



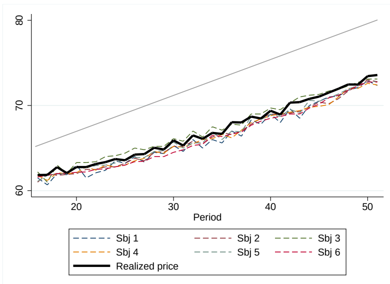
(c) Group 5



(d) Group 5



(e) Group 6



(f) Group 6

Figure 5: Individual prediction and fundamental price for each group (Treatment 2)

Table 2: Mean and standard errors of forecasts in Treatment 1

Groups	Treatment 1				Treatment 2			
	Average 1-10	Std.Dev.	Average 41-51	Std.Dev.	Average 1-10	Std.Dev.	Average 41-51	Std.Dev.
1	58.31	9.35	59.19	0.28	55.43	16.91	67.48	1.44
2	57.80	3.42	58.83	0.29	60.71	5.77	68.08	1.70
3	56.65	6.88	65.72	0.57	53.88	7.95	62.96	1.97
4	37.19	12.92	64.57	10.81	47.88	13.95	70.69	3.17
5	59.44	13.81	65.53	1.06	58.36	4.17	73.70	1.20
6	63.65	6.84	64.79	0.62	57.33	3.72	70.74	1.36

In Treatment 2 all the groups underestimate that the fundamental price follow an increasing trend, but all the groups underestimate the magnitude of this trend. In particular, Group 5 and Group 6 show the highest and quickest coordination, and the series of realized prices is very close to the fundamental price. In Group 1, Group 2 and Group 3 there are at least one player which makes odds predictions also after the learning phase, i.e. also after the fifteenth period. Except for these anomalous predictions, it seems that there is a good level of coordination. Also players in Group 4 underestimate the fundamental value, but only for this group the distance between the market price and the fundamental one decreases during repetitions.

The third result is the heterogeneity both within and between Treatments. In each group we observe different behavior, especially at the beginning of the game when players have few information. Starting from the same initial conditions, each group reaches different equilibrium prices as shown in Table 2.

Table 3: Wilcoxon test for multiple comparison among realized price in different groups - Treatment 1

	Treatment 1											
	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1												
2	3.075	0.002										
3	-6.582	0.000	-6.709	0.000								
4	0.157	0.875	0.064	0.949	5.371	0.000						
5	-7.352	0.000	-7.379	0.000	-5.893	0.000	-6.877	0.000				
6	-8.068	0.000	-8.068	0.000	-5.076	0.000	-7.231	0.000	4.461	0.000		
Group	1		2		3		4		5		6	

Observing information in Table 2 the heterogeneity between Treatments emerges. First of all, we test if this observed differences are statistically significant. Table 3 and Table 4 report the Wilcoxon test of comparison for each pair of groups. In particular, we compare if the realized price of each group is different from the market price of other groups in the same treatment. With few exceptions, the test confirms the presence of heterogeneity. This result suggests that, since players have the same information to make their forecasting, they predict different prices. Taking into account result in Table 2, also difference in the standard deviation emerges, in particular, the volatility in Treatment 2 is higher than that in the treatment with a constant fundamental price.

Since Treatments differs from the value of the dividend, we expect to observe difference between Treatments. We test if there is heterogeneity in terms of volatility and we consider as a measure the standard deviation of individual forecasts in absolute terms, as in Hommes (2011).

Table 4: Wilcoxon test for multiple comparison among realized price in different groups - Treatment 2

	Treatment 2											
	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1												
2	-3.229	0.001										
3	3.597	0.000	6.408	0.000								
4	1.826	0.068	3.832	0.000	0.305	0.761						
5	-4.153	0.000	-1.844	0.065	-6.294	0.000	-4.494	0.000				
6	-1.938	0.052	0.927	0.354	-5.043	0.000	-3.243	0.001	2.373	0.018		
Group	1		2		3		4		5		6	

We measure also the level of entropy in each Treatment using the Shannon Entropy index. The index is given by:

$$S = -\sum_{i=1}^{s} f_i ln f_i \tag{5}$$

where f_i is the relative frequency of the players who make the same forecast. This index is equal to zero in the case of prefect equality of the forecasts. To compute the frequency we split the entire range of the price into windows of width equal to 15. This is a measure of entropy which should be used as a measure of unevenness of the individual predictions within the same Treatment. Figure 6 shows the average standard deviation in each Treatment (blue for Treatment 1 and pink for Treatment 2). As table 2 highlights, the standard deviation is, on average, higher in Treatment 2 [7]. Indeed, in Treatment 1 there is a strong reduction of the heterogeneity around period 5. This means that, since the information about the realized price become available, players quickly coordinate on a common price. In Treatment 2 the high heterogeneity persists until period 15 meaning that players need more time to coordinate in the case of no constant fundamental value.

Looking at the entropy measure shown in Figure 7, similar results emerges. At the beginning of the game there is, on average, the same degree of heterogeneity in both Treatments and, from period 20 on, entropy in Treatment 2 became higher than that in Treatment 1. This means that, since players have few information about past realizations of the price, the entropy is very high in both Treatments. The difference between Treatments emerges after the initial phase of the game, i.e. after period 20, where in Treatment 1 the individual predictions becomes very similar and the index tends to zero. On the other hand, in Treatment 2 the heterogeneity in the forecasts persists after the learning periods highlighting that, in the case of no constant fundamental value, agents find it harder to coordinate their predictions.

Summing up, there is a lack of convergence to the fundamental price in both Treatments and the groups in the same Treatment reach different equilibrium prices, i.e. there is heterogeneity not only between but also within treatments. Comparing the volatility and the entropy in both treatments, a significant difference emerges highlighting that in Treatment 2 the high volatility persists also after the learning phase. This means that, if we introduce a source of instability in the system, i.e. an increasing fundamental price, the volatility increases and the process of convergence takes more time.

[7]We test if the observed differences in the standard deviation are significant running an F test for the homogeneity of variances. The result rejects the null hypothesis of equal variance (F = 0.7814, p-value = 0.000)

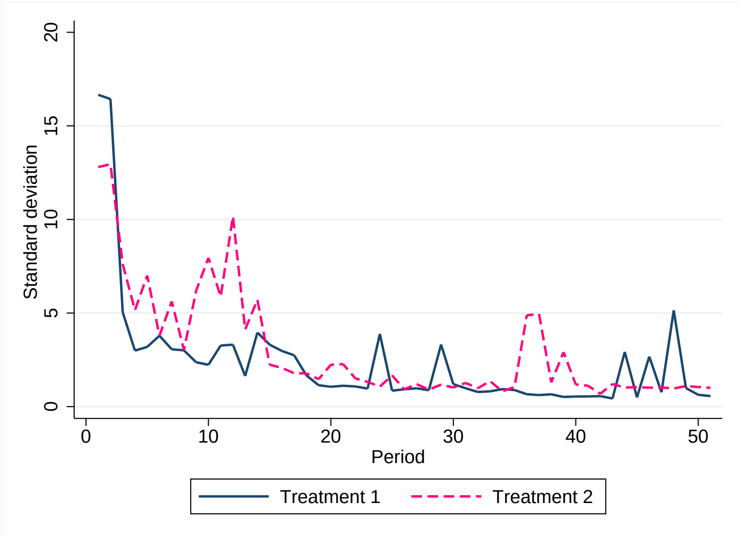


Figure 6: Average standard deviation of individual forecasts by treatment

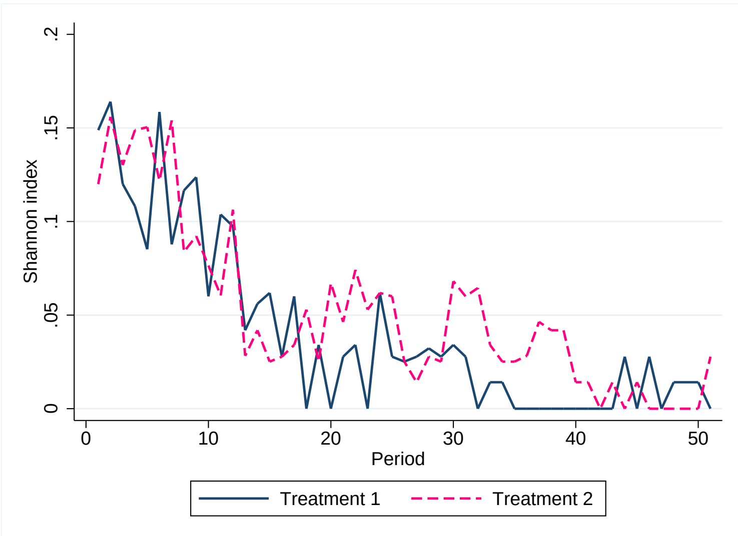
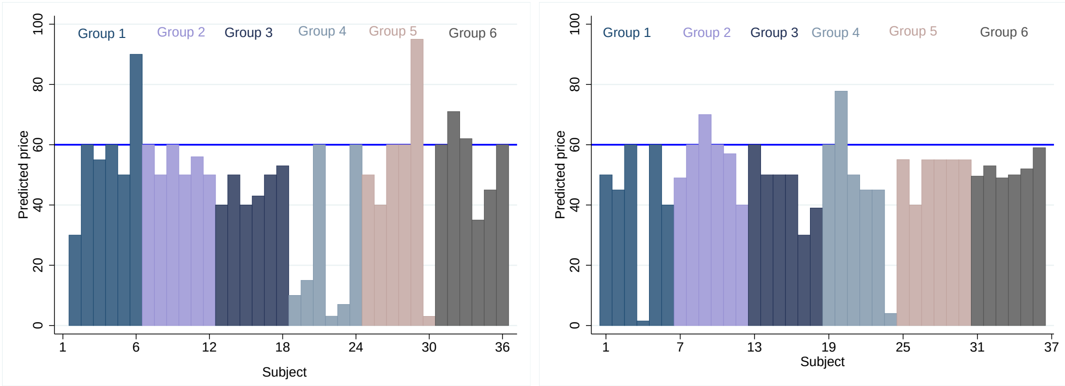


Figure 7: Shannon entropy index by treatment



(a) Treatment 1

(b) Treatment 2

Figure 8: Individual forecasting in the first period. Different color in each subfigure signals different group. The blue line is the fundamental value.

4 Why do agents fail to converge to the fundamental value?

The REH implies that agents, using all the feasible information, are able to understand the real mechanism of the economy and so they are able to make unbiased forecast. This implies that agents do not need any period for learning or for adapting to a new condition, but, since they know the true behavior of the market, the one step ahead forecasting error is (on average) correct.

In our setting, if all agents have rational expectations, and since that the mean dividend and the interest rate are common knowledge, their predictions should be:

$$p^e_{it} = p^f$$

in each period. Within this framework, the possibility that a share of investors has imperfect information, or a lower "degree" or rationality, is ignored on the basis that they would be ruled out - via market selection - by the "smart money" investors, and/or assuming that their impact on aggregate dynamics is negligible (Friedman (1953), Lucas Jr (1978)).

As we said in the previous Section, none of the groups converges to the fundamental price. Why this lack of convergence? There are two main reasons: the first concern the feedback system in the market, the second one deals with individual expectations. Haltiwanger and Waldman (1985) give the definition of *strategic complements* and *strategic substitutes*. Individual decisions are *strategic complements* if agent i has an incentive to play the same strategy of agent j. Conversely, decisions are *strategic substitutes* if player i has convenience to play the agent j opposite strategy. Haltiwanger and Waldman (1989) investigate how the market equilibrium, in both the strategic complements and strategic substitutes cases, depends on the interaction between two kind of agents, i.e. *sophisticated* and *naive* agents. Sophisticated agents make their forecasting in a rational way, i.e. they are able to compute the fundamental value, while naive agents have adaptive expectations. The conclusion of this investigation is that, taking into account strategic complement decisions, the sophisticated agents are ruled out by naive agents. This implies that, in the case of positive feedback system in which strategies are complements, the convergence to the rational expectation equilibrium does not occur.

Figure 8 shows the individual predictions in the first period, i.e. the prediction made at the beginning of the game when players have no information except the interest rate and the mean dividend. These predictions should be seen as the individual belief of the market price. As we see, there is a share of sophisticated agents that predict the fundamental price. The share of rational agents in Treatment 1 is approximately the 30% and in Treatment 2 this share is equal to 20%. As we observed, the realized price diverges from the fundamental value. This implies that sophisticated agents change their strategy during the game because they have an incentive to follow the strategy played by the majority of agents.

The second explanation for the lack of convergence relies with individual expectations. Observing the graphical results it seems that almost all agents do not use rational expectation to make their prediction, but they probably use some kind of *adaptive expectation* (Nerlove (1958)). In this case agents look at the past realization of the price (p_t) and they try to correct their forecasting (p^e_{t-1}) in each period. The expected price can be written as

$$p^e_{t+1} = p^e_{t-1} + \lambda(p_{t-1} - p^e_{t-1}) \quad 0 < \lambda < 1$$

This formulation suggests that agents make systematic forecasting error ($p_t - p^e_{t-1}$) and, moreover, they are not able to immediately adjust their expectations. In contrast to the REH, people are backward looking. This implies that agents should underestimate (overestimate) the true value because of this mechanism of correction. Looking at our results, we can conclude that players, on average, adopt some form of adaptive rule. Indeed, especially in Treatment 2, they systematically underestimate the fundamental value. The adaptive expectation hypothesis can be rewritten as a linear combination of past realization and past prediction

$$p^e_{t+1} = \lambda p_{t-1} + (1-\lambda)p^e_{t-1} \tag{6}$$

The formulation in Equation (6) is the simplest form of adaptive expectation. According to our graphical results, agents in our game use some kind of adaptive expectation since they systematically underestimate or overestimate the fundamental value. Following an approach similar to Bao *et al.* (2012), we estimate the following equation for each agent:

$$p^e_{t+1} = \alpha_0 + \sum_{i=1}^{k} \alpha_i p_{t-i} + \sum_{j=0}^{q} \beta_j p^e_{t-j} + \varepsilon_t \tag{7}$$

This is an Autoregressive Distributed Lag (ADL(k,q)). We estimate different models with different lags and we choose an ADL(4,4), i.e. a model in which we consider four lags of the dependent variable and four lags of the realized price, taking into account the information criteria (AIC, BIC), the presence of serial correlation in the residuals[8] and we test the stationarity condition.

Results are shown in the Appendix in Tables 13-18 for the six groups in Treatment 1, and in Tables 19-24 for groups in Treatment 2. Each column refers to a single agent. For each individual we report the estimated coefficients α_i and β_j, the standard error, the R-squared of the regression, the presence of serial correlation[9], the Phillips-Perron unit root test and the estimate prediction strategy. We categorize players as "ADAPTIVE" when both α_i and β_j coefficients are significant. "AR(q)" refers to expectations based on the past value of the realized price, i.e. those estimation for which only coefficients α_i are significant. We classify as "NAIVE" agents which show only α_1 as a significant coefficient. There are also some individuals for which only some of the coefficients β_j are significant and we classify them as "OBSTINATE".

[8]See Tables 9-10 for the information criteria and Tables 11-12 for the p-value of the Breusch-Godfrey test. We choose the specification for which both the information criteria and the correlation are minimum.

[9]We compute for each individual the Breush-Godfrey test including 20 lags.

Looking at these results it is easy to see that there is heterogeneity in the agents' behavior both within and between groups[10].

In Treatment 1 the following evidence emerges:

- Group 1 and Group 2 show similar pattern of the realized price, but players have heterogeneous expectations. The common features of these groups is that players update their set of available information also with past realizations, i.e. α_i coefficients with $i > 1$ are strongly significant.
- Group 3, Group 5 and Group 6 show similar pattern. Indeed, most of them take into account only the first lag of the realized price, i.e. the last value they are able to see in the game, and the first lag of their own expectation. Since they consider only recent information, and since there are some players that show "obstinate" behavior. they coordinate to a price higher than the fundamental from the early periods and they are not able to correct their forecasting errors with respect to the fundamental price.
- Players in Group 4 behave as if they are myopic, and such behavior leads to a persistent volatility through all the game[11].

Results for Treatment 2 can be summarized as follows:

- the majority of players in Group 1, Group 3 and Group 4 have adaptive expectations. In particular, to form their expectation agents take into account especially past realizations of their own expectations.
- in Group 2 and Group 5 there is a large share of players with obstinate behavior. More in general in these groups players consider only recent information to make their forecasts.
- in Group 6 players have heterogeneity expectations but many of them assign an high weight to past information.

From the analysis of the individual expectations we find out three main results: - the lack of convergence to the fundamental price is due to the fact that the majority of players have adaptive expectations; - the observed heterogeneity within Treatments depends on the heterogeneity of agents' expectations; - there are no significant difference in the expectation formation between Treatments, i.e. the majority of players form their expectation using an adaptive rule also in the case of increasing fundamental value. Since agents have adaptive expectations in both Treatments, in Treatment 2 players take into account past information to make their forecasts. This means that agents use recent information to understand the current price and past information to extrapolate the trend.

5 Heterogeneous expectations and coordination in the group

In this Section we analyze the level of coordination in each group. We compute the *individual average forecast error* to analyze the level of coordination within groups as in Hommes *et al.* (2008). The average forecast error is the quadratic difference between the individual prediction and the realized price. This error should be decomposed into two parts:

[10]Our estimation fails to predict the behavior of 8 agents since there is autocorrelation in the residual.

[11]The low R-square and the not significant coefficients of subject 5 in this group are due to the strange predictions made during the game.

Table 5: Average quadratic errors from market price in Treatment 1

Groups	Average individual error $\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=15}^{T}(p_{it}^e - p_t)^2$	Average dispersion $\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=15}^{T}(p_{it}^e - \bar{p}_t)^2$	Average common error $\frac{1}{T}\sum_{t=15}^{T}(\bar{p}_t^e - p_t)^2$
1	0.38	0.29(76%)	0.09(24%)
2	0.16	0.06(41%)	0.09(59%)
3	0.80	0.59(73%)	0.21(27%)
4	50.27	50.10(99%)	0.17(1%)
5	2.12	1.21(57%)	0.91(43%)
6	0.72	0.42(57%)	0.31(43%)

Table 6: Average quadratic errors from market price in Treatment 2

Groups	Average individual error $\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=15}^{T}(p_{it}^e - p_t)^2$	Average dispersion $\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=15}^{T}(p_{it}^e - \bar{p}_t)^2$	Average common error $\frac{1}{T}\sum_{t=15}^{T}(\bar{p}_t^e - p_t)^2$
1	1.76	0.98(56%)	0.79(44%)
2	40.49	39.81(98%)	0.68(2%)
3	4.48	2.47(55%)	2.01(45%)
4	4.21	3.19(76%)	1.02(24%)
5	0.42	0.30(72%)	0.12(28%)
6	0.54	0.21(39%)	0.33(61%)

$$\frac{1}{NT}\sum_{t=t_0}^{51}\sum_{i=1}^{6}(p_{it}^e - p_t)^2 = \frac{1}{NT}\sum_{t=t_0}^{51}\sum_{i=1}^{6}(p_{it}^e - \bar{p}_t^e)^2 + \frac{1}{T}\sum_{t=t_0}^{51}(\bar{p}_t^e - p_t)^2 \tag{8}$$

The term $\frac{1}{NT}\sum_{t=t_0}^{51}\sum_{i=1}^{6}(p_{it}^e - \bar{p}_t^e)^2$ is the *average dispersion error*, that is the distance between the individual prediction and the average prediction of the group. The second term $\frac{1}{T}\sum_{t=t_0}^{51}(\bar{p}_t^e - p_t)^2$ is the *average common error*, that is the measure of the distance between the average prediction of the group and the realized price. We take into account the observation starting from $t_0 = 15$. Results are shown in Table 5 and Table 6.

Observing results in Table 5, the average individual errors are very small for the Groups 1,2,3,6. Group 4 and Group 5 show high values which depend on the extreme prediction made by one person in each group. Moreover, for these two groups the average dispersion explains more than 90% of the total error. The level of coordination depends on the share of the the error explained by the average common error, i.e. the higher the share the better the level of coordination. Groups that show the lowest individual forecasting error are those who show the best level of coordination. Group 2 shows the lowest individual error and also the best coordination in the Treatment. Looking at Table 6, the individual error is, on average, higher than that registered in Treatment 1. Also in this case the predominant component of the individual error is the average dispersion. Except for Group 2, there is a good level of coordination and for Group 6 the 60% of the individual error is explained by the average common error.

Group 2 (Treatment 1) and Group 6 (Treatment 2) are those with the best coordination in the sense that they show not only low value of the individual average forecasting errors but also an high value of the average common error. Figure 9 shows a summary of the prediction rules adopted in each group. As we point out in the previous Section, the majority of players form their expectations following an adaptive rule, especially in Treatment 2.

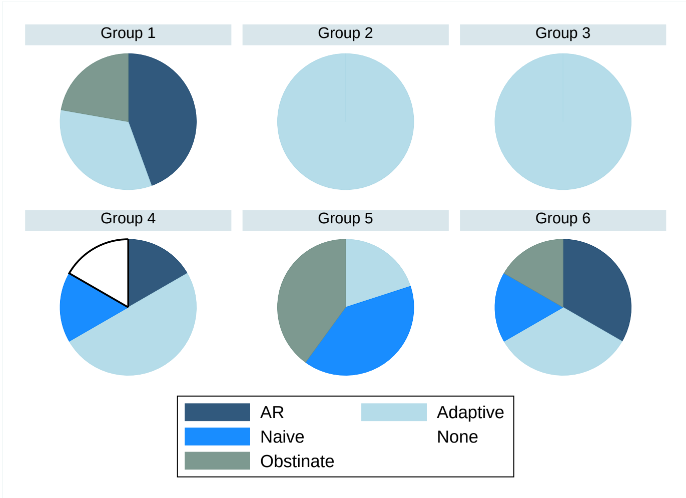
If we take a look at the players expectations in Group 2 (treatment 1) and Group 6 (Treatment 2) in Figure 9, it is easy to see that Players in Group 2 have homogeneous expectations, while this is not the case for Group 6. This implies that the homogeneity of expectations is not a sufficient condition to have a good level of coordination.

What are the reasons behind these different level of coordination? First of all, the high level of coordination derives from a process of learning of others' expectations. One of the measure we take into account is the relation between the average forecasting error at the beginning and at the end of the game. If there is a learning process, or more generally a process of convergence to a specific equilibrium, there should be a reduction of the forecasting error from the beginning to the end of the game. Figure 10 shows the relation between the forecasting errors at the beginning of the game and these errors at the end of the game. At a glance, there is a learning process for all groups since the point lies under the bisector. This implies that the forecasting accuracy is better at the end of the game meaning that players have learned how to coordinate. Group 1 in Treatment 2 shows the best learning process, indeed, the average error at the beginning is equal to 10 and they are able to reduce this value up to 2 by the end of the game. Group 2 in Treatment 1 and Group 5 and Group 6 in Treatment 2 are those with the lowest average forecasting error from the beginning and their errors become close to zero at the end of the game. Although some groups show a strong reduction of their forecasting errors, they do not reach a good level of coordination. To better understand why this happens, we compute the contemporaneous correlation of the forecasting errors for each pair of subjects in the same group. Figures 12- 17 and Figure 18-23 show the scatter plot and the value of the correlation between the individual forecasting errors in each group for each pair of players. Focusing on Figure 13 and Figure 23, i.e. correlation in the groups with the best level of coordination, we find out that significant correlations are always positive. This means that players co-move in the same direction in each period and thus they are able to capture the others' prediction strategy during the whole game.

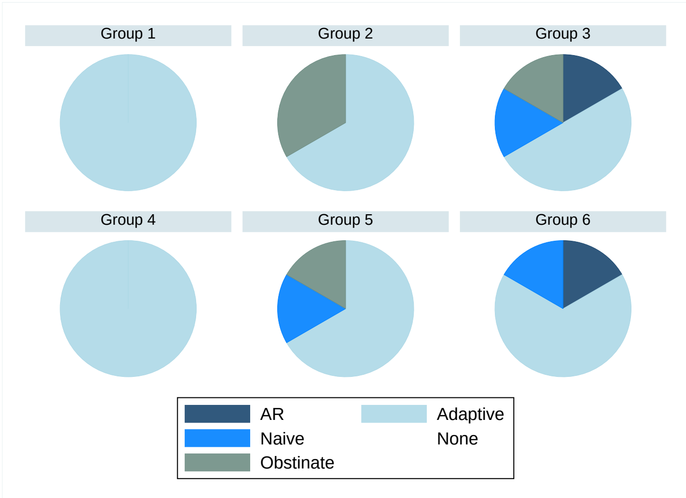
The other factor that influences the level of coordination is linked to the heterogeneity of players' initial belief. In the previous Section we have seen that individual predictions in the first period are quite different (see Figure 8). Using Equation (5) we compute the Shannon entropy index for the individual forecasts in each group. Results in Figure 11 suggest that in some groups the level of heterogeneity is high until the end of the game. Taking a look at Group 2 (Treatment 1) and Group 6 (Treatment 2) an interesting feature emerges. For those groups the entropy index is equal to zero in the first period. Also in Group 5 in Treatment 2 the level of heterogeneity is close to zero at the beginning of the game and this Group shows a good level of coordination very similar to Group 6 in the same Treatment.

Merging the results, we find out that groups in which players have homogeneous expectations do not show the same level of coordination. This implies that the ability to coordinate depends on other factors. We analyze in depth the individual forecasting errors and we conclude that the level of coordination is better if the errors are positively correlated. Moreover, we point out the importance of the initial conditions, i.e. groups with low entropy at the beginning of the game are able to reach a good level of coordination in a few periods.

To sum up, the heterogeneity we observe within groups is strongly influenced not just by the heterogeneous forecasting rules, but also by the initial distribution of the belief and the capacity to learn others' strategies. As suggested by Kirman (2006), agents tend to switch their strategies from time to time and that these switches are coordinated. Moreover, Kirman (1992) argued



(a) Treatment 1



(b) Treatment 2

Figure 9: Individual forecasting rules in both Treatments.

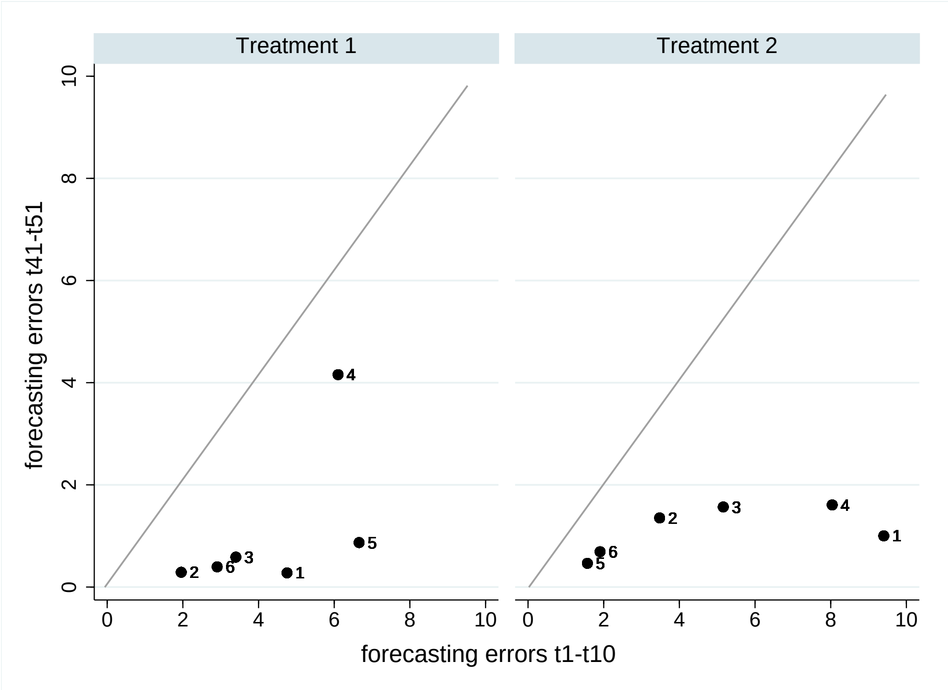


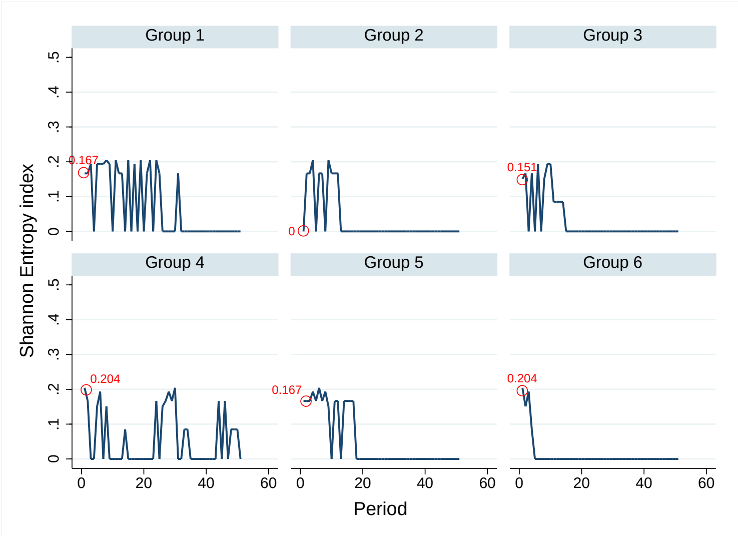
Figure 10: Relation between average forecasting errors at the beginning and at the end of the game.

that a certain degree of heterogeneity is necessary to have a stability in the system. Indeed, in this Section we have shown that, since players have heterogeneous expectations, it is possible to reach a stable, not rational equilibrium if agents are able to coordinate with each other.

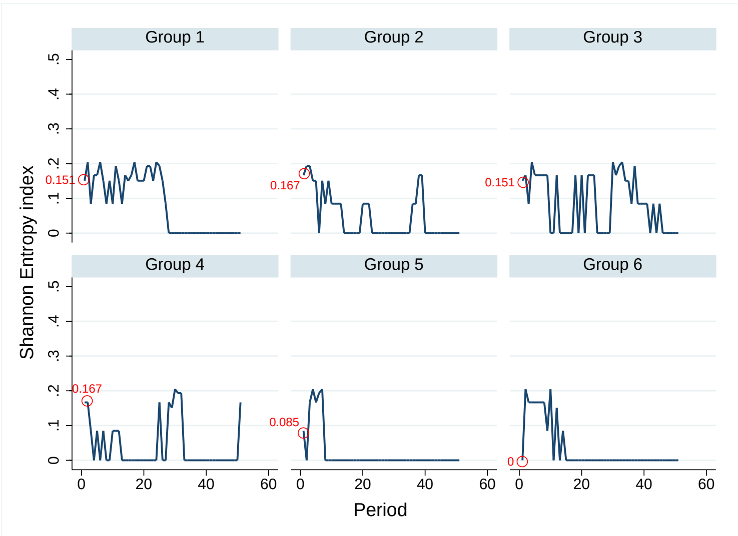
6 Final Remarks

In this work we investigate the individual behavior in an experimental asset market in which participants play in groups of six. In this market players see the mean dividend and the interest rate which are common knowledge for all groups. Moreover, during the game each individual observes the past realization of the market price and her own past predictions. Using all the feasible information, agents in each period make a two-periods ahead forecast of the asset price. The realized price is a function of the average forecasting of the group. The fundamental price is given by the ratio between the mean dividend and the interest rate. We run two treatments in which the only difference is the process which generates the fundamental price: in Treatment 1 both the mean dividend and the interest rate are constant, while in Treatment 2 the mean dividend is increasing during repetitions.

From the graphical analysis emerges that players coordinate to a price higher or lower than the fundamental one. In Treatment 2, players systematically underestimate the fundamental price, but they are able to understand that the mean dividend follows an increasing trend. In addition to this lack of convergence to the rational equilibrium, heterogeneity both within and between Treatments emerges. We investigate the possible reasons for these heterogeneity through the analysis the individual expectations. To analyze the individual expectation, we estimate the future predictions considering four lags of the realized price and four lags of the



(a) Treatment 1



(b) Treatment 2

Figure 11: Shannon entropy index for each group

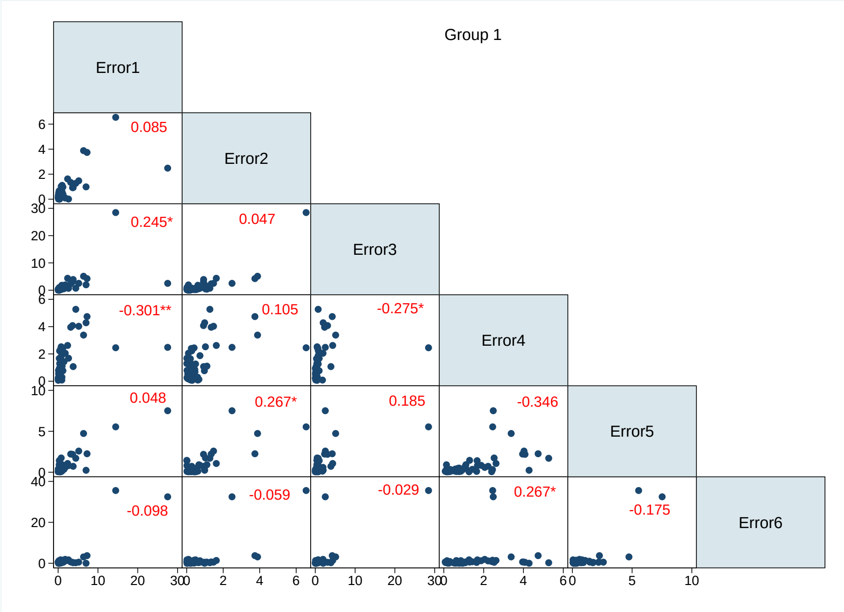


Figure 12: Correlation of individual forecasting errors

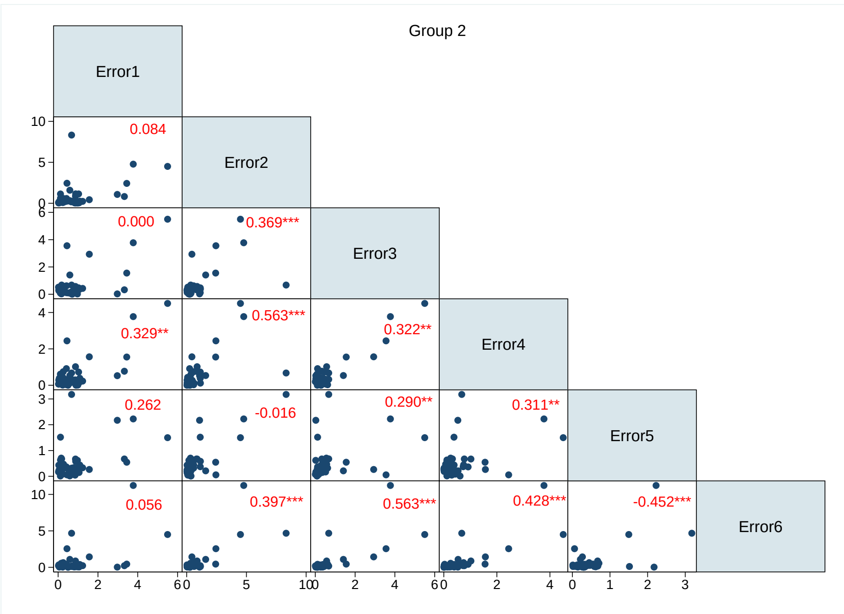


Figure 13: Correlation of individual forecasting errors

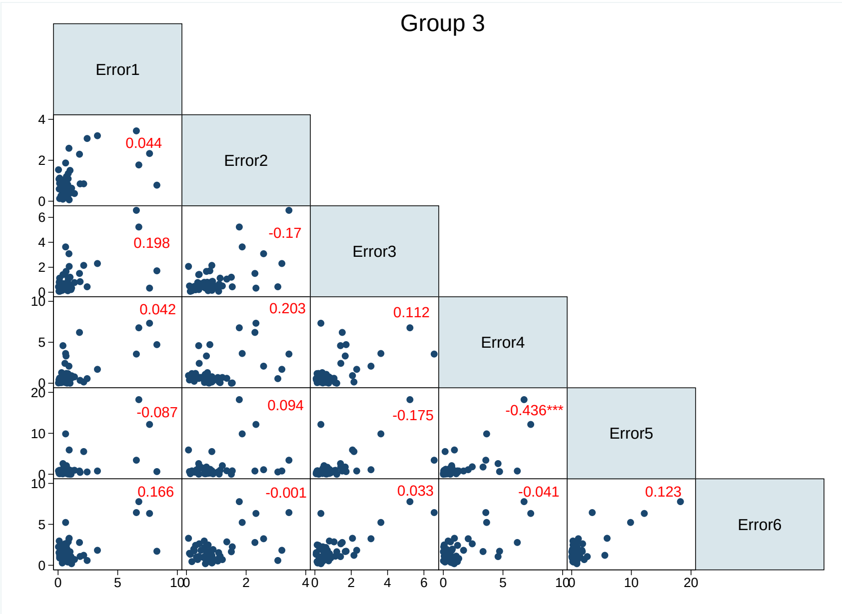


Figure 14: Correlation of individual forecasting errors

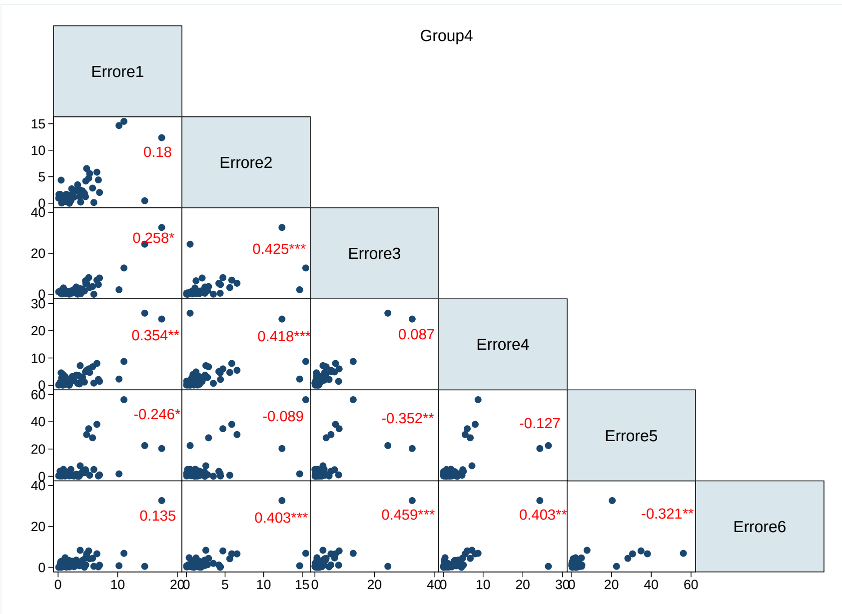


Figure 15: Correlation of individual forecasting errors

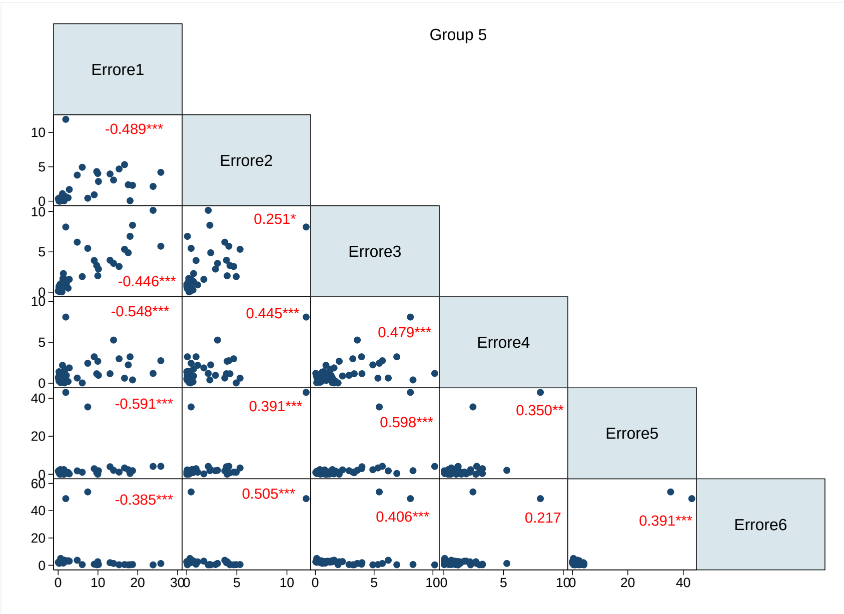


Figure 16: Correlation of individual forecasting errors

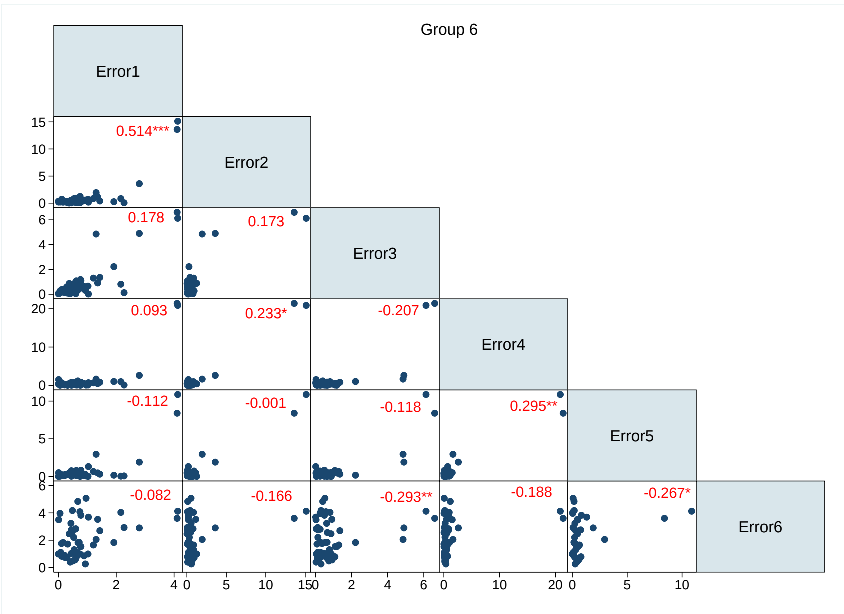


Figure 17: Correlation of individual forecasting errors

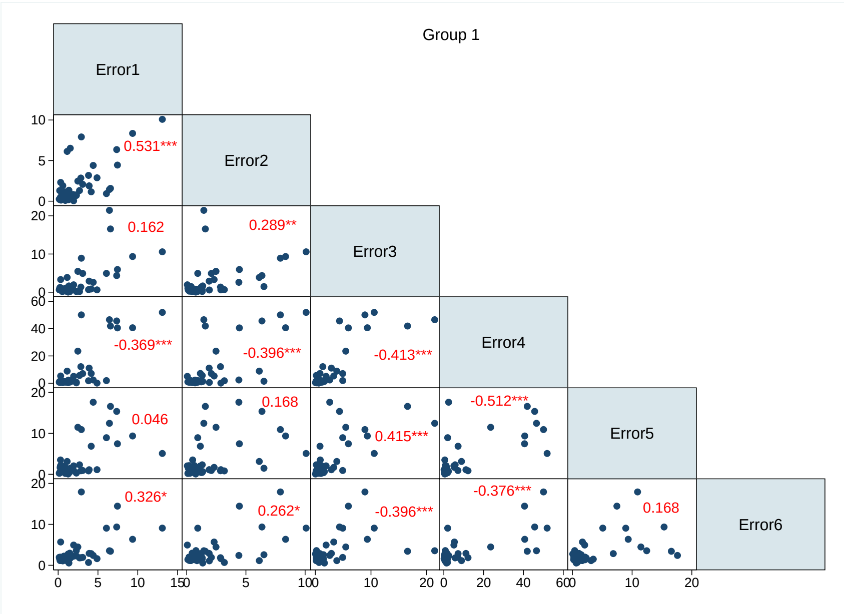


Figure 18: Correlation of individual forecasting errors

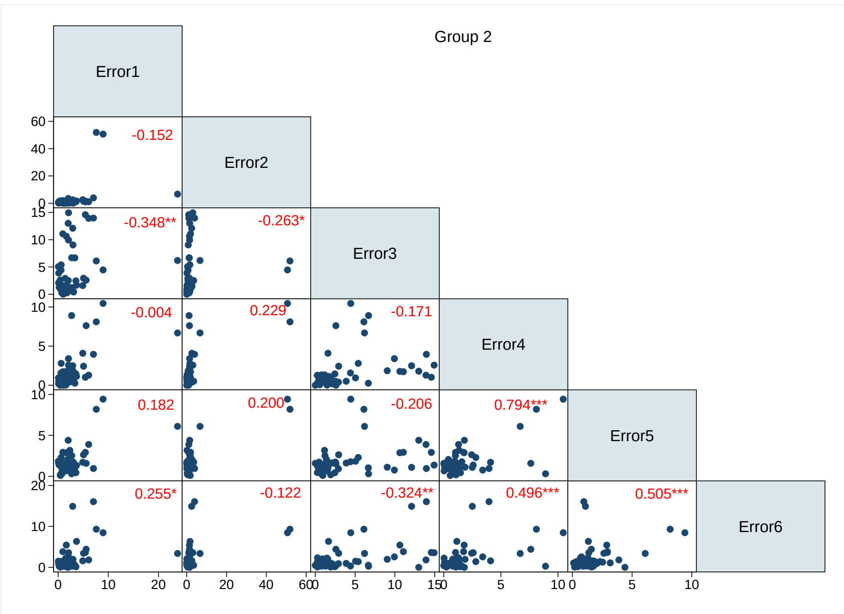


Figure 19: Correlation of individual forecasting errors

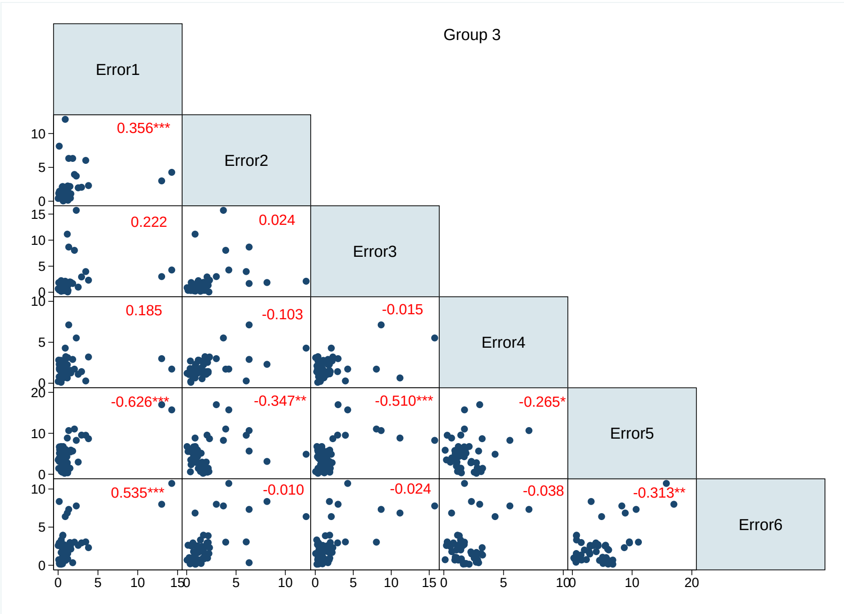


Figure 20: Correlation of individual forecasting errors

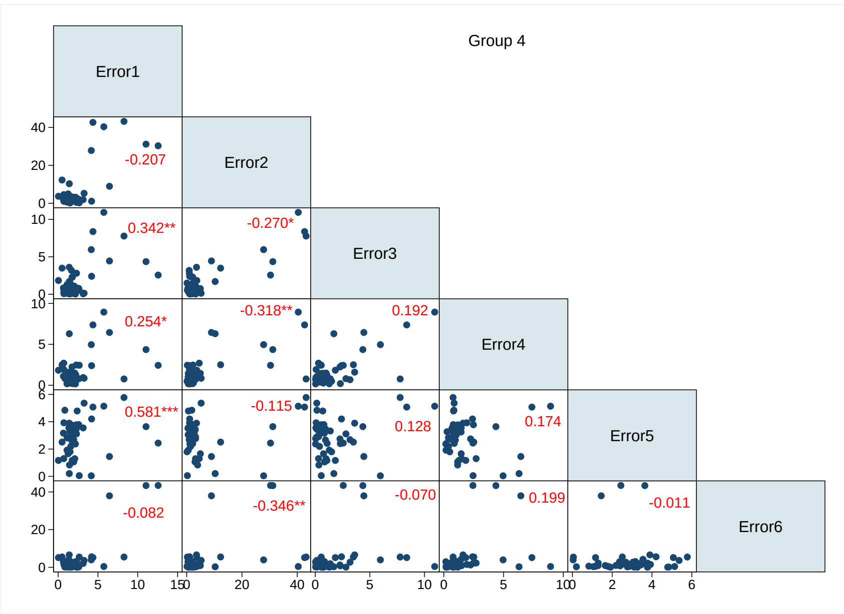


Figure 21: Correlation of individual forecasting errors

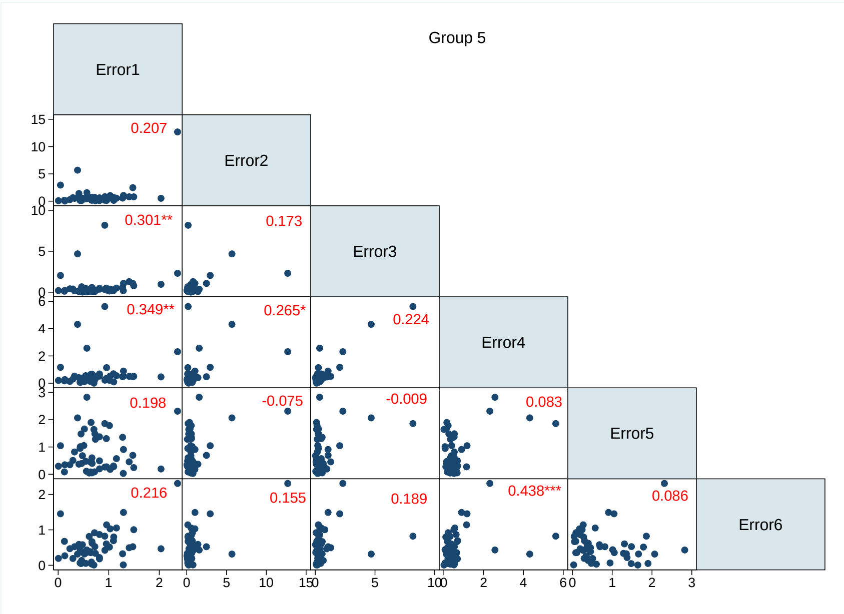


Figure 22: Correlation of individual forecasting errors

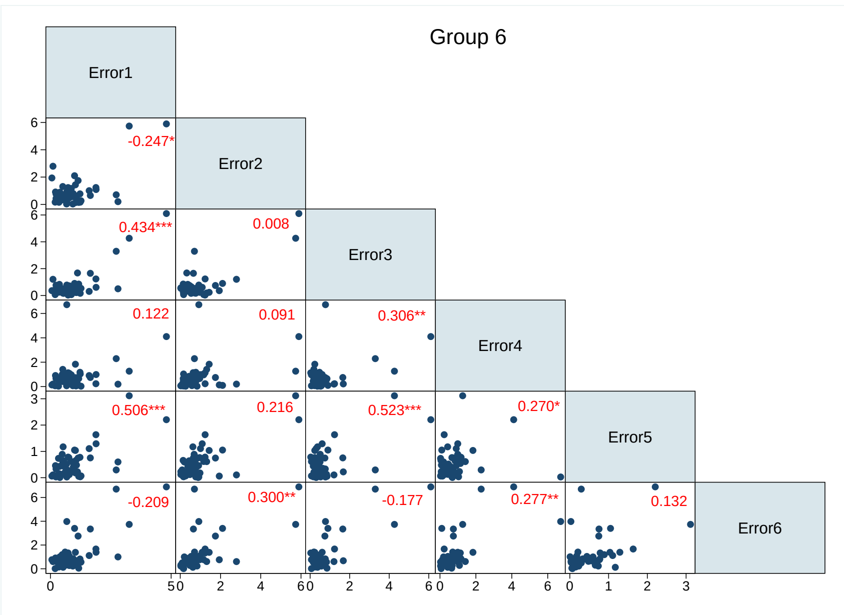


Figure 23: Correlation of individual forecasting errors

individual predictions. This kind of ADL(k,q) model fits very well the behavior of almost all agents. What emerges is that the majority of players form their expectations using an adaptive rule. Comparing the individual expectations in both Treatments, even if agentsin Treatment 2 weight more past information, no significant different emerges.

From the analysis of the individual forecasting errors emerges that groups have different level of coordination. The key result we find out is that the homogeneity of expectations in the same group is not a sufficient condition to have a strong coordination. Analyze the correlation between agents' forecasting errors,

The analysis of the correlation between individual forecasting errors highlights that a positive and significant correlation of these errors leads to a good level of coordination. Finally, we find out that a low level of entropy at the beginning of the game strongly influence the coordination in each group.

Summing up, the introduction of a source of instability, i.e. an increasing dividend, has no impact on the expectation formation at the individual level but it increases the volatility in the market. Moreover, the coordination of agents is not uniquely determinate by the individual expectations.

References

Assenza, T., Bao, T., Hommes, C., and Massaro, D. (2014). Experiments on expectations in macroeconomics and finance. In *Experiments in macroeconomics*, pages 11–70. Emerald Group Publishing Limited.

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

Bloomfield, R. and Hales, J. (2002). Predicting the next step of a random walk: experimental evidence of regime-shifting beliefs. *Journal of financial Economics*, **65**(3), 397–414.

Brock, W. A. and Hommes, C. H. (1998). Heterogeneous beliefs and routes to chaos in a simple asset pricing model. *Journal of Economic dynamics and Control*, **22**(8-9), 1235–1274.

Campbell, J. Y., Lo, A. W.-C., MacKinlay, A. C., *et al.* (1997). *The econometrics of financial markets*, volume 2. princeton University press Princeton, NJ.

Dwyer, G. P., Williams, A. W., Battalio, R. C., and Mason, T. I. (1993). Tests of rational expectations in a stark setting. *The Economic Journal*, pages 586–601.

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

Friedman, M. (1953). *Essays in positive economics*. University of Chicago Press.

Grunberg, E. and Modigliani, F. (1954). The predictability of social events. *The Journal of Political Economy*, pages 465–478.

Haltiwanger, J. and Waldman, M. (1985). Rational expectations and the limits of rationality: An analysis of heterogeneity. *The American Economic Review*, pages 326–340.

Haltiwanger, J. and Waldman, M. (1989). Limited rationality and strategic complements: the implications for macroeconomics. *The Quarterly Journal of Economics*, pages 463–483.

Heemeijer, P., Hommes, C., Sonnemans, J., and Tuinstra, J. (2009). 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.

Hey, J. D. (1994). Expectations formation: Rational or adaptive or...? *Journal of Economic Behavior & Organization*, **25**(3), 329–349.

Hommes, C. (2011). The heterogeneous expectations hypothesis: Some evidence from the lab. *Journal of Economic Dynamics and Control*, **35**(1), 1–24.

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

Hommes, C., Sonnemans, J., Tuinstra, J., and Van de Velden, H. (2005). Coordination of expectations in asset pricing experiments. *Review of Financial Studies*, **18**(3), 955–980.

Hommes, C., Sonnemans, J., Tuinstra, J., and Van De Velden, H. (2007). Learning in cobweb experiments. *Macroeconomic Dynamics*, **11**(S1), 8–33.

Hommes, C., Sonnemans, J., Tuinstra, J., and van de Velden, H. (2008). Expectations and bubbles in asset pricing experiments. *Journal of Economic Behavior & Organization*, **67**(1), 116–133.

Kirman, A. (2006). Heterogeneity in economics. *Journal of Economic Interaction and Coordination*, **1**(1), 89–117.

Kirman, A. P. (1992). Whom or what does the representative individual represent? *The Journal of Economic Perspectives*, pages 117–136.

Lucas Jr, R. E. (1978). Asset prices in an exchange economy. *Econometrica: Journal of the Econometric Society*, pages 1429–1445.

Lucas Jr, R. E. and Prescott, E. C. (1971). Investment under uncertainty. *Econometrica: Journal of the Econometric Society*, pages 659–681.

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

Muth, J. F. (1961). Rational expectations and the theory of price movements. *Econometrica: Journal of the Econometric Society*, pages 315–335.

Nerlove, M. (1958). Adaptive expectations and cobweb phenomena. *The Quarterly Journal of Economics*, pages 227–240.

Palestrini, A. and Gallegati, M. (2015). Unbiased adaptive expectation schemes. *Economics Bulletin*, **35**(2), 1185–1190.

A General Instruction

You are a financial advisor to a pension fund that wants to invest an amount of money to buy an asset. The pension fund will allocate its money between a bank account which pays fix interest and a risky investment. The allocation depends on you forecast accuracy. Your task is to predict the price of the risky asset for 51 periods. Your profit depends on your forecast accuracy. The better your prediction, the higher the profit in each period. The final earning will be given by the sum of the profit you gain in each period.

A.1 Instruction for the forecasting task

At the beginning of each period you must predict the price for the next period, i.e. in period 1 you must predict the price of period 2 and so on. At the beginning of the experiment you should predict the price of the first and the second period. You forecasting for these period must be between 0 and 100. To make these predictions you will have only two information: the mean dividend and the interest rate. From period 3 until the end of the game you will have more information[12]: besides the interest rate and the mean dividend, you will see a graph with the time series of your past prediction and the series of the realized price in the market. The green dots represent the series of the predicted price, while the blue dots represents the realized price in each period. Moreover, you will see the values of these series.

At period t the feasible information will be: the realized price up to period $t-2$, your past prediction up to period $t-1$ and your earning up to period $t-2$.

Once each players have made their prediction for the first and the second period, the realized price in period 1 and your prediction in period 1 and period 2 will be revealed. The same mechanism holds for subsequent periods. After you insert the forecasting your profit will be computed according to the forecasting accuracy. In each period your profit ranges between 0 (bad forecast) and 1 (best forecast). During the experiment your earning will be expressed in ECU (Experimental Currency Unit) and at the end of the game the amount will be converted in Euro (1 ECU = 0.4 Euro).

The market price will be determined by the equilibrium between demand and supply of the stock. The supply of stocks is fixed for the duration of the experiment. The demand of stocks will be given by the aggregate demand of each pension fund of which each participant is the advisor.

A.2 Total profits

Table 7 shows the total profit in Euro in each group. Table 8 reports the descriptive statistics of the cash earned in both treatments.

B Tables

C Estimation of individual prediction rules

[12]During the initial phase we give to each player a sheet with the screenshot of the game with further information.

Table 7: Average payment by group

	Treatment 1	Treatment 2
Group 1	88.80	78.09
Group 2	110.07	86.08
Group 3	88.17	93.34
Group 4	77.81	80.56
Group 5	82.70	100.48
Group 6	105.84	101.49

Table 8: Descriptive statistics of payment

	Mean	Std. Dev	Min	Max
Treatment 1	15.37	12.89	11.68	25.59
Treatment 2	15.00	9.99	9.81	25.59

Table 9: Information Criteria - Treatment 1

	ADL(1, 1)		ADL(2,2)		ADL(3,3)		ADL(4,4)	
Subject	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
1	220.76	226.44	190.52	199.88	172.73	185.67747	141.42	157.88
2	120.61	126.28	112.1	121.46	95.601	108.55234	53.36	69.818
3	181.35	187.02	157.88	167.23	146.65	159.60119	128	144.46
4	189.38	195.05	170.01	179.37	168.6	181.54864	161.05	177.5
5	169.75	175.42	112.38	121.73	68.014	80.965353	67.321	83.779
6	118.76	124.43	106.02	115.38	71.099	84.049693	53.788	70.246
7	143.85	149.52	126.78	136.13	115.53	128.48259	95.634	112.09
8	115.72	121.4	50.217	59.573	23.058	36.009119	-51.52	-35.06
9	42.009	47.685	23.465	32.821	2.2757	15.226693	-36.05	-19.6
10	109.33	115	27.328	36.684	-18.93	-5.9787253	-16.55	-0.094
11	121.07	126.74	64.07	73.426	58.724	71.675155	44.58	61.038
12	49.255	54.931	-9.869	-0.513	-19.04	-6.0853933	-44.46	-28
13	174.29	179.96	99.431	108.79	96.31	109.26108	80.552	97.01
14	92.474	98.149	82.933	92.289	71.048	83.9986	62.177	78.635
15	153.68	159.36	152.95	162.31	136.69	149.64194	127.35	143.81
16	200.86	206.53	182.11	191.46	171.42	184.37051	162.37	178.83
17	212.7	218.38	202.12	211.48	168.4	181.34658	156.23	172.69
18	133.98	139.66	103.76	113.11	87.569	100.52042	89.845	106.3
19	239.67	245.35	222.68	232.03	221.96	234.90779	220.56	237.02
20	244.22	249.9	238.33	247.69	236.3	249.24763	220.24	236.7
21	175.93	181.6	173.57	182.93	164.01	176.96593	164.14	180.6
22	229.68	235.36	225.76	235.12	201.78	214.72791	195.09	211.55
23	409.81	415.48	404.79	414.14	399.26	412.20644	390.34	406.8
24	195.09	200.77	189.54	198.9	185.92	198.86695	156.28	172.74
25	312.69	318.36	307.95	317.31	303.71	316.65889	300.92	317.38
26	141.55	147.23	115.28	124.64	107.3	120.24928	104.76	121.21
27	183.08	188.75	139.08	148.43	114.49	127.43721	116.23	132.69
28	164.63	170.3	165.62	174.97	163.54	176.48715	161.52	177.97
29	163.71	169.39	154.71	164.06	145.2	158.15401	145.76	162.22
30	72.255	77.931	65.253	74.609	68.735	81.685607	72.497	88.954
31	128.47	134.15	115.15	124.51	68.446	81.397446	65.882	82.34
32	103.8	109.48	98.224	107.58	54.847	67.797679	54.188	70.646
33	140.37	146.05	125.52	134.88	91.228	104.17953	79.782	96.24
34	116.74	122.42	104.75	114.11	94.981	107.93219	92.312	108.77
35	113.94	119.62	80.678	90.034	64.321	77.271674	67.736	84.194
36	140.82	146.5	114.08	123.43	114.84	127.7867	114.33	130.79

Table 10: Information Criteria - Treatment 2

	ADL(1, 1)		ADL(2,2)		ADL(3,3)		ADL(4,4)	
Subject	AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
1	225.93	231.61	199.1	208.46	220.03012	232.98	204.6	221.05
2	207.17	212.85	152.69	162.05	177.66975	190.62	176.53	192.99
3	180.45	186.13	408.2	417.56	126.87811	139.83	114.68	131.14
4	416.61	422.29	214.12	223.47	377.31744	390.27	357.19	373.64
5	265.88	271.55	205.32	214.68	213.12688	226.08	210.71	227.16
6	217.86	223.53	276.02	285.37	184.21299	197.16	177.74	194.2
7	279.74	285.42	367.12	376.47	236.00816	248.96	234.54	250.99
8	373.57	379.25	301.15	310.5	361.7466	374.7	357.66	374.12
9	306.58	312.26	185.15	194.51	296.55492	309.51	293.45	309.9
10	205.44	211.11	77.517	86.873	148.00698	160.96	111.31	127.76
11	105.89	111.57	168.02	177.37	73.267574	86.219	74.987	91.444
12	186.25	191.93	109.39	118.75	161.96718	174.92	153.08	169.53
13	129.39	135.07	203.86	213.22	79.706817	92.658	75.76	92.218
14	230.81	236.48	238.26	247.61	169.03668	181.99	158.96	175.42
15	244.18	249.86	93.646	103	220.84647	233.8	179.91	196.37
16	99.369	105.04	255.37	264.72	87.686376	100.64	78.829	95.286
17	283.52	289.2	145.89	155.25	224.69208	237.64	224.59	241.05
18	148.93	154.61	116.23	125.59	137.98534	150.94	83.478	99.935
19	161.4	167.08	354.5	363.85	108.43299	121.38	107.76	124.22
20	360.35	366.02	191.71	201.07	349.8425	362.79	343.41	359.87
21	194.28	199.95	187.77	197.12	182.82506	195.78	182.47	198.93
22	196.96	202.64	184.73	194.09	174.63629	187.59	161.66	178.12
23	205.13	210.81	230.07	239.42	164.16166	177.11	123.56	140.02
24	317.71	323.38	49.983	59.339	214.47617	227.43	206.2	222.66
25	89.439	95.114	-23.81	-14.46	31.759689	44.711	34.191	50.649
26	28.847	34.522	85.505	94.861	-32.622354	-19.67	-30	-13.54
27	164.73	170.41	73.463	82.819	48.590901	61.542	42.448	58.906
28	125.44	131.12	109.1	118.46	47.044476	59.996	15.375	31.833
29	126.54	132.21	36.242	45.598	81.114647	94.066	47.566	64.024
30	59.963	65.638	73.177	82.533	28.20435	41.155	28.724	45.181
31	75.258	80.933	97.43	106.79	60.127071	73.078	57.943	74.4
32	149.27	154.94	54.815	64.171	93.639318	106.59	90.136	106.59
33	68.047	73.722	153.06	162.42	44.744136	57.695	48.154	64.611
34	163.67	169.34	9.8552	19.211	135.5598	148.51	78.858	95.316
35	18.267	23.943	3.9161	13.272	-2.8625397	10.088	2.4225	18.88
36	45.669	51.345			-9.1142218	3.8368	-11.11	5.3479

Table 11: Breush-Godfrey test for autocorrelation up to 20 lags - Treatment 1

ADL(1.1)	ADL(2.2)	ADL(3.3)	ADL(4.4)
.04497221	.70740166	.06906673	.61693958
.35248651	.00754329	.00160015	.25696191
.34784263	.04215838	.32996119	.19720005
.5747241	.34634766	.69367723	.52779671
.7450133	.21808757	.41504783	.38485453
.14885972	.27450356	.598198	.29070712
.26131274	.07026125	.13641375	.57469519
.4958191	.53949361	.06115906	.7182538
.08629488	.10585359	.16861862	.21212992
.00089042	.90404816	.81164251	.43167646
.51644267	.68276758	.19013669	.01072095
.58723895	.39459728	.0111075	.04107524
.0181308	.72337034	.41580048	.39494805
.70993978	.38030862	.67705869	.24168822
.41681483	.07530421	.08465744	.09087274
.56484822	.20697959	.18532454	.15702471
.93294763	.0025107	.01890709	.02233776
.39966126	.30901834	.26641288	.42818232
.50957214	.51156951	.48602456	.12482267
.79701531	.9224687	.2633633	.55522832
.34539047	.08955935	.49055637	.6182678
.82144842	.52346498	.02668943	.08535798
.07998922	.08717034	.14877713	.19789681
.83048157	.63952673	.20410169	.52763234
.98807008	.96076529	.98603568	.15550967
.35551617	.04911142	.22502769	.23605575
.97818922	.06334106	.17316717	.20053368
.84639272	.84966901	.59667303	.1012042
.67005668	.50212224	.48203237	.45367224
.80480723	.86485734	.8466601	.85536109
.73724996	.09998947	.25094849	.28957841
.04137271	.01754667	.30609664	.40021085
.05804941	.02324973	.52709096	.43201337
.1119964	.3873685	.39410919	.23332112
.03964297	.50304265	.22199936	.16693911
.03277498	.98005816	.46186895	.7423395

Table 12: Breush-Godfrey test for autocorrelation up to 20 lags - Treatment 2

ADL(1.1)	ADL(2.2)	ADL(3.3)	ADL(4.4)
.44562509	.22862086	.40178059	.25912932
.56966577	.18485197	.68379167	.62955764
.08788707	.01180694	.05569599	.21947831
.74436195	.01068158	.0392992	.05454795
.3180731	.40039877	.19731624	.07099022
.04634738	.18438755	.14662549	.11031091
.31836508	.81092403	.41231941	.50356887
.39783655	.51653122	.61048537	.51910202
.65460618	.73564854	.09411208	.44610856
.38973594	.90468564	.01971998	.23465186
.10472399	.73499492	.26828964	.2441124
.49410121	.63813117	.56766914	.20907943
.02799434	.07207093	.74563615	.20095615
.09315393	.01946086	.78504889	.49632134
.52920681	.43680175	.00686398	.18166397
.72731105	.41741892	.12266277	.09994463
.54237075	.22035072	.80510297	.38213766
.99987493	.20863902	.00266357	.11992016
.29258886	.87538493	.45657975	.00645964
.99244409	.95784654	.03538239	.00555412
.77814837	.51657932	.18379424	.03747168
.1624028	.45404459	.0521288	.51397249
.52348378	.79376375	.38129269	.53035491
.0013302	.91700741	.71742647	.41740411
.79038845	.15022358	.41512676	.58616725
.55562975	.5823021	.41024517	.30959288
.9932468	.34244154	.87485058	.80896041
.57796764	.78355941	.08876307	.58619161
.88819507	.23892093	.07061918	.08354214
.18140892	.44213322	.17580021	.04892362
.71480852	.20563992	.36154299	.08081847
.00504172	.27640539	.33211908	.1240018
.6087902	.4592036	.63448425	.65239999
.9935365	.44720448	.01156021	.03818134
.87218619	.73671642	.95094062	.92574702
.99871476	.71455202	.24582467	.30417796

Table 13: Individual estimation for Group 1 - Treatment 1

	1	2	3	4	5	6
p_t^e	0.151	-0.155	-0.0706	0.245	0.147	0.0964
	0.129	0.104	0.134	0.149	0.163	0.137
p_{t-1}^e	0.228*	-0.0864	-0.0817	-0.239	0.378***	0.607***
	0.128	.104	0.134	0.148	0.12	0.0953
p_{t-2}^e	0.066	-0.0998	0.188	0.157	-0.200**	-0.238*
	0.115	0.102	0.122	0.149	0.0786	0.132
p_{t-3}^e	-0.063	0.236**	0.068	0.282**	-0.102	-0.073***
	0.078	0.094	0.091	0.137	0.081	0.025
p_{t-1}	1.562***	0.853***	0.101	0.257	0.450**	-0.079
	0.452	0.177	0.426	0.556	0.212	0.17
p_{t-2}	0.158	0.811***	-0.077	0.52	-0.287*	-0.088
	0.444	0.148	0.408	0.499	0.162	0.163
p_{t-3}	-1.382***	-0.14	1.109***	-0.536	0.156	-0.234
	0.419	0.155	0.405	0.488	0.159	0.141
p_{t-4}	-1.190***	-0.570***	0.582**	0.221	0.00338	0.159
	0.237	0.088	0.272	0.339	0.143	0.138
Constant	87.08*	9.007	-48.46	5.463	26.94*	50.02***
	47.6	15.17	41.51	45.94	15.81	13.29
Observations	46	46	46	46	46	46
R-squared	0.67	0.803	0.725	0.489	0.922	0.844
Autocorrelation	NO	NO	NO	NO	NO	NO
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	NO	NO	NO
Prediction strategy	ADAPTIVE	ADAPTIVE	AR(3)	OBSTINATE	ADAPTIVE	OBSTINATE

Table 14: Individual estimation for Group 2 - Treatment 1

	1	2	3	4	5	6
p_t^e	-0.0847	0.610***	-0.341***	0.304*	-0.144	0.864***
	0.132	0.071	0.104	0.16	0.138	0.118
p_{t-1}^e	-0.128	0.182***	-0.515***	0.0279	0.0433	-0.606***
	0.116	0.056	0.101	0.13	0.126	0.126
p_{t-2}^e	0.289**	0.085	-0.067	0.208***	0.113	0.480***
	0.11	0.055	0.094	0.057	0.105	0.091
p_{t-3}^e	0.037	-0.128**	0.037	0.039	0.189*	-0.204***
	0.12	0.049	0.037	0.062	0.105	0.061
p_{t-1}	1.70***	0.056	0.285***	0.672***	0.517**	0.456***
	0.423	0.087	0.101	0.129	0.252	0.094
p_{t-2}	1.10***	-0.208**	0.132	-0.346**	-0.211	-0.226*
	0.318	0.095	0.124	0.167	0.224	0.117
p_{t-3}	0.340*	-0.158**	0.113	-0.115	-0.191	0.264**
	0.175	0.064	0.113	0.094	0.182	0.109
p_{t-4}	-0.305*	-0.142**	0.206**	0.092	0.194*	-0.073
	0.169	0.054	0.085	0.062	0.1	0.053
Constant	-114.9***	41.37***	67.06***	7.078	28.71	2.632
	38.23	9.933	9.106	16.95	24.04	12.7
Observations	46	46	46	46	46	46
R-squared	0.61	0.944	0.851	0.729	0.512	0.742
Autocorrelation	NO	NO	NO	NO	YES	YES
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	NO	NO	NO
Prediction strategy	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE

Table 15: Individual estimation for Group 3 - Treatment 1

	1	2	3	4	5	6
p_t^e	0.985***	0.480***	-0.037	0.354**	0.672***	0.348**
	0.137	0.147	0.146	0.156	0.16	0.164
p_{t-1}^e	-0.523***	-0.014	0.660***	0.199	-0.494***	0.028
	0.18	0.151	0.142	0.152	0.161	0.145
p_{t-2}^e	0.238*	0.301*	-0.044	0.309**	0.208	0.217*
	0.136	0.151	0.157	0.144	0.143	0.109
p_{t-3}^e	-0.181***	-0.380***	-0.272**	-0.375**	0.195	-0.048
	0.057	0.114	0.113	0.147	0.123	0.098
p_{t-1}	0.621***	0.535***	0.005	1.031**	1.259**	1.201***
	0.187	0.133	0.29	0.462	0.495	0.17
p_{t-2}	-0.234	0.168	0.660**	-0.093	-0.806*	-0.685**
	0.152	0.151	0.281	0.437	0.444	0.26
p_{t-3}	0.492***	0.167	0.225	0.079	-0.258	0.017
	0.138	0.121	0.235	0.319	0.433	0.24
p_{t-4}	-0.414**	-0.158	-0.305	-0.39	0.024	-0.131
	0.154	-0.10	0.192	0.313	0.31	0.163
Constant	1.225	-5.783	7.272	-7.65	12.87	4.074
	6.141	4.307	8.25	12.19	22.69	6.329
Observations	46	46	46	46	46	46
R-squared	0.91	0.976	0.809	0.756	0.868	0.898
Autocorrelation	NO	NO	NO	NO	NO	YES
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	NO	YES	NO
Prediction strategy	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE

Table 16: Individual estimation for Group 4 - Treatment 1

	1	2	3	4	5	6
p_t^e	0.017	0.038	0.125	0.168	0.087	0.446***
	0.17	0.14	0.17	0.152	0.162	0.118
p_{t-1}^e	0.314*	-0.006	-0.027	0.552***	-0.152	0.138
	0.166	0.14	0.151	0.15	0.48	0.149
p_{t-2}^e	0.136	0.185	-0.033	-0.284*	0.356	-0.166
	0.155	0.135	0.154	0.157	0.424	0.134
p_{t-3}^e	0.064	0.191	0.049	-0.243**	-0.547	0.216*
	0.122	0.125	0.048	0.097	0.339	0.109
p_{t-1}	0.276*	0.968***	0.789***	0.421***	0.34	0.415***
	0.15	0.144	0.079	0.118	2.781	0.080
p_{t-2}	0.371**	0.173	-0.149	0.246*	-2.082	-0.057
	0.152	0.186	0.155	0.131	2.431	0.1
p_{t-3}	-0.101	0.031	0.221	0.129	0.669	-0.208*
	0.17	0.196	0.167	0.139	2.334	0.115
p_{t-4}	-0.181	-0.481***	-0.034	0.019	1.952	0.141
	0.173	0.173	0.177	0.122	1.539	0.086
Constant	7.18	-5.404	4.288*	-1.037	27.6	4.717**
	4.577	3.454	2.201	2.743	35.04	1.828
Observations	46	46	46	46	46	46
R-squared	0.908	0.935	0.974	0.948	0.282	0.976
Autocorrelation	NO	NO	NO	NO	NO	NO
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	YES	NO	NO	YES
Prediction strategy	ADAPTIVE	AR(4)	NAIVE	ADAPTIVE	-	ADAPTIVE

Table 17: Individual estimation for Group 5 - Treatment 1

	1	2	3	4	5	6
p^e_t	0.489***	0.567***	0.906***	-0.038	-0.119	0.017
	0.166	0.156	0.176	0.158	0.163	0.165
p^e_{t-1}	0.196	-0.233	-0.139	-0.264	0.0821	-0.022
	0.47	0.168	0.194	0.169	0.147	0.166
p^e_{t-2}	-0.002	0.050	-0.094	-0.031	-0.003	0.015
	0.344	0.137	0.094	0.168	0.141	0.158
p^e_{t-3}	0.218	0.056	-0.028	-0.158	-0.034	-0.001
	0.192	0.095	0.069	0.133	0.042	0.012
p_{t-1}	-0.789	1.632***	0.151	1.350***	0.974***	1.107***
	3.108	0.118	0.167	0.244	0.2	0.083
p_{t-2}	-0.581	-0.742**	-0.054	-0.157	0.226	-0.048
	2.303	0.276	0.162	0.304	0.265	0.202
p_{t-3}	0.629	-0.395	0.157	0.148	-0.097	0.016
	2.142	0.256	0.182	0.285	0.213	0.193
p_{t-4}	0.0238	0.184	0.077	0.198	0.003	-0.008
	1.874	0.146	0.169	0.22	0.2	0.181
Constant	56.36	-8.315**	1.461	-3.059	-1.704	-2.967
	40.04	3.22	4.043	4.746	4.718	2.08
Observations	46	46	46	46	46	46
R-squared	0.49	0.972	0.97	0.896	0.926	0.985
Autocorrelation	NO	NO	NO	NO	NO	NO
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	YES	YES	NO	NO
Prediction strategy	OBSTINATE	ADAPTIVE	OBSTINATE	NAIVE	NAIVE	NAIVE

Table 18: Individual estimation for Group 6 - Treatment 1

	1	2	3	4	5	6
p^e_t	0.441***	-0.116	0.020	0.145	0.227	0.627***
	0.155	0.161	0.141	0.158	0.164	0.168
p^e_{t-1}	-0.077	0.22	0.222*	0.017	-0.072	0.421*
	0.123	0.167	0.126	0.184	0.182	0.212
p^e_{t-2}	-0.08	0.006	0.360***	-0.083	-0.204	-0.299
	0.096	0.154	0.121	0.183	0.173	0.242
p^e_{t-3}	-0.013	-0.012	0.217	0.036	-0.047	0.193
	0.085	0.041	0.135	0.045	0.094	0.208
p_{t-1}	0.777***	0.861***	0.519**	0.803***	1.208***	0.252
	0.159	0.183	0.226	0.253	0.205	0.372
p_{t-2}	0.221	0.689***	0.146	0.471	-0.041	0.101
	0.207	0.219	0.24	0.28	0.273	0.385
p_{t-3}	-0.049	-0.431**	-0.25	-0.029	-0.118	0.044
	0.175	0.162	0.226	0.239	0.207	0.314
p_{t-4}	-0.171	-0.24	-0.162	-0.353**	-0.023	-0.325
	0.128	0.158	0.163	0.166	0.159	0.219
Constant	-3.173	1.647	-4.933	-0.504	4.583	-0.924
	3.579	3.089	5.297	4.722	3.573	9.29
Observations	46	46	46	46	46	46
R-squared	0.931	0.932	0.864	0.865	0.904	0.925
Autocorrelation	NO	NO	NO	NO	NO	NO
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	NO	NO	YES
Prediction strategy	ADAPTIVE	AR(3)	ADAPTIVE	AR(4)	NAIVE	OBSTINATE

Table 19: Individual estimation for Group 1 - Treatment 2

	1	2	3	4	5	6
p_t^e	0.504***	0.222	0.316*	-0.2	0.508***	0.921***
	0.139	0.16	0.165	0.137	0.163	0.169
p_{t-1}^e	-0.029	0.074	0.290**	1.212***	-0.233	0.182
	0.162	0.134	0.112	0.321	0.184	0.253
p_{t-2}^e	-0.004	0.272**	-0.112	0.782*	-0.061	-0.505**
	0.162	0.119	0.126	0.394	0.115	0.232
p_{t-3}^e	0.360***	-0.106	0.136***	-0.605***	0.059	0.247*
	0.132	0.096	0.037	0.17	0.075	0.131
p_{t-1}	0.741***	0.784***	1.006***	-4.816**	0.579***	0.497***
	0.133	0.091	0.057	1.954	0.149	0.121
p_{t-2}	0.306*	0.206	-0.312*	-3.278	-0.189	0.247
	0.156	0.156	0.17	2.182	0.159	0.151
p_{t-3}	-0.476***	-0.339**	-0.442***	4.899***	0.003	-0.503***
	0.141	0.129	0.111	1.189	0.196	0.107
p_{t-4}	-0.312**	-0.081	-0.007	2.743**	0.095	-0.158
	0.122	0.126	0.145	1.113	0.154	0.107
Constant	-5.674	-1.561	8.172**	22.71	15.80**	4.35
	6.056	4.414	3.611	38.75	7.692	5.259
Observations	46	46	46	46	46	46
R-squared	0.798	0.888	0.954	0.646	0.643	0.869
Autocorrelation	NO	NO	NO	NO	NO	NO
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	NO	NO	NO
Prediction strategy	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE

Table 20: Individual estimation for Group 2 - Treatment 2

	1	2	3	4	5	6
p_t^e	0.300*	0.750***	0.646***	0.005	0.578***	0.021
	0.169	0.166	0.161	0.109	0.164	0.148
p_{t-1}^e	0.113	-0.591**	0.132	0.047	0.134	-0.115
	0.119	0.279	0.205	0.096	0.184	0.143
p_{t-2}^e	0.261**	0.421	-0.311	-0.181**	0.027	0.297**
	0.12	0.286	0.211	0.078	0.158	0.117
p_{t-3}^e	-0.109	-0.237	0.119	0.044	0.065	0.055
	0.115	0.239	0.171	0.058	0.056	0.063
p_{t-1}	-0.017	0.916	0.563	0.838***	0.685***	0.732***
	0.257	1.708	0.5	0.062	-0.044	0.1
p_{t-2}	-1.359***	-0.82	-0.3	0.062	-0.258*	-0.087
	0.297	1.566	0.606	0.107	0.131	0.166
p_{t-3}	1.384***	0.0851	-0.47	-0.191*	-0.216*	0.251
	0.36	1.721	0.567	0.097	0.126	0.162
p_{t-4}	0.122	0.0415	0.323	0.118	-0.00244	-0.344***
	0.333	1.092	0.414	0.0719	0.11	0.116
Constant	20.81*	27.14	19.84	17.45***	-0.906	12.81
	11.54	46.44	20.72	4.643	4.099	7.716
Observations	46	46	46	46	46	46
R-squared	0.666	0.401	0.49	0.928	0.955	0.801
Autocorrelation	NO	NO	NO	NO	NO	NO
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	NO	NO	NO
Prediction strategy	ADAPTIVE	OBSTINATE	OBSTINATE	ADAPTIVE	ADAPTIVE	ADAPTIVE

Table 21: Individual estimation for Group 3 - Treatment 2

	1	2	3	4	5	6
p^e_t	0.327**	0.698***	0.103	0.417**	0.044	1.119***
	0.152	0.15	0.111	0.156	0.166	0.103
p^e_{t-1}	0.637***	-0.523***	0.088	0.124	0.305	-0.558***
	0.123	0.167	0.118	0.169	0.231	0.128
p^e_{t-2}	-0.038	0.165	-0.082	0.103	-0.179	0.0234
	0.127	0.169	0.123	0.179	0.222	0.117
p^e_{t-3}	-0.119**	-0.183*	0.068	0.274***	-0.049	0.0433
	0.047	0.106	0.097	0.099	0.164	0.073
p_{t-1}	0.803***	1.589***	0.640*	0.670***	1.633*	0.078
	0.082	0.239	0.335	0.109	0.84	0.122
p_{t-2}	-0.08	0.5	0.507*	-0.033	0.33	-0.079
	0.145	0.301	0.3	0.13	0.858	0.115
p_{t-3}	-0.575***	-1.209***	-0.408	-0.359***	-0.373	0.218
	0.093	0.208	0.302	0.125	0.835	0.134
p_{t-4}	0.020	-0.238	0.032	-0.17	-0.311	-0.0361
	0.126	0.27	0.275	0.117	0.55	0.113
Constant	1.52	11.10**	3.215	-1.449	-27.62**	11.68***
	2.542	4.586	6.708	2.592	12.36	2.739
Observations	46	46	46	46	46	46
R-squared	0.962	0.892	0.76	0.981	0.789	0.96
Autocorrelation	NO	NO	NO	NO	NO	NO
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	YES	NO	NO
Prediction strategy	ADAPTIVE	ADAPTIVE	AR(2)	ADAPTIVE	NAIVE	OBSTINATE

Table 22: Individual estimation for Group 4 - Treatment 2

	1	2	3	4	5	6
p^e_t	0.609***	0.809***	0.382**	0.624***	0.540***	-0.089
	0.159	0.165	0.162	0.164	0.104	0.152
p^e_{t-1}	0.184	-0.667*	-0.010	-0.357**	0.024	0.006
	0.187	0.359	0.164	0.145	0.109	0.135
p^e_{t-2}	0.027	0.397	0.239	0.484***	0.221**	-0.181*
	0.14	0.292	0.152	0.172	0.093	0.095
p^e_{t-3}	0.057	-0.239	-0.4	-0.181*	0.084	-0.037
	0.07	0.188	0.108	0.103	0.0813	0.059
p_{t-1}	0.523***	2.787	0.861***	1.394***	0.917***	0.701***
	0.071	1.896	0.155	0.193	0.081	0.226
p_{t-2}	-0.039	-2.194*	-0.116	-0.588***	-0.523***	0.693**
	0.113	1.154	0.199	0.199	0.102	0.266
p_{t-3}	-0.238**	-0.141	-0.218	-0.474**	-0.207*	-0.373
	0.088	1.26	0.219	0.2	0.115	0.222
p_{t-4}	-0.103	0.858	-0.14	0.069	-0.005	0.257
	0.077	0.885	0.182	0.198	0.082	0.191
Constant	-0.936	-37.94**	3.245	1.554	-2.889**	1.995
	1.123	18.02	2.286	1.73	1.206	2.6
Observations	46	46	46	46	46	46
R-squared	0.992	0.784	0.96	0.976	0.989	0.942
Autocorrelation	YES	YES	YES	NO	NO	NO
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	NO	NO	NO
Prediction strategy	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE	ADAPTIVE

Table 23: Individual estimation for Group 5 - Treatment 2

	1	2	3	4	5	6
p_t^e	0.559***	0.244	0.463***	0.449***	0.127	0.524***
	0.161	0.168	0.149	0.112	0.11	0.167
p_{t-1}^e	0.188	0.12	-0.134	0.069	0.725***	-0.099
	0.164	0.169	0.14	0.103	0.115	0.196
p_{t-2}^e	0.031	-0.059	-0.096	0.203**	0.034	0.077
	0.159	0.132	0.065	0.079	0.091	0.194
p_{t-3}^e	0.029	0.069	0.066	-0.009	-0.065	-0.011
	0.13	0.0541	0.049	0.057	0.093	0.129
p_{t-1}	0.600***	1.055***	1.048***	0.575***	0.178	1.019***
	0.15	0.071	0.158	0.12	0.181	0.11
p_{t-2}	-0.343*	-0.23	0.106	0.027	-0.077	-0.023
	0.178	0.171	0.224	0.167	0.199	0.203
p_{t-3}	-0.043	-0.197	-0.239	0.022	0.024	-0.288
	0.186	0.167	0.176	0.136	0.139	0.182
p_{t-4}	-0.024	0.002	-0.221*	-0.349***	0.033	-0.216
	0.12	0.135	0.122	0.099	0.13	0.144
Constant	0.464	-0.047	0.582	1.094	2.173*	1.105
	0.953	0.509	1.097	1	1.105	1.209
Observations	46	46	46	46	46	46
R-squared	0.996	0.999	0.995	0.997	0.994	0.996
Autocorrelation	NO	NO	NO	NO	NO	YES
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	NO	NO	NO
Prediction strategy	ADAPTIVE	NAIVE	ADAPTIVE	ADAPTIVE	OBSTINATE	ADAPTIVE

Table 24: Individual estimation for Group 6 - Treatment 2

	1	2	3	4	5	6
p_t^e	-0.109	-0.054	0.082	-0.730***	0.105	0.827***
	0.155	0.153	0.168	0.087	0.167	0.163
p_{t-1}^e	0.215	-0.054	0.179	-0.436***	-0.203	0.228
	0.137	0.151	0.153	0.090	0.146	0.208
p_{t-2}^e	-0.109	-0.230**	0.025	-0.325***	-0.005	-0.236
	0.139	0.101	0.132	0.097	0.141	0.165
p_{t-3}^e	-0.195**	0.01	0.024	-0.273***	0.013	-0.0003
	0.089	0.0948	0.090	0.098	0.072	0.099
p_{t-1}	1.386***	0.927***	1.119***	0.439*	1.141***	0.429***
	0.152	0.226	0.155	0.255	0.087	0.091
p_{t-2}	-0.021	0.673**	0.146	0.437*	-0.145	-0.003
	0.261	0.276	0.225	0.247	0.204	0.112
p_{t-3}	-0.406*	0.087	-0.701***	0.969***	0.082	-0.180**
	0.235	0.245	0.219	0.268	0.195	0.084
p_{t-4}	0.265	-0.334*	0.123	0.925***	0.002	-0.05
	0.192	0.185	0.215	0.179	0.141	0.096
Constant	-2.086*	-1.902	0.709	0.125	0.989	-0.262
	1.076	1.453	0.953	1.278	0.661	0.823
Observations	46	46	46	46	46	46
R-squared	0.992	0.985	0.994	0.989	0.998	0.998
Autocorrelation	NO	NO	NO	YES	NO	NO
Unit Root (p)	NO	NO	NO	NO	NO	NO
Unit Root (p^e)	NO	NO	NO	NO	NO	YES
Prediction strategy	ADAPTIVE	ADAPTIVE	AR(2)	ADAPTIVE	NAIVE	ADAPTIVE