Università Politecnica delle Marche
Dipartimento di Scienze Economiche e Sociali

Adaptive Expectations with Correction Bias: Evidence from the lab

Annarita Colasante, Antonio Palestrini, Alberto Russo, Mauro Gallegati

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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: in the first one the fundamental value is constant, while in the second the fundamental price increases over repetitions. The aim of this work is twofold: on the one hand, based on the finding of the recent literature about expectations, we investigate whether agents make their prediction according to adaptive expectation instead of rational one. On the other hand, we test the accuracy of the aggregate forecasts compared with the individual ones. Results show that there is heterogeneity both within and between groups. Agents follow adaptive rules to predict future prices and this implies that, in the majority of the cases, they coordinate on a price different from the fundamental value. We find that there is a *collective rationality* instead of *individual rationality*. Indeed, each player makes systematic error forecast but, at the aggregate level, there are no significant forecasting errors in the case in which the fundamental value is constant. In the context of increasing fundamental value, players are able to capture the trend but they underestimate that value.

JEL Class.: C92, G12, G17
Keywords: Expectation, Experiments, Bounded rationality

Indirizzo: Dipartimento di Scienze Economiche e Sociali, Università Politecnica delle Marche. E-mail: a.colasante@univpm.it, a.palestrini@univpm.it, alberto.russo@univpm.it, mauro.gallegati@univpm.it

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1 Introduction

The recent financial crisis highlighted the importance of agents' behavior in the financial market and, in turn, the impact of individual financial choices on the real economy. Agents make their choices of everyday life based on their expectations. As suggested in Assenza *et al.* (2014), we should think of an economy as an expectation feedback mechanism, that is expectations influence individual decisions and these choices define the realization of the main macro or financial variables.

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, based on two sources of information: *i*) the past realization of the asset price in the market, which is function of the average individual expectations, and *ii*) the current information about the mean dividend and the current interest rate. We run two different treatments in which the unique difference is the fundamental price. Each treatment involves six groups of six players. In the Treatment 1 the fundamental price is constant and equal to 60, while in Treatment 2 the fundamental price increases over repetitions. The aim of this work is to understand how agents form their expectation about future prices and we try to understand if, also in absence of communication, the aggregate expectations are unbiased. The key difference with respect to the existing literature is that we analyze expectation formation in a context characterized by price instability. We take into account a dividend with a drift with the goal of analyzing the mechanism of the *error correction bias.* This theoretical approach is based on the evidence that Rational Expectations are a mean-zero expectation schemes. On the contrary, even though adaptive expectation schemes often seem to be a good representation of

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actual agents' behaviors in empirical analysis (see Chow (2011)), this scheme does not seem to satisfy the unconditional mean-zero requirements, i.e., the necessary condition for rationality. The idea behind the error correction is to include a term in the adaptive expectation scheme in order to fulfill the requirement of zero unconditional mean. We discuss this approach in more detail in Section 2.

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, each player must predict the price that, in turn, depends on the expectations of other players. This means that players should forecast an endogenous price and, to do so, they must be able to infer the predictions of other participants.

The Rational Expectation Hypothesis (REH), firstly introduced by Muth (1961) and then analyzed in depth by Lucas Jr and Prescott (1971), is the bearing-wall of the mainstream approach. According to this hypothesis, agents make no systematic errors in the forecasting, taking into account the entire set of available information[1]. Muth take into account the early work of Galton (Galton (1907)) in which he pointed out that individual expectations are wrong but aggregating individual predictions give unbiased expectations. Recent studies, based on both simulation and experimental evidence, show that this approach is often unrealistic, that is agents have not sufficient capabilities to make rational predictions (see for example (Sargent, 1993), Evans and Honkapohja (2001) and Branch (2004)). An alternative hypothesis is that agents form their expectation according to an adaptive rule, that is the forecast is a function of both past expectations and past realization.

The mainstream approach does not consider the adaptive expectation scheme appropriate to forecast models since it may not satisfy the necessary condition for rationality. This condition is based on the assumption that agents make not systematic predictions errors and, as a consequence, the errors unconditional mean is equal to zero. The increasing experimental evidence (Hommes (2011), Anufriev and Hommes (2012)) shows that individual make forecasting errors in predicting the future value of an assets or the price of a commodity. Moreover, it has been shown that a combination of different form of adaptive expectations rules produces a process which fits very well the experimental data.

[1]Muth based its analysis on 3 assumptions: 1) Information is scarce, and the economic system generally does not waste it. 2) The way expectations 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".

In this work we introduce the possibility to revise the classical adaptive expectation scheme in order to have the condition of zero unconditional mean. We propose a theoretical model to prove that, if we introduce a *bias correction parameters* in the baseline scheme, then the unconditional mean is equal to zero. Indeed, it can be proved that this correction does not alter the stability of the system but increases the volatility of variables with expectation introducing a trade off between volatility and bias that can be analyzed in the model validation step of an economic analysis.

The paper is organized as follows: in Section 2 we show the error correction approach, in Section 3 there is a description of the experiment and the main results. Expectations are analyzed in Section 4, while in Section 5 we check the error correction bias in our setting. Finally, Section 6 concludes while appendix A describes the experimental design.

2 Error correction mechanism

In this Section we show how the adaptive expectation scheme, under certain assumptions, should satisfy the rationality condition, i.e. zero unconditional mean. Usually people show behavior consistent with the *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 errors ($p_t^e - p_t$) in each period. The expected price, in $t+1$, can be written as

$$p_{t+1}^e = p_t^e + \lambda(p_t - p_t^e) \quad 0 < \lambda \leq 1 \tag{1}$$

or it can be rewritten as a linear combination of past realization and past prediction:

$$p_{t+1}^e = \lambda p_t + (1-\lambda)p_t^e \tag{2}$$

The formulation in Equation (1) suggests that agents make systematic forecasting error ($p_t - p_{t-1}^e$) and, moreover, agents include this error in their own future predictions. This implies that individual should underestimate (overestimate) the true value because of this mechanism of correction. Taking into account this definition, it is possible to assert that adaptive expectation schemes may generate a bias[2]. Adaptive expectations are *backward looking* because they take into account only past information to predict future values. For example, if agents use as an

[2]This is the reason to introduce in macroeconomic models rational expectations within the *determinate parametric space* (Blanchard and Kahn (1980)).

expectation of variable x_t the mean of past 3 periods

$$x^e_{t+1} = \frac{1}{3}(x_t + x_{t-1} + x_{t-2})$$

and the variable has a drift, say $\Delta x_{t+1} = d$, then the error/bias $\Xi_{t+1} = x^e_{t+1} - x_{t+1}$ is

$$\Xi_{t+1} = \frac{1}{3}((x_{t-2} + 2d) + (x_{t-2} + d) + x_{t-2}) - (x_{t-2} + 3d)$$

$$\Xi_{t+1} = (x_{t-2} + d) - (x_{t-2} + 3d) = -2d$$

We can note two things:

1. The bias is negative (expectation is below if variable trends up and above if trends down)

2. The bias has and order of magnitude comparable to the drift.

On the contrary, as discussed in the introduction, Galton's discovery suggests that agents *collectively and in simple situations* are able to estimate *unconditional* means.

This condition of a mean-zero error may be a problem in *adaptive learning schemes*, as the above simple example suggest, since it could produce agent's expectation that over or underestimates economics future variables; *i.e.*, with a non-zero bias.

To see the reason consider the time process of the error

$$\Xi_t = x^e_t - x_t = \lambda x_{t-1} + (1-\lambda)x^e_{t-1} - x_t \tag{3}$$

that, adding and subtracting x_{t-1} from the RHS and rearranging terms, may be written as

$$\Xi_t = x^e_t - x_t = (1-\lambda)[x^e_{t-1} - x_{t-1}] - \Delta x_t \tag{4}$$

with the following recursive AR(1) structure

$$\Xi_t = (1-\lambda)\Xi_{t-1} - \Delta x_t. \tag{5}$$

Now it is easy to see that even in situations in which the x_t variable follows a very simple deterministic process, $\Delta x_t = d$ (as it is the case in the Treatment 2 described in paragraph 3), the error process

$$\Xi_t = (1-\lambda)\Xi_{t-1} - d \tag{6}$$

does not go to zero but converges to $\Xi = -d/\lambda$.

Furthermore, many econometric studies show that even in situations in which the adaptive expectation process seems a reasonable representation of agents' behavior (Chow (2011)), the parameter λ may be time variant.

What agents have to do in order to correct for the bias? Following the analysis in Palestrini and Gallegati (2015), consider the following generalization of the adaptive scheme

$$x^e_{t+1} = \lambda_t x_t + (1 - \lambda_t)x^e_t + \zeta_t. \tag{7}$$

Equation (7) generalizes the standard adaptive scheme in two respects: 1) It has a time variant learning parameter λ_t following an *i.i.d.* random process (between 0 and 1) with mean $1-\lambda$, and 2) there is a bias correction parameter, ζ.

As before, we can compute the error process

$$\Xi_{t+1} = x^e_{t+1} - x_{t+1} = \lambda_t x_t + (1 - \lambda_t)x^e_t + \zeta_t - x_{t+1} \tag{8}$$

and add and subtract x_t to the RHS,

$$\Xi_{t+1} = -(1 - \lambda_t)x_t + (1 - \lambda_t)x^e_t + \zeta_t - \Delta x_{t+1} \tag{9}$$

that simplifies to[3]

$$\Xi_{t+1} = (1 - \lambda_t)\Xi_t + \zeta_t - \Delta x_{t+1}. \tag{10}$$

Equation (10) is a stochastic random difference process that has a stationary solution provided that the stability conditions are met[4].

If unconditional expectation exists we can take the unconditional expectation operator in both sites and equate to zero searching for a solution with $E[\Xi_{t+1}] = 0$, that is

$$(1 - \lambda)0 + \zeta_t - E[\Delta x_{t+1}] = 0. \tag{11}$$

Solving for ζ_t we get

$$\zeta_t = E[\Delta x_{t+1}], \tag{12}$$

showing that, to perfectly correct for the bias, agents individually (time series dimension) or collectively (cross series dimension) have to estimate the drift of the economic variable for which there are expectations.

Summing up, if agents are able to estimate the trend of the variable, they should take into account this information to form their expectations. Including an unbiased estimated value of the drift in the expectation process, i.e. the term ζ_t, leads to unbiased forecast also in the case of adaptive expectation.

[3]In case in which $\lambda_t = 1$ (static expectation), the error process is, obviously, $\Xi_{t+1} = \zeta_t - \Delta x_{t+1}$.

[4]See Babillot *et al.* (1997), and Bhattacharya and Majumdar (2007) pg. 304.

3 Learning to forecast in a financial market

We run a *Learning to Forecast* experiment based on *Asset Price Model* (Campbell *et al.* (1997)) in order to understand the mechanism of expectation formation in a financial market. In this model there are 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 $p^f = \frac{\bar{d}}{r}$.

Following the experimental design approach proposed in Hommes *et al.* (2005), we include stabilizing fundamentalist robots. 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 realization and about their profit. From the third repetition, participants are able to see the realized price until period $t-1$ and their own forecast and 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.

The existing literature about the analysis of expectation in the lab should be divided into three main categories. The first, proposed by Smith *et al.* (1988), consists in a double auction market in which players buy and sell assets. This kind of experiment, proposed also in Noussair *et al.* (2001), Dufwenberg *et al.* (2005) and Kirchler (2009), show that players usually follow an adaptive rule to form their forecast and that a lot of bubbles emerge if players have no experience in this setting. The main disadvantage of this method is that expectation are inferred and not directly observable. The pioneer work of the second category is that by Dwyer *et al.* (1993). In this experiment players predict the future price of an exogenous series, i.e. the time series of the asset price is generated ex ante and the individual predictions do not influence the realization of the series. Bloomfield and Hales (2002) and Dwyer *et al.* (1993) propose an experiment in which the series is a random walk, while Hey (1994) proposed an autoregressive process. Results in this kind of analysis are mixed, meaning that some players behave rationally while other use an adaptive expectation scheme. The limitation of this setting is related to the independence of individual expectations and the realization of the future price. Finally, the third category includes the so-called Learning to Forecast experiment proposed by Marimon *et al.* (1993) in which the task is to forecast the future price of an endogenous series. This means that the realized price is a function of the individual forecasts, i.e. the market is an expectations feedback mechanism. There are a lot of contributions in this field both using negative (Hommes *et al.* (2007), Bao *et al.* (2012)) and positive (Hommes *et al.* (2005), Bottazzi *et al.* (2011), Anufriev and Hommes (2012)) feedback system. Evidence from these experiments suggest that, in general, there is a strong coordination in

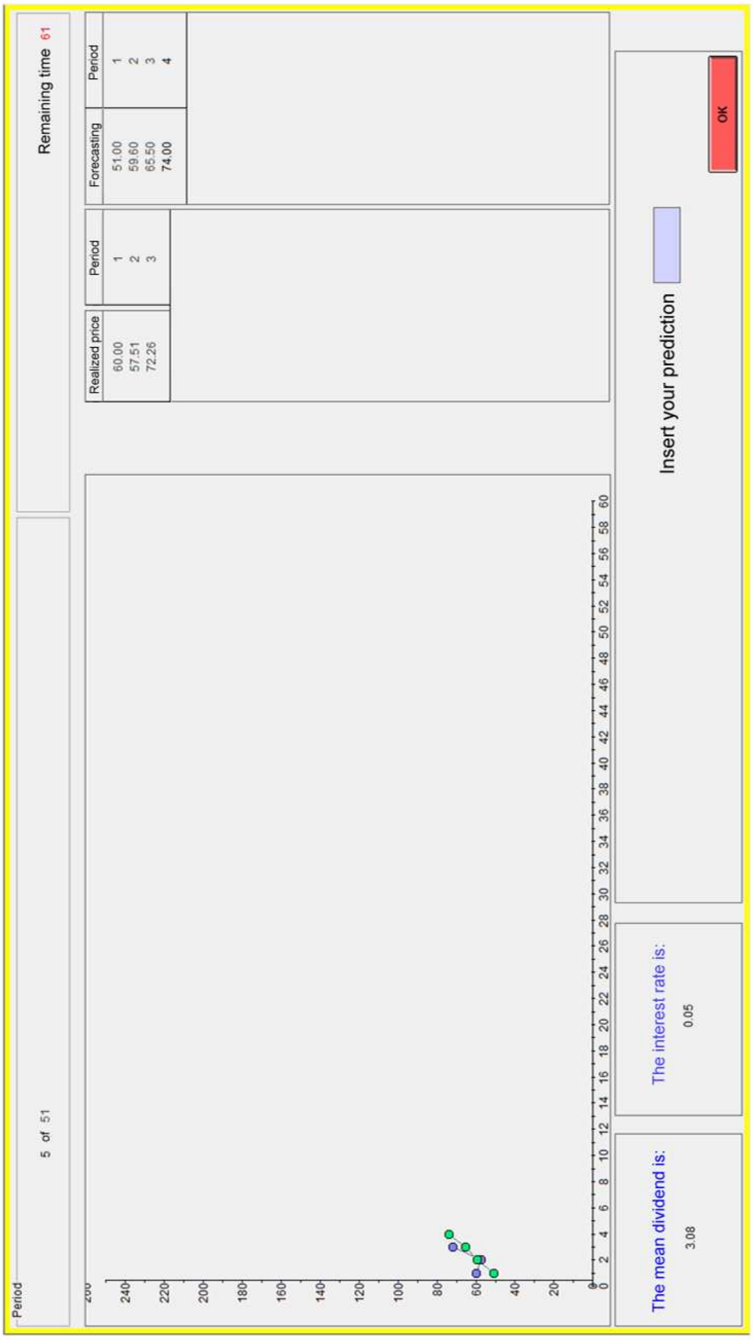


Figure 1: The screen-shot of the experiment in Treatment 1

the group and that there is a convergence to the rational equilibrium only if we consider negative feedback. See Hommes (2014) for an exhaustive review of the main results of the Learning to Forecast experiments.

We run a Learning to Forecast experiment in which we consider two different treatments: *Treatment 1* in which the mean dividend, and so the fundamental price, is constant over repetition; *Treatment 2* in which the mean dividend follows an increasing linear trend.

Participants to the experiment are divided in groups of six and they receive only qualitative information. Players know that they are advisors of a pension fund and this funds take 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, and they are informed about the mean dividend and the interest rate. Taking into account these information, agents could compute, and so predict, the fundamental price. Moreover, they also know that the higher their prediction the higher the realized price will be.

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 agent, in each period, chooses how much to invest in the risky asset according to a maximization of her own future expected wealth. This means that the demand for the risky asset derives from the solution of the problem. By equating domand and supply we obtain the equilibrium price given by:

$$p_t = \frac{1}{1+r}\left[\bar{p}^e_{t+1} + \bar{d}_t + \varepsilon_t\right] \tag{13}$$

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 :

$$p_t = \frac{1}{1+r}\left[(1-n_t)\bar{p}^e_{t+1} + n_t p^f_t + \bar{d}_t + \varepsilon_t\right] \tag{14}$$

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 share of robot traders[5] is a function of the absolute distance between the

[5] 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.

realized market price and the fundamental price. According to Hommes *et al.* (2005), the share of this traders is defined by the following equation:

$$n_t = 1 - exp\left(-\frac{1}{200}\left|p_{t-1} - p_f\right|\right) \tag{15}$$

According to Equation (15), 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[6].

Following the approach of Hommes (2013), the payoff function depends on the distance between the individual prediction and the realized market price, as in equation (16):

$$\begin{cases} \pi_{it} = \left(1 - \frac{(p_t - p^e_{it})^2}{7}\right) & if\, |p_t - p^e_{it}| < 7 \\ \\ \pi_{it} = 0 & \text{otherwise} \end{cases} \tag{16}$$

The experiment involves in total 72 participants (37 female), half of them plays in Treatment 1. In both treatments we randomly allocate players in group of 6. We consider $r = 5\%$ and the small shock is such that $\varepsilon \sim N(0, 0.25)$. In Treatment 1 the mean dividend is constant $\bar{d}$ and so the fundamental price is equal to $p^f = 60$. In Treatment 2 the mean dividend increases step-by-step by 0.02. This means that $\bar{d}_t \in [3, 4]$ and 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 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 depends on the final 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[7]. In Appendix there are the summary of the instruction and the average payment per group.

[6]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. Moreover, how bubbles in the financial markets emerge are a very interesting topic which is out of our analysis.

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

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

On the left panel of Figure 2, Figure 3, Figure 4 and Figure 5 we observe agents prediction with respect to the realized price. On the right panel we show the predictions after period 15, i.e. after the learning period[8].

Remember that, under the Rational Expectation Hypothesis, the individual prediction should be equal to the value of p^f which is represented by the continuous gray line in all the Figures. At a glance, in both treatments none of the groups converges to the fundamental price. We run a t-test and a Wilcoxon test to investigate if the difference between the fundamental value and the realized price is statistically significant. Results are shown in Table 1. Both the parametric and non parametric tests confirm that the realized price is different from the fundamental value in all groups.

In Treatment 1 two groups converge quickly to an equilibrium price very close to the fundamental value. Three groups overestimate the fundamental price and Group 4 converge very slowly to a price near the fundamental one. In Treatment 2 agents make their predictions following the increasing trend of the fundamental price, but they systematically underestimate the magnitude of the drift. In particular, Group 5 and Group 6 show the highest and quickest coordination, and the series of realized prices in Group 5 is very close to the fundamental price. In Group 1, Group 2 and Group 3 there are at least one player which make odds predictions also after the learning phase, i.e. also after the twentieth period. Except for these anomalous predictions, it seems that there is a good level of coordination.

From the graphical inspection a certain degree of heterogeneity both within and between groups emerges. According with Yalçın (2010), one of the assumption of the *Efficient Market Hypothesis* (Fama (1970)) is that agents have rational expectations and they are able to predict the fundamental price. Our results show the failure of convergence to the fundamental price and different individuals'

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

prediction strategies. These results should be explained by two reasons. First, in our setting there is a positive feedback system and this means that individual strategies are *strategic complements*, i.e. if player i increases her own prediction, player j has an incentive to follow the same strategy (Bulow *et al.* (1985), Camerer and Fehr (2006)). Second, we consider a payoff function which depends on the realized price instead of on the fundamental price.

As Haltiwanger and Waldman (1985) and Haltiwanger and Waldman (1989) pointed out, players have different capabilities to form expectations. Indeed, some players, *"the sophisticated agents"*, are able to compute the fundamental value, while other players use rules of thumb to make their predictions. In a context characterized by strategic complements, the share of rational agents are crowed out by the bounded rational agents. This means that agents who have the capability to compute the fundamental price adjust their behavior in order to maximize their profits and there is no incentive for a rational players to predict the fundamental value when the others are going away from it.

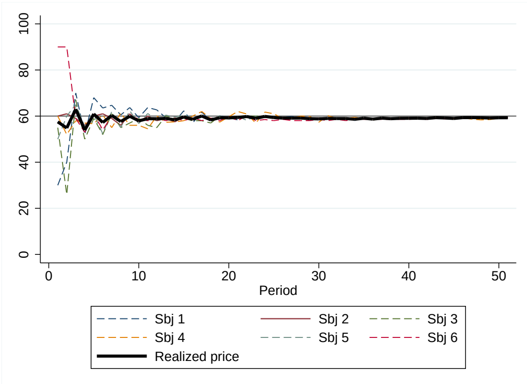
Two key features emerges from this eye inspection. First, there is a strong coordination among players despite the absence of any form of communication[9]. We analyze in detail this aspect in the next Section. Second, players face the same situation and start the game with the same information but reach very different equilibria. This means that the common knowledge of the dividend, the interest rate and the market price is not a sufficient condition to induce the same expectation among agents and so, there is heterogeneity both within and between groups.

4 Individual versus aggregate expectations

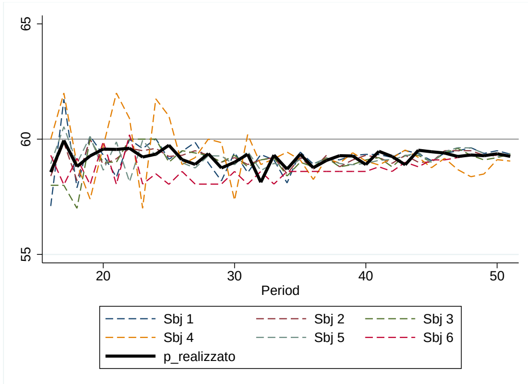
In the early '900, Galton (1907) observed two phenomena emerging from a competition. The first observation concerns the concept called *The Wisdom of Crowd*, that is the median of the collective forecast is equal to the realized value. This is the cornerstone of the REH proposed by Muth (1961). Even though he does not refer directly to the Galton's work, Muth formalized the idea that heterogeneous uncorrelated expectations may be represented by aggregated expectation with bias on average equal to zero. The second observation is that the distribution of the forecast is skewed with respect to the median.

Lucas Jr and Prescott (1971) give the definition of *Individual Rational Expectation* which is quite different from the collective rational expectations. According to Lucas Jr and Prescott (1971), each agent is able to predict without systematic

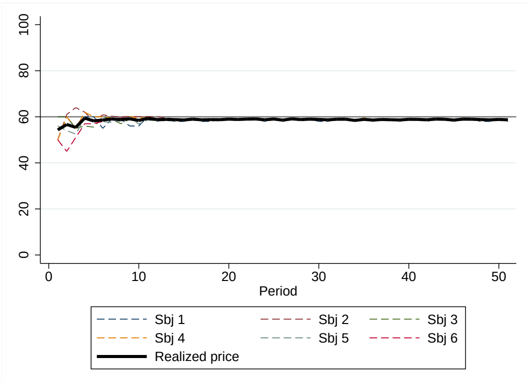
[9]For the sake of completeness we run a Wilcoxon test for each individual series in order to compare the difference between each pair of agents and the difference between individual predictions and the realized price. Results are shown in Appendix B.



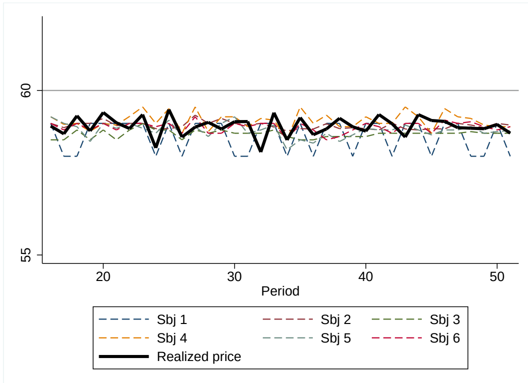
(a) Group 1



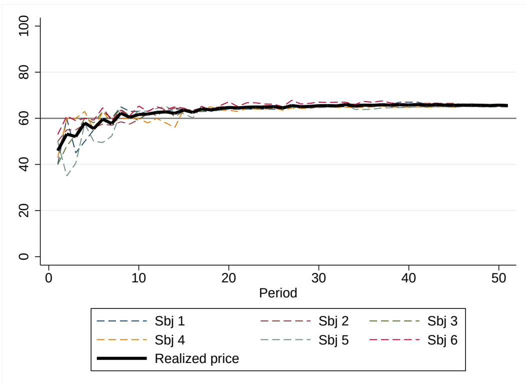
(b) Group 1



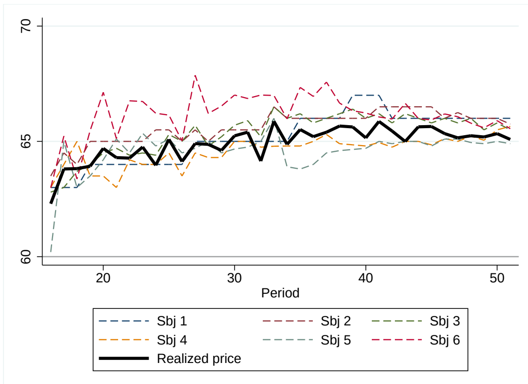
(c) Group 2



(d) Group 2

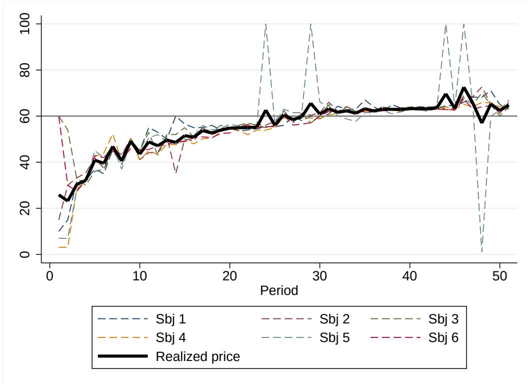


(e) Group 3

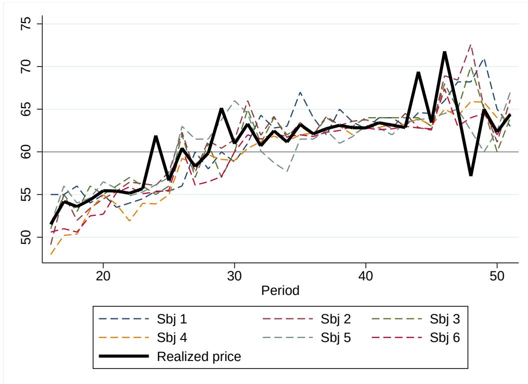


(f) Group 3

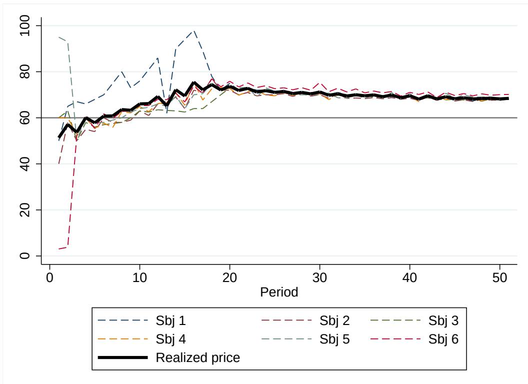
Figure 2: Individual prediction and fundamental price for each group (Treatment 1)



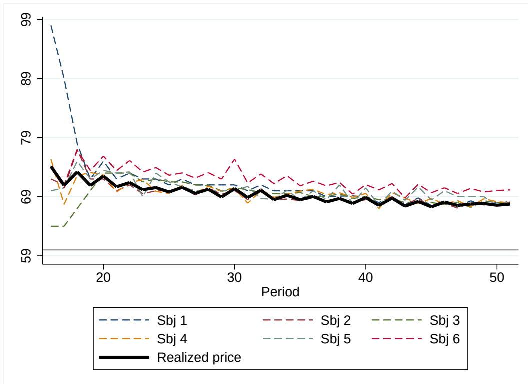
(a) Group 4



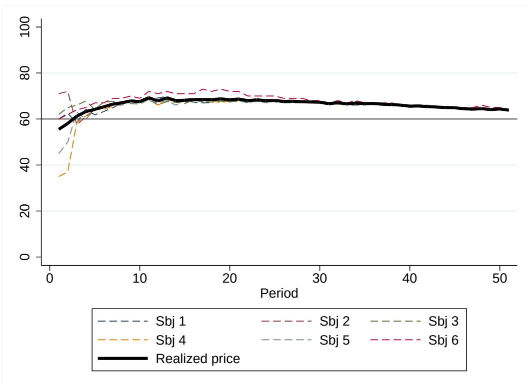
(b) Group 4



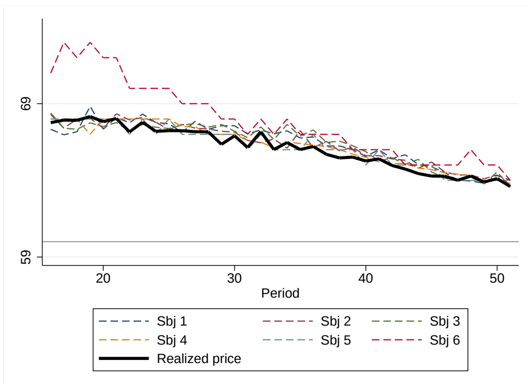
(c) Group 5



(d) Group 5

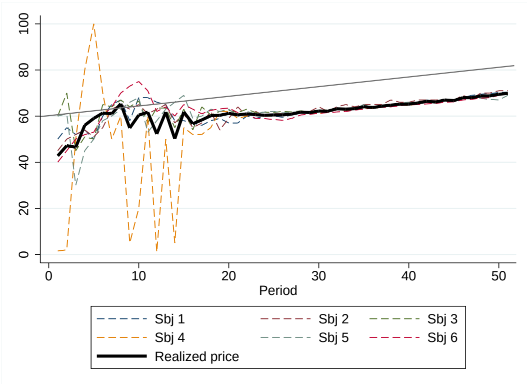


(e) Group 6

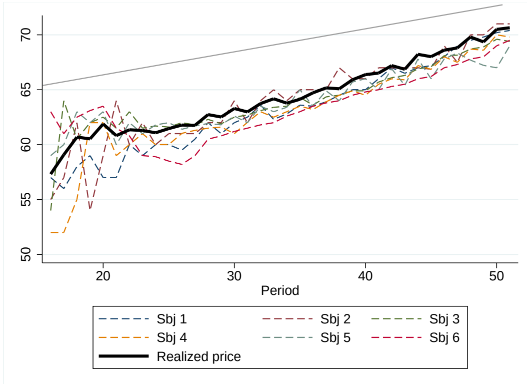


(f) Group 6

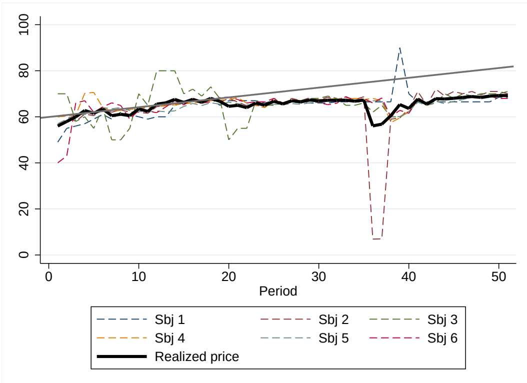
Figure 3: Individual prediction and fundamental price for each group (Treatment 1)



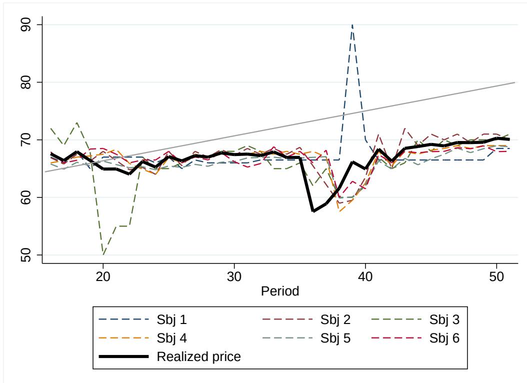
(a) Group 1



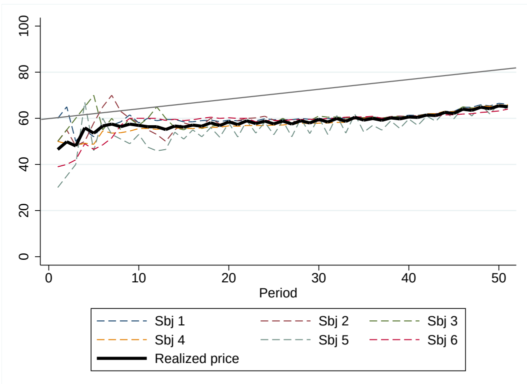
(b) Group 1



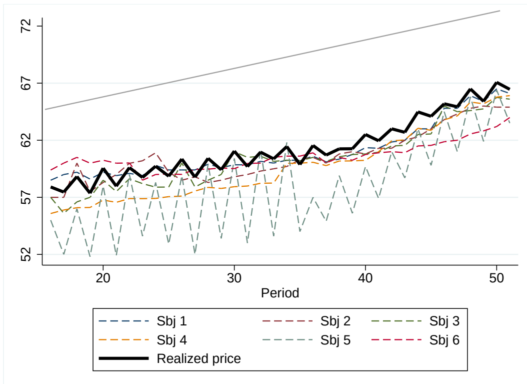
(c) Group 2



(d) Group 2

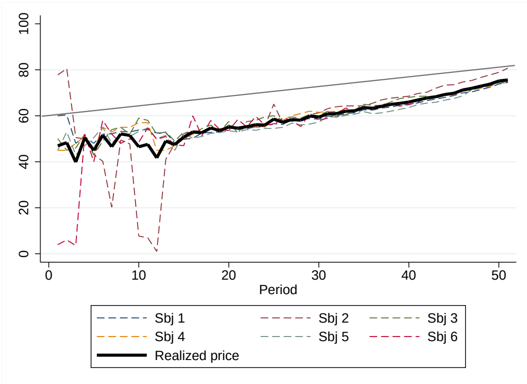


(e) Group 3

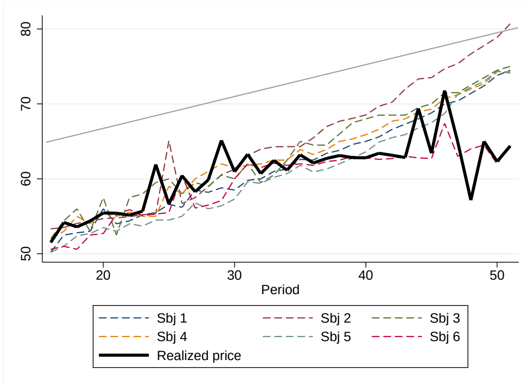


(f) Group 3

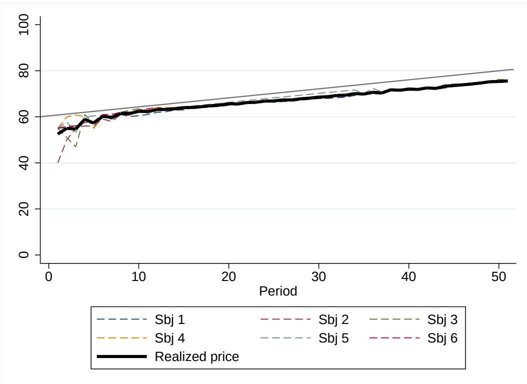
Figure 4: Individual prediction and fundamental price for each group (Treatment 2)



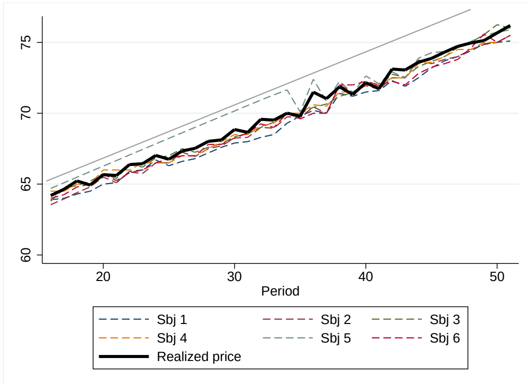
(a) Group 4



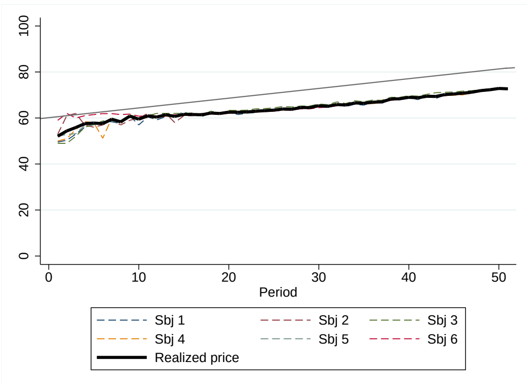
(b) Group 4



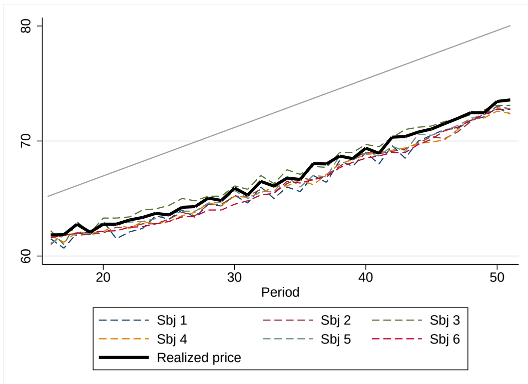
(c) Group 5



(d) Group 5

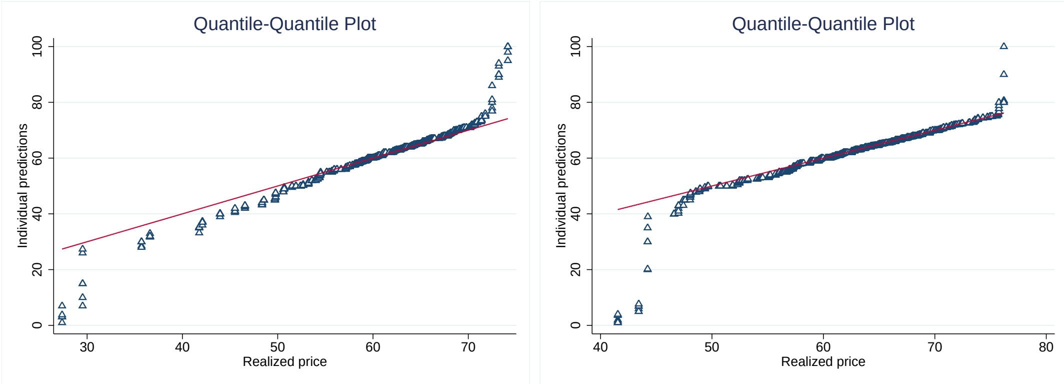


(e) Group 6



(f) Group 6

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



(a) Treatment 1

(b) Treatment 2

Figure 6: Quantile plot of the individual price by treatment

errors the future value of a variable because they take into account all the feasible information at time t, i.e.

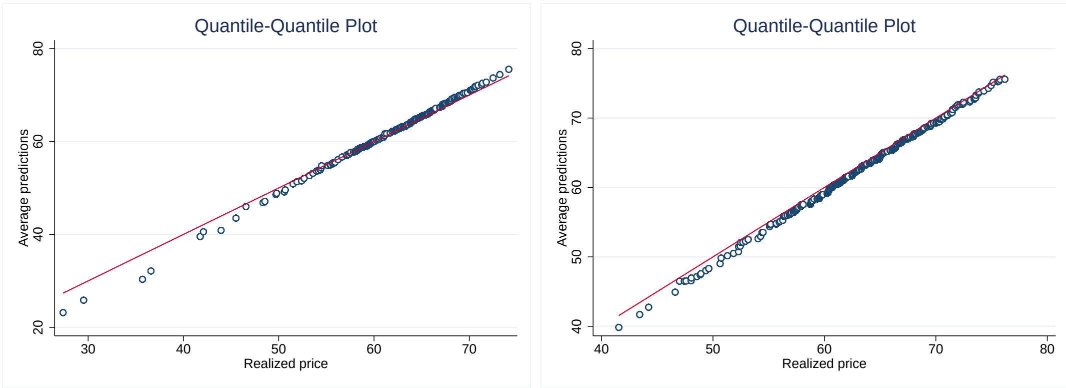
$$p^e_{t+1} = E(p_{t+1}|\Omega_t) = E_t p_{t+1}$$

where Ω_t is the information set. The key feature of this approach is that the expected value of future forecasting error is equal to zero:

$$E_t(p_{t+1} - E_t p_{t+1}) = 0$$

Figure 6 shows the comparison of the probability distribution of the realized price and the predicted price in each treatment, and Figure 7 shows the same relation between the realized price and the average price of groups. The *q-q plot* is a useful tool to compare the distributions of two variables. If the two distributions being compared are similar, the points in the plots will approximately lie on the bisector. It easy to see that in the case of individual predictions (Figure 6) the plot highlights a linear relation between the variables but the points are not perfectly aligned on the bisector, especially in Treatment 1. On the other hand, in the distribution of the average predictions is close to that of the realized price, especially concerning Treatment 2.

As we said, we should consider *individual rationality*, as suggested by Lucas Jr and Prescott (1971), or the concept of *collective rationality* which is the foundation of the Galton's conjecture. The former thought suggests that each agent can overestimate or underestimate the objective variable, in our cases the market price, but the average of the individual forecasting error should be equal to zero. Conversely, the latter concept suggests that each individual make systematic forecasting errors but, if we consider the average aggregate predictions, we are able to obtain



(a) Treatment 1

(b) Treatment 2

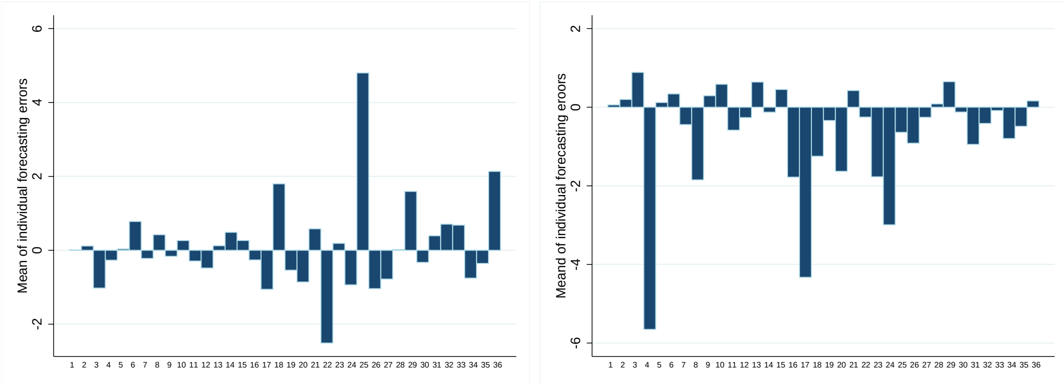
Figure 7: Quantile plot of the average price by treatment

unbiased forecasts. We compute the average of the individual forecasting error for all periods to test the hypothesis of individual rationality. Moreover, we compute the average forecasting errors of the group to confirms the Galton's hypothesis. Results are shown in Figure 8 and Figure 9, respectively.

Looking at Figure 8, we observe that some agents overestimate and others underestimate the realized price, but the mean value for each player is different from zero. This result discard the hypothesis of the individual rationality. In Figure 9 we show the difference between the average group forecast and the realized price. It is easy to see that these errors are close to zero. We test if the average errors with respect to the realized price are statistically different from zero running a t-test and a Wilcoxon test. Results are shown in Table 2. The test result highlights that the mean Treatment 1 is equal to zero, while the mean in Treatment 2 is significantly negative. Kirman (1993), in fact, suggests that it is an oversimplification to take a look at the individual behavior but we should consider the aggregate outcome which emerges from the agents' interactions. Moreover, Kirman (2010) and Chen and Yeh (2002) highlight that the rational equilibrium can be seen as an emergent property of a system with interactive bounded rational agents.

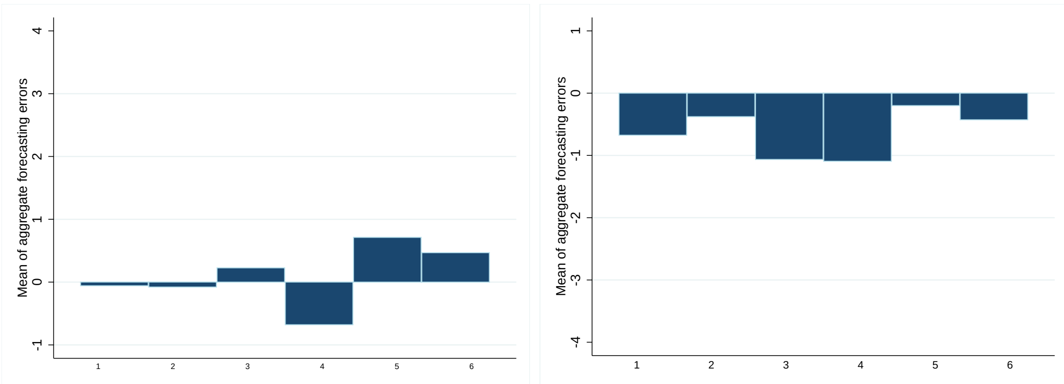
We can conclude that, in our sample, the Lucas' concept of rationality is not verified. Moreover, the concept of collective rationality, is true only in the case in which the variable to estimate is constant over time, while there is a bias also at the aggregate level if the value to estimate changes over time.

As stressed in the previous Section, there is a good level of coordination in almost all of the groups. As suggested in Kirman (2014), in some situation it is rational to be not fully rational. In our context this results in a situation in which is more convenient to "follow the crowd" instead to predict the fundamental price. This means that each agents try to understand the expectations of other players



(a) Treatment 1 (b) Treatment 2

Figure 8: Average of individual forecasting errors by treatment



(a) Treatment 1 (b) Treatment 2

Figure 9: Average of aggregate forecasting errors by treatment

Table 2: Average forecasting errors with respect to the realized price (t-test and Wilcoxon test).

	t-test			Wilcoxon	
	Mean	t	p-value	z	p-value
Treatment 1	0.098	0.9110	0.36	3.833	< 0.01
Treatment 2	-0.640	-5.177	< 0.01	-13.000	< 0.01

Table 3: Mean and standard errors of forecasts in Treatment 1

Groups	Average 1-10	Std.Dev.	Average 11-20	Std.Dev.	Average 21-30	Std.Dev.	Average 31-40	Std.Dev.	Average 41-51	Std.Dev.
1	58.31	9.35	59.02	1.66	59.25	0.91	58.93	0.38	59.19	0.28
2	57.80	3.42	58.83	0.46	58.89	0.29	58.76	0.31	58.83	0.29
3	56.65	6.88	63.23	1.87	64.99	0.88	65.67	0.88	65.72	0.57
4	37.19	12.92	51.16	4.24	58.89	8.19	62.57	1.54	64.57	10.81
5	59.44	13.81	71.01	7.81	71.33	1.45	69.65	1.11	65.53	1.06
6	63.65	6.84	68.50	1.69	67.87	0.94	66.51	0.61	64.79	0.62

Table 4: Mean and standard errors of forecasts in Treatment 2

Groups	Average 1-10	Std.Dev.	Average 11-20	Std.Dev.	Average 21-30	Std.Dev.	Average 31-40	Std.Dev.	Average 41-51	Std.Dev.
1	55.43	16.91	58.44	11.25	60.98	1.34	63.87	1.19	67.48	1.44
2	60.71	5.77	66.09	4.59	66.00	2.32	63.78	11.53	68.08	1.70
3	53.88	7.95	56.78	1.98	58.32	1.98	59.62	1.85	62.96	1.97
4	47.88	13.95	50.54	9.41	57.35	2.57	63.34	2.33	70.69	3.17
5	58.36	4.17	64.02	1.24	67.10	1.09	70.37	1.23	73.70	1.20
6	57.33	3.72	61.47	0.91	63.96	1.00	66.90	1.30	70.74	1.36

and try to coordinate in order to obtain more profits. We analyze the level of coordination in each group looking at the volatility of predictions during repetitions to investigate the process of individual learning. We split the entire series of 51 periods in different sub-samples of ten periods and then we compute these statistics in order to analyze if there is a convergence through the fundamental value and to examine the volatility of the process. Results are shown in Table 3 and Table 4.

Firstly, the volatility is higher in the second Treatment and this is due to the variability of the fundamental value. Except for few groups, i.e. Group 4 in Treatment 1 and Group 2 in Treatment 2 [10], we can observe a strong reduction of the volatility from the starting period to the end of the game. This means that players coordinate on a common strategy after, at least, 10 periods. This analysis confirm the Galton's statement about the accuracy of the aggregate predictions instead of the individual ones.

5 Is there evidence for the correction bias?

As mentioned in the previous Section, we can consider the individual rationality or the collective one. In general, 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 update and correct their forecast. This implies that agent 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

[10] The standard deviation of the price is strongly influenced by the very high and low predictions of one player in the group.

is (on average) correct. In our setting, if all agents are rational expectations, and since that the mean dividend and the interest rate are common knowledge, their predictions should be:

$$p_{it}^{e} = p^{f}$$

in each period. Within this framework, the possibility that a share of investors has imperfect information, or a lower "degree" of 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, 1978).

The analysis in the previous sections suggests that there is not evidence for rational expectations, neither individually nor collectively. 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*. Indeed, especially in Treatment 2, they systematically underestimate both the fundamental value and the realized price.

As pointed out, if players form their expectations using an adaptive scheme, they introduce a correction based on their own previous error. As in equation (1), agents assign the weight λ to their previous forecasting errors. This obviously implies that there is a correlation among individual forecasting errors. On the other hand, under the REH, since that the rationality condition holds, we should expect absence of correlation.

In order to test if there is serial independence of the forecasting errors we run the following regression:

$$\Xi_{it} = \beta_0 + \beta_1 \Xi_{it-1} + \varepsilon_{it}$$

where Ξ_{it} is the difference between the predicted and the realized price for each agent, *i.e.*, the individual forecasting error. Under the REH we should observe $\beta_1 = 0$. The estimation[11] results for each treatment are shown in Table 5.

The t ratio associated to the β_1 coefficients suggests that the REH is strongly rejected while there is evidence that players use an adaptive scheme.

Once established that expectations are adaptive, we are interesting in the analysis of the error correction bias as described in Section 2.

Firstly, we compute the absolute distance between the predicted price and the fundamental price in Treatment 2 and we compute a regression including only period dummy ($|\Xi_{it}| = \beta_0 + \gamma_1 Period_1 + \gamma_2 Period_2 + ... + \gamma_{51} Period_{51} + \varepsilon_{it}$). Results in Table 6 shows that as the time increases the distance between individual predictions and the fundamental value decreases. This evidence suggests

[11] We run a pooled estimation in each treatment.

Table 5: Output Regression: Correlation of forecasting errors

	Treatment 1	Treatment 2
Ξ_{it-1}	.3891***	.5334***
	0.000	0.000
Constant	.0743	-.3059***
	.3728	.0007
N	1800	1800
R^2	0.211	0.327
Standard error in parentheses; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$		

two aspects: first, this confirms that players take into account the fundamental value to form their expectations; second, especially in Treatment 2, this result supports the theory of the error correction.

To better investigate the latter point, we make the assumption that agents use the simplest adaptive rule described by equation (2) and we estimate the following equation for Treatment 2 [12]:

$$p^e_{it} = \beta_1 p^e_{it-1} + \beta_2 p_{it-2} + \beta_3(p^e_{it} - pf_t) + \varepsilon_{it} \tag{17}$$

using the Blundell and Bond estimator (Blundell and Bond (1998)). We consider the lagged values of the predicted price, the realized price and the fundamental value as instruments[13].

Estimation results shown in Table 7 suggests that the model of simple adaptive rule seems to fit well the behavior in our game; in fact, the coefficients β_1 and β_2 are strongly significant. The coefficient of the forecasting error with respect to the fundamental value is small but significant. a positive and significant coefficient means that as the distance between the prediction and the fundamental price increases, players adjust their forecasts in order to fill the gap.

Mixing results from the descriptive statistics and from the econometric analysis, we can conclude that players are able to understand that there is an up-warding trend in the fundamental price but they systematically underestimate the trend. This support that there is some sort of correction in expectation formation but we

[12]Since we are interested in understanding if players are able to understand, and so correct the trend, we take into account only data for Treatment 2.

[13]Both the predicted and the realized series are stationary. We run the unit root test for panel with serial correlation (Pesaran (2007)). The results are $z = -6.229, p - value = 0.000$ for Treatment 1 and $z = -6.699, p - value = 0.000$ for Treatment 2. So the null hypothesis of integration is strongly rejected.

Table 6: Output Regression: Forecasting errors with respect to the fundamental price

	Treatment 2		Treatment 2
Period 1	0.000	Period 26	-4.302***
	(.)		(1.509)
Period 2	-1.188	Period 27	-4.152***
	(1.509)		(1.509)
Period 3	-1.726	Period 28	-4.216***
	(1.509)		(1.509)
Period 4	-5.405***	Period 29	-4.093***
	(1.509)		(1.509)
Period 5	-3.006**	Period 30	-4.140***
	(1.509)		(1.509)
Period 6	-7.229***	Period 31	-3.809**
	(1.509)		(1.509)
Period 7	-6.101***	Period 32	-4.061***
	(1.509)		(1.509)
Period 8	-7.188***	Period 33	-3.597**
	(1.509)		(1.509)
Period 9	-5.879***	Period 34	-3.755**
	(1.509)		(1.509)
Period 10	-4.958***	Period 35	-3.538**
	(1.509)		(1.509)
Period 11	-5.934***	Period 36	-1.495
	(1.509)		(1.509)
Period 12	-3.239**	Period 37	-1.302
	(1.509)		(1.509)
Period 13	-5.828***	Period 38	-2.334
	(1.509)		(1.509)
Period 14	-3.562**	Period 39	-1.973
	(1.509)		(1.509)
Period 15	-6.083***	Period 40	-2.550*
	(1.509)		(1.509)
Period 16	-5.514***	Period 41	-2.970**
	(1.509)		(1.509)
Period 17	-5.481***	Period 42	-2.843*
	(1.509)		(1.509)
Period 18	-6.131***	Period 43	-2.801*
	(1.509)		(1.509)
Period 19	-5.506***	Period 44	-3.209**
	(1.509)		(1.509)
Period 20	-5.671***	Period 45	-2.926*
	(1.509)		(1.509)
Period 21	-4.971**	Period 46	-3.453**
	(1.509)		(1.509)
Period 22	-4.999***	Period 47	-3.283**
	(1.509)		(1.509)
Period 23	-4.889***	Period 48	-3.527**
	(1.509)		(1.509)
Period 24	-4.581***	Period 49	-3.404**
	(1.509)		(1.509)
Period 25	-4.756***	Period 50	-3.717**
	(1.509)		(1.509)
		Period 51	-3.354**
			(1.509)
Constant	12.074***		
	(1.067)		
R2	0.057		
N	1836		

Standard error in parentheses; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

Table 7: Output Regression: Adaptive expectation estimation

	Treatment 2
p_{it-1}	0.366***
	(0.057)
p_{it-2}	0.647***
	(0.058)
$(p^e - pf)$	0.087*
	(0.045)
N	1476
Sargan	$\chi^2_{11} = 126.31$
(p-value)	0.000
Hansen	$\chi^2_{11} = 2.33$
(p-value)	0.997
$AR(1)$	$z = -1.74$
(p-value)	0.082

Standard error in parentheses; $*p < 0.05$, $**p < 0.01$, $***p < 0.001$

are not able to proof that this *error correction term* fulfill the zero mean condition.

Furthermore, there is a lot of heterogeneity between and within groups. Tables from 10 to 21 (appendix B) show the pairwise Wilcoxon test within each group for the two treatments. In the lower triangular matrix there are the z statistics (and the p-values) comparing time series of expectations for each couple of agents, whereas the last two columns of every table show the the z statistics (and the p-values) comparing the time series of expectations and the realized price for each agent. The tables show different behaviors between agents and different ability to learn the realized price.

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. 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.

If we assume that agents have rational expectation, they are able to predict the fundamental price. Since all players are able to predict this value, the realized price should converge to the fundamental price. Our results show that groups in both treatments coordinate to a price higher or lower than the fundamental one. Especially in Treatment 2, players systematically underestimate the fundamental price, but they are able to understand that the mean dividend follows an increasing trend.

We firstly investigate if there is evidence for individual rationality. Results show that players fail to predict the fundamental value and that agents have adaptive expectations rather than rational ones. One of the main interesting results is the coordination among players, despite the absence of communication, that leads to the emergence of *collective rationality*. This concept refers to the process by which agents learn the others prediction strategies and they are able to coordinate on the same price which is different from the fundamental value.

Since the experimental results suggest that players use adaptive expectation scheme, we analyze if, in a context in which the fundamental price follows a trend, the error correction mechanism (Palestrini and Gallegati (2015)) works. First of all, from the graphical analysis emerges that players are able to understand that the fundamental price follows an increasing linear trend, but agents systematically underestimate the magnitude of this trend. Estimation results confirm that players take into account the increasing fundamental price in making their forecasting. Thanks to these results we should conclude that there is a correction mechanism but it does not satisfy the zero mean condition, i.e. the rationality condition.

This work shows also different behaviors between agents and different ability to learn the realized price.

The emergence of the heterogeneity both within and between groups and the rejection of the rational expectation hypothesis suggest that we need a model more sophisticated than the Neoclassical one. The next step is to extrapolate the individual prediction strategy using individual estimation and understand the mechanism of coordination that brought to the observed aggregate result.

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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[14]: 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.

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

A.2 Total profits

Table 8 shows the total profit in Euro in each group. Table 9 reports the descriptive statistics of the cash earned in both treatments.

Table 8: 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 9: 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

B Tables

Table 10: Wilcoxon test for Group 1 - Treatment 1

Group 1 - Treatment 1														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													1.547	0.122
2	1.611	0.107											-0.366	0.715
3	2.934	0.003	1.673	0.094									-0.75	0.066
4	2.252	0.024	1.263	0.207	-0.255	0.799							-1.837	0.4533
5	1.211	0.226	-0.017	0.9866	-1.396	0.162	-1.225	0.221					0.965	0.334
6	3.631	0.000	3.072	0.002	1.432	0.152	0.901	0.377	3.051	0.002			-3.356	0.001
	1		2		3		4		5		6		Realized price	

Table 11: Wilcoxon test for Group 2 - Treatment 1

Group 2 - Treatment 1														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													-2.493	0.013
2	-2.238	0.025											2.222	0.026
3	1.247	0.214	6.333	0.000									-3.852	0.000
4	-3.485	0.001	-1.351	0.177	-6.029	0.000							3.449	0.001
5	1.107	0.269	5.171	0	-0.411	0.681	5.661	0.000					-3.243	0.001
6	-0.279	0.78	2.493	0.013	-3.665	0.000	3.988	0.000	-2.776	0.006			-1.753	0.08
	1		2		3		4		5		6		Realized price	

Table 12: Wilcoxon test for Group 3 - Treatment 1

Group 3 - Treatment 1														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													2.287	0.022
2	-0.907	0.645											3.759	0.000
3	-0.199	0.843	0.631	0.528									3.384	0.001
4	1-995	0.051	3.271	0.001	2.583	0.01							-2.821	0.005
5	1.6	0.11	3.254	0.001	2.274	0.023	-0.308	0.758					-2.025	0.043
6	-2.864	0.004	-2.375	0.018	-2.845	0.004	-4.928	0.000	-4.77	0.000			6.168	0.000
	1		2		3		4		5		6		Realized price	

Table 13: Wilcoxon test for Group 4 - Treatment 1

Group 4 - Treatment 1														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													-0.544	0.587
2	0.281	0.779											-1.322	0.186
3	0.034	0.973	-0.268	0.789									-0.084	0.933
4	1.272	0.204	0.716	0.474	1.272	0.203							-4.265	0.000
5	0.489	0.625	0.194	0.846	0.532	0.594	-0.492	0.623					-0.647	0.518
6	1.071	0.284	0.656	0.512	1.105	0.269	-0.057	0.955	0.308	0.758			-4.349	0.000
	1		2		3		4		5		6		Realized price	

Table 14: Wilcoxon test for Group 5 - Treatment 1

Group 5 - Treatment 1														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													5.486	0.000
2	3.838	0.000											-2.953	0.003
3	3.779	.000	-0.097	0.923									-0.609	0.542
4	3.367	0.001	-0.840	0.401	-0.643	0.521							0.403	0.687
5	2.101	0.036	-1.989	0.047	-1.906	0.057	-1.322	0.186					1.275	0.202
6	0.345	0.73	-3.598	0.000	-3.323	0.001	-3.015	0.003	-2.025	0.043			4.265	0.000
	1		2		3		4		5		6		Realized price	

Table 15: Wilcoxon test for Group 6 - Treatment 1

Group 6 - Treatment 1														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													3.168	0.002
2	-0.482	0.623											3.421	0.001
3	-0.177	0.859	0.181	0.857									3.131	0.002
4	0.379	0.705	0.872	0.383	0.479	0.632							1.631	0.103
5	0.932	0.351	1.393	0.164	1.141	0.254	0.437	0.662					0.037	0.97
6	-2.807	0.005	-2.378	0.017	-2.596	0.01	-3.206	0.001	-3.475	0.001			6.125	0.000
	1		2		3		4		5		6		Realized price	

Table 16: Wilcoxon test for Group 1 - Treatment 2

Group 1 - Treatment 2														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													-1.64	0.101
2	-0.379	0.705											0.169	0.866
3	-0.937	0.349	-0.476	0.634									-0.225	0.822
4	0.673	0.501	1.159	0.247	-0.255	0.799							-4.387	0.000
5	-0.573	0.567	-0.08	0.936	-1.396	0.163	-1.225	0.221					-1.059	0.290
6	-0.556	0.578	0.097	0.923	1.432	0.152	0.901	0.368	3.051	0.002			-0.881	0.378
	1		2		3		4		5		6		Realized price	

Table 17: Wilcoxon test for Group 2 - Treatment 2

Group 2 - Treatment 2														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													-2.643	0.001
2	-0.95	0.342											0.347	0.729
3	-1.566	0.117	-0.704	0.482									0.0556	0.955
4	-2.079	0.038	-0.436	0.663	0.583	0.56							0.422	0.673
5	0.879	0.379	1.355	0.175	2.059	0.04	2.702	0.007					-3	0.003
6	-1.49	0.136	-0.121	0.904	0.949	0.343	0.422	0.673	-2.396	0.017			-0.909	0.363
	1		2		3		4		5		6		Realized price	

Table 18: Wilcoxon test for Group 3 - Treatment 2

Group 3 - Treatment 2														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													0.262	0.793
2	0.904	0.366											-1.734	0.083
3	0.241	0.81	-0.435	0.663									-1.659	0.097
4	3.427	0.001	2.436	0.015	2.848	0.004							-5.783	0.000
5	3.969	0.000	3.186	0.001	3.762	0.000	1.73	0.083					-5.549	0.000
6	0.151	0.88	-0.174	0.862	0.526	0.599	-2.296	0.022	-2.952	0.003			-2.09	0.037
	1		2		3		4		5		6		Realized price	

Table 19: Wilcoxon test for Group 4 - Treatment 2

Group 4 - Treatment 2														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													-2.818	0.005
2	-0.733	0.464											0.394	0.694
3	-0.489	0.625	0.281	0.779									0.206	0.837
4	-0.291	0.771	0.462	0.644	0.281	0.779							-2.418	0.016
5	0.947	0.344	1.349	0.178	1.359	0.174	1.252	0.211					-3.74	0.000
6	0.107	0.915	0.79	0.43	0.592	0.554	0.208	0.836	-0.783	0.434			-2.878	0.004
	1		2		3		4		5		6		Realized price	

Table 20: Wilcoxon test for Group 5 - Treatment 2

Group 5 - Treatment 2														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													-5.38	0.000
2	-0.157	0.875											-5.924	0.000
3	-0.552	0.581	-0.361	0.718									-1.697	0.09
4	-0.602	0.547	-0.452	0.651	-0.037	0.971							-1.331	0.183
5	-1.198	0.231	-0.997	0.319	-0.659	0.51	-0.669	0.503					5.015	0.000
6	-0.469	0.639	-0.318	0.751	0.06	0.952	0.141	0.888	0.803	0.422			-1.612	0.107
	1		2		3		4		5		6		Realized price	

Table 21: Wilcoxon test for Group 6 - Treatment 2

Group 6 - Treatment 2														
Subject	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value	z	p-value
1													-5.933	0.000
2	-0.355	0.738											-4.509	0.000
3	-0.967	0.333	-0.732	0.47									1.828	0.068
4	-0.184	0.854	0.141	0.888	0.83	0.401							-5.737	0.000
5	-0.398	0.69	-0.127	0.899	0.679	0.497	-0.231	0.817					-5.362	0.000
6	-0.827	0.401	-0.331	0.74	0.455	0.649	-0.602	0.547	-0.204	0.838			-1.781	0.075
	1		2		3		4		5		6		Realized price	