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Abstract

Bao et al. (2017) find that bubbles are less likely to emerge in experimental asset markets when subjects make price forecasts only (Learning to Forecast treatment, LtF) than when they make trading quantity decisions (Learning to Optimize treatment, LtO) or both price forecasts and quantity decisions (mixed treatment). This paper provides two explanations for this difference. First, the subjects in the LtO and mixed treatment usually have a high intensity of choice parameter, which leads them to switch faster between the decision rules and a greater fraction of the population to choose the destabilizing strong trend-following rule. Second, the actual quantity decision may deviate substantially and persistently from the conditionally optimal level given the price forecasts in the mixed treatment, which amplifies the price deviation from the fundamental value. Our findings are helpful for understanding the root of financial bubbles and financial crisis, and designing policies to stabilize the market.

Keywords: Asset Bubble, Heuristic Switching Model, Learning to Forecast, Learning to Optimize, Experimental Economics

JEL Classification: C91, C92, D83, D84, R30

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1 Introduction

"What causes financial bubbles?" Since the 2007 financial crisis, this question has attracted renewed attention among academics and policymakers. The occurrence of bubbles challenges the rational expectations paradigm in economics. Under the rational expectations hypothesis, agents are assumed to be able to (1) make unbiased predictions of future asset prices and (2) make optimal trading quantity decisions conditional on their forecasts. Empirical tests on rational expectations (and thus on financial bubbles) face the difficulty of "testing two joint hypotheses". When an asset price deviates from its rational fundamental value, it is difficult to assess whether this deviation is caused by market participants' incorrect forecasts or by their non-optimal trading quantity, given their price forecast. To study the causes of financial bubbles, Bao et al. (2017) conduct a laboratory experiment on bubble formation with human subjects.

There are three treatments in their experiment: Treatment 1, which follows the "learning-to-forecast (LtF) experiment" design (Marimon et al., 1993) where subjects make only a price forecast; Treatment 2, which follows the "learning-to-optimize (LtO) experiment" design (Smith et al., 1988) where subjects directly indicate their trading quantity; and a mixed treatment where subjects submit both a price forecast and a quantity decision. Bao et al. (2013, 2017) find that the price tends to deviate more from the rational expectation equilibrium in the LtO and the mixed treatments than in the LtF treatment. The bubbles are largest in the mixed treatment, followed by the LtO treatment, and the smallest in the ltF treatment. Based on this result, they conjecture that the issue of bounded rationality is more severe for quantity decisions than for expectation formation, but they do not provide a model to fully explain the mechanism in their paper.

This paper aims to provide a computational micro-foundation for the sharp difference in the LtF treatment with the LtO and mixed treatments in Bao et al. (2017). More specifically, we want to answer two questions:

1. Is there a way to describe the bounded rationality in subjects' quantity decision in the LtO and mixed treatment? If so, what is that?
2. Why do the asset prices deviate even more from the fundamental value in the mixed treatment compared to the LtO treatment?

To answer the first question, we apply the heuristic switching model (HSM, Anufriev and Hommes, 2012) to the data of Bao et al. (2017). The HSM assumes that agents choose from a menu of forecasting heuristics, and switch to the forecasting rules that generates smaller forecasting error in the recent past. This model provides a very good description of the data in a number of Learning to Forecast experiments, e.g. Hommes et al. (2005, 2007, 2008), Bao et al. (2012), Bao and Hommes (2015). In this paper, we derive a variation of it (the extended HSM) that is also applicable to data on quantity decisions. The HSM and the extended HSM capture the price dynamics in these three treatments quite well. The results of the HSM show that there is a larger fraction of subjects following the strong trend rule in the LtO treatment than in the LtF treatment.

To answer the second question, we first plot the actual quantity decision in the LtO and mixed treatment. After that, we derive the conditional optimal level of quantity decision given the subjects' price forecast in the mixed treatment. Following a similar method to Stöckl et al. (2010), we derive the relative deviation of quantity (RDQ) and absolute relative deviation of quantity (RADQ), and find that there is large and persistent deviation of quantity from its conditionally optimal level in the mixed treatment, which amplifies the bubble.

The main contribution of this paper is that we extend the HSM model so that it is also applicable to learning to optimize experiments. Based on this extended model, we provide a computational micro-foundation of the difference between the LtF, LtO and mixed treatments in Bao et al. (2017). Our finding that subjects switch faster between the decision rules when they are faced with quantity decision tasks is helpful to understand the root of financial bubbles in real life. Based on our results, we speculate that a trading adviser based AI technology may be helpful to the market stability if it can reduce the irrationality of quantity decision made by human traders substantially.

The rest of this paper is organized as follows: Section 2 reviews the related literature and briefly clarifies the contributions. Section 3 describes the data source and experimental design. Section 4 presents the HSM and the results of applying it to the experimental data. Section 5 discusses the dynamics of the actual quantity decision and the conditionally optimal level. Finally, Section 6 concludes.

2 Literature Review

This paper is related to previous studies on the LtF and LtO experiments. Marimon and Sunder (1993, 1994), Marimon et al. (1993), Adam (2007) and Pfajfar and Zakelj (2009) study the interaction between individual forecasts and aggregate market prices in macroeconomic models[1]. Hommes et al. (2005, 2008) conduct LtF experiments to study bubble formation in an asset market. The results of these papers usually show that bubbles emerge due to bounded rationality in individual expectation formation. The market price tends to converge toward the fundamental price when agents use adaptive expectations, and the price diverges when they use trend-following expectations. Bao et al. (2013, 2017) investigate the price dynamics and bubble formation in both the LtF and the LtO designs and find that bubbles tend to be larger in the LtO treatment. Investigating the data from Bao et al. (2013, 2017) provides us the opportunity to draw a comparison between the two treatments and to disentangle the behavioral factor that causes the difference in the frequency of bubbles in the two treatments.

The HSM was proposed by Anufriev and Hommes (2012) as an extension of Brock and Hommes (1997), and it was then widely used in the experimental macroeconomics literature. The HSM can explain the different price dynamics (monotonic convergence, persistent oscillations, and dampened oscillations) in different markets in an asset pricing experiment. The model assumes that agents choose from a pool of forecasting heuristics. At each period, these heuristics deliver price forecasts in the next period, and the realized market

[1]For a theoretical model on learning and heterogeneous expectations, see, e.g., Branch (2004) and Branch and Evans (2006, 2007)

price depends on these forecasts. The weights of different forecasting heuristics on the realized prices change over time because the subjects are learning based on evolutionary selection: The better a heuristic performed in the past, the larger the share of the population that will follow it and, consequently, the higher its impact in determining the price of the next period. Consequently, the realized market price and the impact of the forecasting heuristics co-evolve in a dynamic process with mutual feedback. This nonlinear evolutionary model exhibits path dependence, explaining the coordination of different forecasting heuristics and causing different aggregate price dynamics. Numerous previous studies, such as Anufriev et al. (2013) and Bao et al. (2012), apply the HSM to explain the experimental data from the LtF asset pricing experiment. However, none of these studies connects the HSM to the LtO treatment.

There are many theories about the mechanism of bubble formation. DeLong et al. (1990) present a simple overlapping-generation model of an asset market in which irrational noise traders affect prices and earn higher expected returns that cause bubbles. Tirole (1982) uses a general equilibrium model to argue that bubbles cannot exist if it is commonly known that the initial allocation is interim Pareto efficient. When faced with uncertainty, people tend to use a variety of simple rules or heuristics to make decisions (Kahneman, 2003). Recently, Heemeijer et al. (2009) have shown that in LtF experiments, individuals often use simple predictive rules to form their expectations. In the positive feedback mechanism market, there are two frequently used strategies: the adaptive expectation rule and the trend-following expectation rule. Bao et al. (2012) argue that if the adaptive expectation strategy dominates the market, then the price will tend to converge toward the fundamental price. On the other hand, if trend rules are the dominant rules, then the price will diverge from the fundamental price. In other words, if large bubbles are observed in the market, then one possible explanation would be that people are users of trend-extrapolating strategies. In this paper, we investigate whether larger bubbles in the LtO and mixed treatments are caused by a larger fraction of subjects using the trend-chasing strategy.

Since the HSM is a model with heterogeneous expectations, our paper is also related to studies on financial bubbles and switching behavior using the agent-based modelling approach, e.g. Anufriev et al. (2015), Chen and Yeh (2001), Chiarella and He (2003), Dawid and Delli Gatti (accepted), Gaunersdorfer (2000), van der Hoog and Dawid (2017), Huang et al. (2010, 2013), Jawadi et al. (forthcoming), Westerhoff (2003). For a comprehensive survey of applying agent-based modeling to experimental economics, see Arifovic and Duffy (forthcoming).

3 Experimental Data

3.1 Data Source

We use the data from Bao et al. (2017). In their experiment, there were eight markets consisting of 6 subjects in each of the LtF, LtO, and mixed treatments. The total number of subjects who participated in this experiment was 144. The experiment consisted of 50 periods.

3.2 Experimental Design

In this experiment, the fundamental value of the asset is constant over time. There are six subjects in each market, and they play the role of a professional advisor to a trading company.

The three treatments are as follows. In the LtF treatment, the subjects are asked to predict the market price of the asset in each period. The price should be predicted one period ahead. The subject's earnings from the experiment will depend on the accuracy of his/her predictions. The smaller a subject's prediction error is, the more s/he will earn.

In the LtO treatment, the subjects are asked in each period to decide how many units of the asset s/he will buy or sell. The subject's earnings from the experiment will depend on the profitability of his/her trading decisions. The larger a subject's profit is, the more s/he will earn.

In the mixed treatment, the subjects will be asked to make his/her price prediction and his/her choice of the asset quantity in each period. To eliminate any possible hedging, the earnings for the entire experiment will be either the payoff from the LtF treatment or the payoff from the LtO treatment, with equal probability between them.

The price determination function in this experiment is given by equation (1), where is the average prediction of the price p_{t+1} by six subjects in each market. Equation (1) denotes that the price determination process is a function of the average individual forecast. This experimental asset market is a positive feedback system, the realized price is higher when the average forecast is higher.

$$p_{t+1} = 66 + \frac{20}{21}(\bar{p}^e_{t+1} - 66) + \epsilon_t \tag{1}$$

The rational expectations condition is $\bar{p}^e_{t+1} = p^f = E_t(p_{t+1})$. Based on the experimental design, $p^f = 66$ is the unique Rational Expectations Equilibrium (REE) of the system. If all agents have rational expectations, the realized price becomes $p_t = p^f + \epsilon_t = 66 + \epsilon_t$. When the price is p^f, the expected excess return of the risky asset is 0 and the optimal demand for the risky asset by each agent is also 0.

4 Heuristic Switching Model

This part aims at addressing the first question in the introduction. To understand the forecasting and quantity decision rules by the individual subjects in the experiment and why the bubbles are larger when subjects make quantity decisions, we apply the HSM to investigate the fractions of people using different heuristics. This model is proposed by Anufriev and Hommes (2012). It is particularly useful when the behavior of subjects deviates from the REE benchmark and demonstrates high level of heterogeneity. It fits the price dynamics, namely, monotonic convergence, persistent oscillations and dampened oscillations, in different groups in the asset pricing experiment of Hommes et al. (2005) very well. The HSM is based on the assumption that subjects switch between four forecasting rules based on their performance. HSM helps to explain the behavioral bias when subject makes the prediction. In the previous, the model was mainly applied to the LtF asset price experiment.

Since the original HSM model deals with forecasting data only, we extend it so that it can also be applied to the quantity decisions. This section illustrates how we use HSM to explain the bubble difference among the three treatments. This section is organized as follows: Section 4.1 shows the estimation of simple forecasting heuristics that can be used in the HSM, Section 4.2 describes the HSM in the LtF treatment, Section 4.3 mainly depicts the extended HSM in the LtO treatment, and Section 4.4 shows the results of the simulation.

4.1 Estimation of Simple Forecasting Heuristics

We estimate the linear prediction rules to check whether the simple linear regression can well fit the rule of the subject's prediction; if not, are there any structural changes during the price prediction?

We apply two kinds of heuristics to the LtO treatment and the mixed-Q of the mixed treatment. The first rule is the simple adaptive rule:

$$p^e_{h,t} = p^e_{t-1} + w(p_{t-1} - p^e_{t-1})$$

Which describes the relationship between the price prediction and last observed price. All results are shown in Table B3 and Table B4 in Appendix B. The coefficient w is near 1 for all subjects in the LtF treatment and the mixed-F of the mixed treatment[2] . w is significant at the 5% level for almost all subjects in the LtF treatment. In the LtO treatment and the mixed-Q of the mixed treatment, the coefficient w is positive for most subjects and between 0.3 and 1. Moreover, w is significant for half of the subjects in the LtO treatment and the mixed-Q of the mixed treatment. The adjusted R^2 in the LtF, LtO treatments and the mixed-F, the mixed-Q of the mixed treatment are 0.9995, 0.9831, 0.8363 and 0.9792, respectively; the MSEs are 1.42, 54.96, 20422.50 and 124.62, respectively. The MSE is greatest in the mixed-F of the mixed treatment. As shown in Tables B1 to B4, almost all the subjects in the LtF treatment and the mixed-Q of the mixed treatment pass the asymptotic Chow (AC) test. Regarding the LtO treatment and the mixed-F of the mixed

[2] We use the estimation result of First Order Heuristic, $p^e_{i,t} = \alpha_i p_{t-1} + \beta_i p^e_{i,t-1} + \gamma_i(p_{t-1} - p_{t-2})$, in the LtF treatment and the mixed-F of the mixed treatment from Bao et al. (2017) and all results are in Table B1 and Table B2 in Appendix B, see Appendix C for more details.

treatment, half of the subjects pass the AC test. These results show that some subjects employ heuristic prediction rules during their learning process. The second rule is the trend rule that individuals deduce the price prediction from the last observed price; the trend rule is as follows:

$$p^e_{h,t} = p_{t-1} + \gamma(p_{t-1} - p_{t-2})$$

If γ is positive, it implies that when the previous observed price increases, the subjects will expect the price to increase in the future; when γ is negative, the rule is also called a contrarian rule. The negative coefficient implies that when the previous observed price increases, then the subjects will expect the price to decrease. Tables B5 and B6 in Appendix B show the results of the trend rule. To summarize, regarding the results of the trend rule in the LtF treatment, the coefficient γ is positive and in the range between 0 and 1.24; the mean and median are 0.4. Regarding the LtO treatment, the coefficient γ is positive and in the range between 0.2 and 2.03; the mean and median are 1.02 and 0.94, respectively. All coefficients γ are significantly different from 0 at 5% level in the LtF treatment and significant for 43 out of 48 subjects in the LtO treatment. Regarding the mixed-F and the mixed-Q of the mixed treatment, the coefficients γ are significantly different from 0 for 29, and 39 (out of 48 subjects), respectively. The mean and median are 0.82, 0.57 and 1.02, 0.62 in the mixed-F and mixed-Q of the mixed treatment, respectively. The adjusted R^2 is very high in the three treatments, that is, 0.9995, 0.9935, 0.8363 and 0.9913 for the LtF, LtO treatments, and the mixed-F, the mixed-Q of the mixed treatment, respectively. Regarding the MSE of the regression, the MSE is 1.42 in the LtF treatment. The MSEs are 20.35 and 42.30 in the LtO treatment and the mixed-Q of the mixed treatment, respectively. The MSE of the regression in the mixed-F of the mixed treatment is very large at 20422.50. The results of the AC test indicate that subjects employ heuristic prediction rules during their learning process. We conclude that there is heterogeneity of the price prediction rules, so we have to employ HSM to fit the data. We will describe the HSM used for expectation formation in the following subsection.

4.2 The Heuristic Switching Model with Benchmark Parameter Settings

There are four rules in this model:

The adaptive expectation rule (ADA) is as follows:

$$p^e_{1,t+1} = wp_t + (1-w)p^e_{1,t} \tag{2}$$

The weak-trend rule (WTR) is as follows:

$$p^e_{2,t+1} = p_t + \gamma_w(p_t - p_{t-1}) \tag{3}$$

The strong-trend rule (STR) is as follows:

$$p^e_{3,t+1} = p_t + \gamma_s(p_t - p_{t-1}) \tag{4}$$

The fourth rule is an anchoring and adjustment heuristic (A&A), as in Tversky and Kahneman (1974):

$$p^e_{4,t+1} = \frac{(p^f + p_t)}{2} + (p_t - p_{t-1}) \tag{5}$$

The coefficients used in the first three rules are the medians of the successful (significant, without serial correlation and structural break) rules that we obtain from the estimations in section 4.1, that is, $w = 0.85$, $\gamma_w = 0.3$ and $\gamma_s = 1.3$. Additionally, we use the same coefficients so that the results in this heterogeneous agent model can be compared to those from homogeneous models. The first rule (ADA) describes the relationship between the price forecast, the last period market price, and price forecast in the last period. It illustrates that individuals will be reflective by correcting their predictions concerning the one-period lagged price prediction, and this rule will help maintain price stability. The coefficient w estimates the strength of individuals' correction. If w is larger, then the past price prediction is given less weight, and the autocorrelation of prices tends to be lower. The second rule (WTR) and the third rule (STR) are the trend rules, which indicates that the price prediction for the next period is the price in the last period p_{t-1} plus a constant times the price trend in the last period $(p_t - p_{t-1})$. The coefficient γ captures the strength with which subjects extrapolate the past trend. The strong trend rule contributes to the instability of the prediction process. The fourth rule is the same as that of Tversky and Kahneman (1974). In the fourth rule (A&A), there is a time-varying anchor that is $\frac{p_t+p^f}{2}$, which is the mean of the last price and the sample mean of all past prices. According to Anufriev and Hommes (2012), the A&A rule is successful in explaining persistent oscillations.

The subjects switch between these four rules according to their performance. The performance of the heuristic i, $i \in \{1, 2, 3, 4\}$ is as follows:

$$U_{i,t} = -(p_t - p^e_{i,t})^2 + \eta U_{i,t-1} \tag{6}$$

The first term is the squared error of prediction. The payoff function of the subjects in the LtF treatment is a decreasing function of the squared error of prediction. In the LtF treatment, agents aim to minimize their prediction error that leads to the negative sign of the first term.

Parameter η measures the strength of agents' memory, ranging from 0 to 1. Intuitively, η measures the weight that the agent gave to the past error compared to the most recent error. When $\eta = 0$, the agent considers only the most recent information. For those $\eta > 0$, all past errors are taken into account.

The fraction of agents using heuristic i is defined as $n_{i,t}$, which is given by a discrete choice model with asynchronous updating (Hommes et al., 2005. Diks and Van der Weide, 2005).

$$n_{i,t} = \delta n_{i,t-1} + (1-\delta)\frac{exp(\beta U_{i,t-1})}{\sum_{i=1}^{4} exp(\beta U_{i,t-1})} \tag{7}$$

The parameter $\delta \in [0, 1]$ reflects the inertia of agents. In other words, it measures the inertia of subjects sticking to their rule. When $\delta = 1$, agents do not update their information. When $\delta < 1$, a fraction of $1-\delta$ subjects update the weights of rules and information.

The parameter $\beta > 0$ denotes the intensity of the choice of rules: the "sensitivity" to switch to another strategy. The higher the β is, the faster the subjects will switch to more successful rules in the recent previous periods. When $\beta = 0$, agents will place equal weight on each rule. When $\beta = +\infty$, all agents who updated will switch to the most successful rule.

4.3 Modeling Switching Behavior in the LtO Treatment

In contrast to the LtF treatment, in the LtO treatment, the performance of the agent is measured by the profit from trading instead of prediction error. Hence, the performance of the agent is measured as follows:

$$\pi_t = W_t - \frac{1}{2}Var(W_t)^2 \tag{8}$$

where π_t is the profit that the agent earned in the LtO treatment and W_t is the total wealth. For simplicity, Bao et al. (2017) assume that the expected variance of the asset value is $6q_t^2$. Therefore, we can rewrite the performance in the following manner:

$$\pi_t = (p_t + y - Rp_{t-1})q_t - 3q_t^2 \tag{9}$$

Thus, in the LtO treatment, the performance of heuristic i, $i \in \{1, 2, 3, 4\}$ is as follows:

$$U_{i,t} = \pi_t + \eta U_{i,t-1} = (p_t + y - Rp_{t-1})q_t - 3q_t^2 + \eta U_{i,t-1} \tag{10}$$

The four rules are identical to those in section 4.2. All the other parameters, such as β, η and δ, are the same as the HSM in the LtF treatment. Subjects in the LtO treatment seek to maximize their total profit. For this reason, the sign of the first two terms in equation is positive.

Regarding the mixed treatment, since the subjects should make a prediction of the price and decide the quantity one period ahead and their payment is randomly in either the LtF or the LtO treatment (Bao et al., 2017), we assume that they follow the two performances. First, they apply the performance in the LtF treatment for mixed-F of the mixed treatment. Second, they follow the performance of the LtO treatment for the mixed-Q of the mixed treatment.

We obtain the fitted price prediction for the LtO treatment from equation (11)[3]:

$$p^e_{i,t+1} = 6q^*_{i,t} + 1.05p_t - 3.3 \tag{11}$$

We use the equation above to obtain the fitted price prediction in the LtO treatment and the mixed-Q of the mixed treatment.

[3] See Bao et al. (2017) for more details.

4.4 Empirical Results of the Heuristic Switching Model

We use the benchmark parameter settings $\beta = 0.4$, $\eta = 0.7$, $\delta = 0.9$, which is exactly the same as Anufriev and Hommes (2012). Moreover, we set the initial weight of the four heuristics equally, $[n_1, n_2, n_3, n_4] = [0.25, 0.25, 0.25, 0.25]$ as the HSM benchmark model and perform a one-period ahead simulation from this HSM for all these treatments. We use the HSM to fit data of the LtF treatment and the mixed-F of the mixed treatment, and the extended HSM to fit the data of LtO treatment and the mixed-Q of the mixed treatment.

Figure 1 and Figure 2 constitute examples of the results of the simulation in the LtF, LtO treatments, and the mixed-F, the mixed-Q of the mixed treatment. As shown in Figures 1 and 2 (all other graphics are in Appendix A, from Figures A1 to A4), the HSM fits the experimental data quite well. The left panel illustrates the experimental and simulated price dynamics, and the right panel depicts the weight of the four heuristics. First, we explain the result of the LtF treatment. It is difficult to determine the dominant rule among these four heuristics from the top panel of Figure 1. Almost all subjects in the LtF treatment learn over time: From period 1 to period 25, the STR or the WTR dominates all other rules, while after period 25 until the end, the ADA is dominant. Second, the bottom panel of Figure 1 illustrates the simulation results of the LtO treatment. The STR is the dominant rule in the LtO treatment.

The top panel of Figure 2 illustrates the dynamics of the asset price and the weights of the heuristics in the mixed-F of the mixed treatment. There is no breakpoint. The trend rules (including WTR and STR) are the main rules. The bottom panel of Figure 2 illustrates the ADA and STR dominate all other rules in the mixed-Q of the mixed treatment. Next, we use the numerical results to explain some conclusions drawn from the graphics.

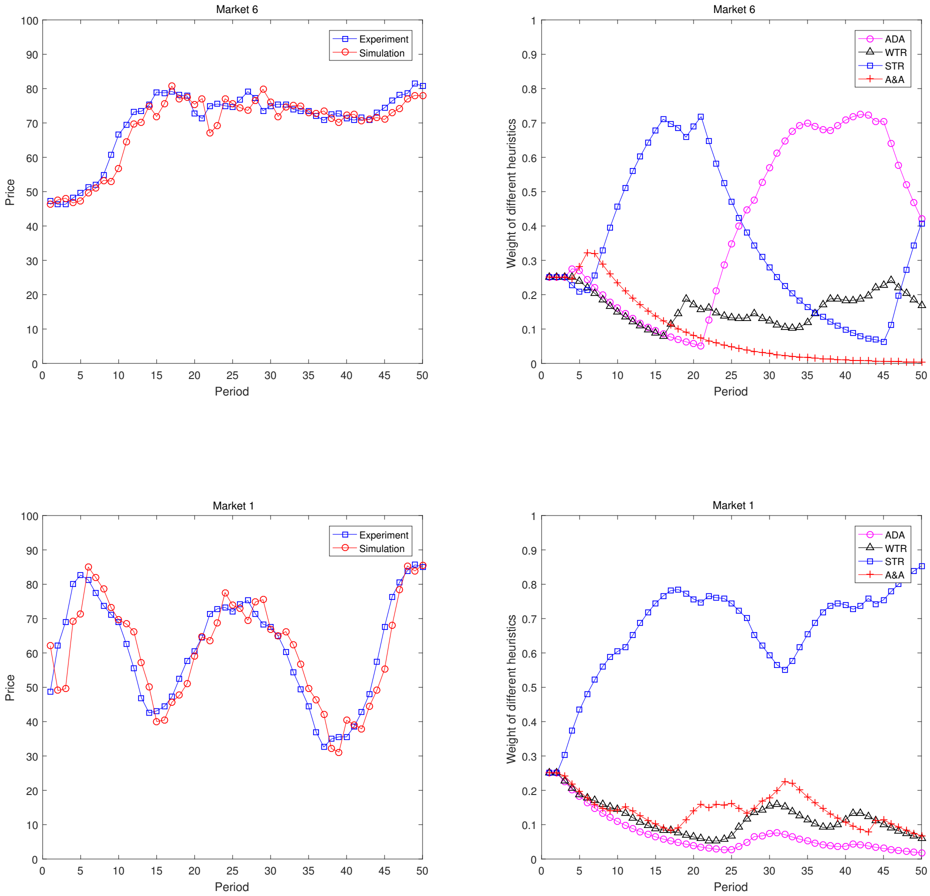

Figure 1: Experimental data (blue line with squares) and simulated asset price (red line with circles) using the HSM (left panel) and the weights of the different heuristics (right panel) in one typical market (market 6 and market 1, respectively) from the LtF treatment (top panel) and the LtO treatment (bottom panel). The x-axis is the period, and the y-axis is the price (left panel) and the weight of the heuristics (right panel).

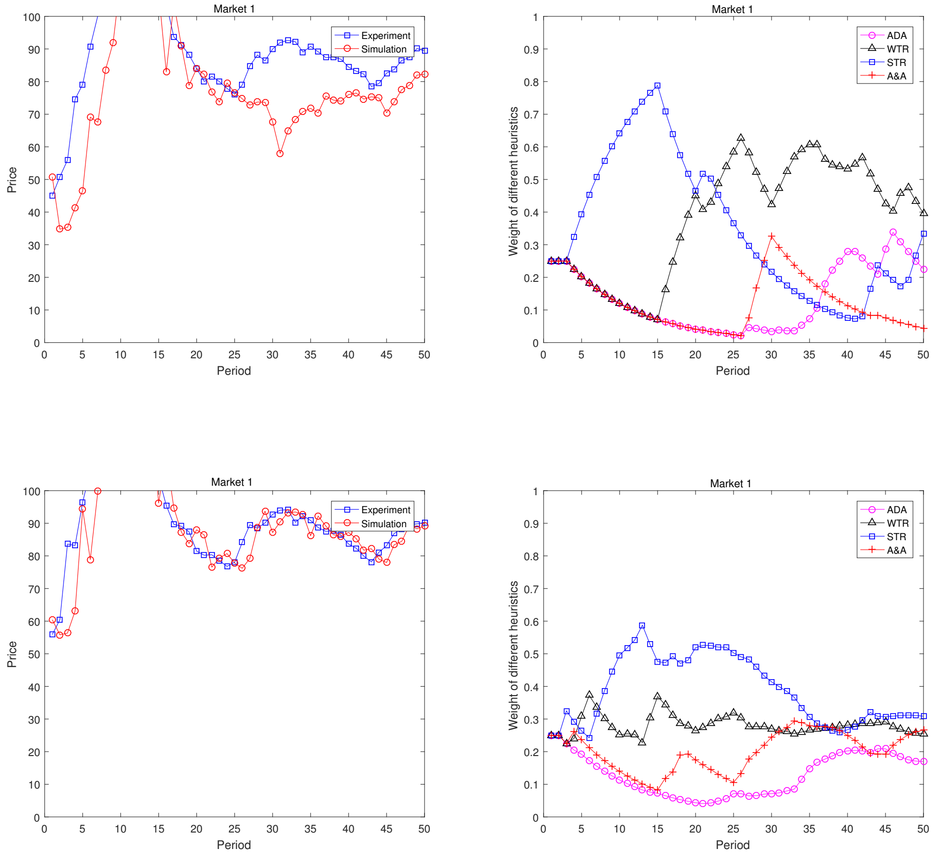

Figure 2: Experimental data (blue line with squares) and simulated asset price (red line with circles) using the HSM (left panel) and the weights of the different heuristics (right panel) in one typical market (market 1) from the mixed-F (top panel) of the mixed treatment and the mixed-Q (bottom panel) of the mixed treatment, respectively. The x-axis is the period, and the y-axis is the price (left panel) and the weight of the heuristics (right panel).

Table 1 shows the MSE of the regression and simulation in all markets in each treatment. The MSEs are the smallest in the LtF treatment and the greatest in the mixed treatment. Additionally, the average MSE in the mixed-F of the mixed treatment is larger than that in the mixed-Q of the mixed treatment, and they are 160.2 and 125.4, respectively. These results explain why the HSM fits better in the mixed-Q of the mixed treatment than in the mixed-F of the mixed treatment. Additionally, the MSE in bold shows the best rule among the four rules. The MSE of the WTR is the smallest in the LtF treatment; however, the difference between the MSE of the ADA and the WTR is minimal. The MSEs of the ADA and STR are the smallest in the LtO treatment. Regarding the mixed treatment, the MSEs of the ADA and WTR are the smallest in the mixed-F treatment, and the MSE of the WTR is the smallest for mixed-Q. Based on the MSE, we know that the WTR performs best in the LtF treatment and that the ADA and STR perform well in the LtO treatment. The ADA and WTR fit well in the mixed-F of the mixed treatment, and the WTR fits well in the mixed-Q of the mixed treatment. Furthermore, Table 1 also shows the best model, which is underlined. The HSM benchmark is the model in which we use the same parameter (β, η and δ) settings as in Anufriev and Hommes (2012). We use the grid search to find the parameters (β, η and δ) that minimize the average MSE in each market and to find the optimal parameterization for the HSM (HSM optimal). Comparing the four rules with the HSM benchmark model shows that in the mixed-Q of the mixed treatment, the HSM benchmark model gives the minimum MSE, which implies that the HSM benchmark model fits better (4 out of 8 markets). The HSM optimal gives the minimum MSE compared to all other models.

The results of grid search show that the mean β is 3.33 in the LtF treatment, 8.29 in the LtO treatment, 1.63 in the mixed-F of the mixed treatment and 6.05 in the mixed-Q of the mixed treatment (The mean β is 3.84 in the mixed treatment). Additionally, the mean δ is 0.2050 in the LtF treatment, 0.0140 in the LtO treatment, 0.3260 in the mixed-F of the mixed treatment and 0.1988 in the mixed-Q of the mixed treatment (Then mean δ is 0.2624 in the mixed treatment). The t-test shows that β is significantly larger ($p = 0.0004$) and δ is lower ($p = 0.05$) in the LtO treatment than in the LtF treatment. Hence, β is higher and δ is lower in the LtO treatment than in the LtF treatment. This result also holds in the mixed treatment β is significantly higher (p=0.0029) and δ is lower (p=0.02) in the mixed-Q than the mixed-F of the mixed treatment.). We observe that a higher β and a lower δ in the data of trading quantity decision than the data of price prediction in the mixed treatment. We can conclude that more individuals will update their information and make a decision in a more flexible manner when they make a quantity decision rather than a price forecast. Furthermore, there is a higher β in the LtO and mixed treatments than the LtF treatment. It implies individuals in the LtO treatment may make their decisions more flexibly than those in the LtF treatment.

In summary, among the simple heuristics, MSE of the WTR is smaller than the other rules in the LtF treatment, while MSE of the ADA and STR is smallest in the LtO treatment. Comparing the four heuristics with the HSM benchmark model shows that the HSM benchmark model fits better in the mixed-Q of the mixed treatment. Besides, compared to all other models, the HSM optimal best fits the data since the HSM optimal gives the minimum MSE. Additionally, the MSE is quite small in the mixed-Q of the mixed treatment (compared to the mixed-F of the mixed treatment) and in the LtO treatment shows that the extended HSM works well for the LtO treatment.

Table 1
The MSE of the one-period-ahead forecast for different markets in the LtF treatment (top session), the LtO treatment (middle session), and the mixed-F and the mixed-Q of the mixed treatment (bottom sessions). HSM Benchmark is the HSM with the parameters $\beta = 0.4$, $\eta = 0.7$, and $\delta = 0.9$. HSM Optimal is the HSM with the parameters that give the best fit according to the MSE in this market in each treatment, with the parameters β, η and δ shown in the bottom. The figures in bold are the minimum MSE among the four heuristics, and the underlined figures are the minimum MSE among all models.

	LtF1	LtF2	LtF3	LtF4	LtF5	LtF6	LtF7	LtF8
ADA	8.3649	4.7072	4.3691	4.6005	13.7179	12.0459	2.7296	6.1180
WTR	**8.3078**	**4.6804**	**4.3466**	**4.5718**	**13.6678**	**12.0358**	**2.7199**	**6.0973**
STR	8.4660	4.7453	4.4887	4.6764	13.8379	12.2294	2.8044	6.2322
A&A	8.8708	5.6756	4.6489	4.8471	13.8762	12.3009	2.7436	6.1822
HSM Benchmark	8.6694	4.8246	4.5409	4.7493	13.9972	12.2071	2.8364	6.2942
HSM Optimal	7.4563	4.1856	3.8692	4.2674	13.5770	9.0967	2.7013	5.5272
$\beta \in [0, 10]$	0.2	3.3	2.5	0.4	4.5	6.5	1.9	7.3
$\eta \in [0, 1]$	0.75	1	0.39	0.67	0.19	0.72	0.68	0.65
$\delta \in [0, 1]$	0	0.04	0.2	0	0.74	0	0.65	0.01
	LtO1	LtO2	LtO3	LtO4	LtO5	LtO6	LtO7	LtO8
ADA	44.0922	**94.4517**	111.2568	84.7529	**13.2343**	**74.0424**	**46.3615**	48.1030
WTR	**44.0737**	95.2830	110.1813	84.7187	13.2364	74.0565	46.4340	48.0936
STR	44.1173	99.2919	**109.9373**	**84.7414**	13.2417	74.1344	46.8206	**48.0906**
A&A	46.5726	94.7488	113.9210	91.2697	14.5023	74.4668	46.3574	49.0776
HSM Benchmark	44.0793	94.5960	110.7003	84.7872	13.2368	74.0993	46.3514	48.1771
HSM Optimal	27.4231	57.8884	66.2478	47.7612	7.5233	39.9163	33.9680	33.6557
$\beta \in [0, 10]$	2.5	5.8	9.4	8.6	10	10	10	10
$\eta \in [0, 1]$	0	0.69	0.03	0.24	0.06	0.07	0.15	0.06
$\delta \in [0, 1]$	0	0	0.04	0.07	0	0	0	0
				mixed				
	mixed-F1	mixed-F2	mixed-F3	mixed-F4	mixed-F5	mixed-F6	mixed-F7	mixed-F8
ADA	279.7659	59.78121	17.4844	132.9651	53.8440	**19.5676**	**122.3475**	**592.9426**
WTR	**279.7415**	59.8258	16.9798	**131.2609**	**53.8001**	19.5857	122.4008	596.4636
STR	279.8915	59.9672	**16.2146**	131.8075	54.0016	19.6614	122.6615	608.5776
A&A	280.0972	**59.5672**	19.2327	131.9479	54.1945	19.6067	131.9401	608.2595
HSM Benchmark	280.7491	59.6762	18.2106	135.0289	54.1912	19.5586	122.4454	590.2956
HSM Optimal	56.2114	25.6583	16.2143	80.2756	47.6096	17.9525	38.6626	240.5224
$\beta \in [0, 10]$	2.4	1	1.2	1.2	1.8	4.3	0.6	0.5
$\eta \in [0, 1]$	0.12	0.93	0.99	0.03	0.22	0.37	0.09	0
$\delta \in [0, 1]$	0.64	0.3	0.16	0.23	0.13	0.98	0.17	0
	mixed-Q1	mixed-Q2	mixed-Q3	mixed-Q4	mixed-Q5	mixed-Q6	mixed-Q7	mixed-Q8
ADA	81.2151	98.4156	46.6729	172.1084	59.4021	35.4682	59.7764	425.0688
WTR	81.2058	100.6770	49.5465	**171.4561**	59.4498	35.4423	**59.7742**	**423.1306**
STR	81.1924	108.2134	58.6038	173.0944	59.6794	**35.3881**	59.8763	428.8609
A&A	81.1939	103.8190	45.7606	173.0307	59.6017	35.4785	63.3038	486.0557
HSM Benchmark	**81.1637**	**96.0801**	**43.3184**	171.7686	**59.3945**	35.5940	59.8112	455.6837
HSM Optimal	46.1489	72.9935	36.0537	89.9091	47.6096	28.7006	44.4057	228.2831
$\beta \in [0, 10]$	9.7	1.4	9.5	7.6	1.8	7.1	5.1	6.2
$\eta \in [0, 1]$	0.1	0.86	0.77	0.01	0.22	0.7	0.17	0.27
$\delta \in [0, 1]$	0.32	0.12	0	0.14	0.13	0.84	0	0.17

Table 2 below reports the dominant rules in the three treatments and shows that the weight of the adaptive rule is the greatest among the four heuristics in the LtF treatment and the STR is the dominant rule in the LtO treatment. On average, the STR is the dominant rule in the mixed treatment[4]. It also shows that the weight of ADA is largest in the LtF treatment compared with the LtO and mixed treatments, while the weight of STR in the LtF treatment is the smallest among these three treatments (p-value is 0.0000 when comparing the weight of ADA and STR in LtF with the LtO and mixed treatments). These results are in line with the conclusion from the graphs of the simulation.

Based on the results above, we can conclude that the extended HSM fits well

[4]The t-test shows that p-value is near 0 when comparing the weight of ADA or STR with the other three rules in the three treatments.

Table 2
The table shows the average weight of the four heuristics in the LtF, LtO treatments, and the mixed-F, mixed-Q of the mixed treatment. The second column and third column are the average weight of the four heuristics in the LtF treatment and the LtO treatment, respectively. The fourth column and fifth column are the average weight of the four heuristics in the mixed-F and mixed-Q of the mixed treatment, respectively.

	LtF	LtO	mixed	
			mixed-F	mixed-Q
ADA	**0.4037**	0.2865	0.2610	**0.3624**
WTR	0.2881	0.2028	0.2247	0.1692
STR	0.1864	**0.3492**	**0.3249**	0.3264
A&A	0.1218	0.1615	0.1894	0.1412

in the LtO treatment. There is always a high intensity of choice parameter (β) and a lower inertia parameter (δ) in the LtO treatment than in the LtF treatment, which causes a larger fraction of individuals to switch to the STR. β is larger in the mixed treatment (p=0.07, significant at 10% level), which leads individuals to switch faster to the STR, while the ADA dominates all other rules in the LtF treatment. Since, as described in section 4.2, the ADA illustrates that individuals will be reflective by correcting their predictions concerning the one-period lagged price prediction. This rule will help to maintain price stability. The STR describes the relationship between the price prediction, the last period market price, and the last period price prediction. STR illustrates the instability of the prediction process. Bao et al. (2012) argue that if the adaptive expectation strategy dominates the market, then the price will tend to converge toward the fundamental price; in contrast, if trend rules are the dominant rules, then the price will show a pattern of divergence. In other words, if large bubbles are observed in the market, then one possible explanation would be that people are users of the trend-rule. The results of our HSM analysis may provide another explanation for the larger bubbles in the LtO treatment than in the LtF treatment in Bao et al. (2017).

5 Conditional Optimality of the Quantity Decision in the Mixed Treatment

This part addresses the second question in the introduction. Bao et al. (2017) find that the deviation of the market price from the fundamental the price deviation is the greatest in the mixed treatment and speculate that it is due to the inconsistency between the quantity decision and the conditionally optimal level given the price forecast. In this paper, we study the time series property of the quantity decisions and the conditionally optimal one suggested by the price forecast. First, we construct the summary of statistics in Table 3. Table 3 illustrates the summary of statistics of quantity decision of each market and the average of all markets in the LtO (top panel) and mixed (bottom panel) treatments, respectively. The statistics are mean (left panel), median (middle panel) and variance (right panel), respectively. For each statistic, we calculate the value for all periods, period 1 to 25 and period 26 to 50.

Table 3
Summary Statistics of Quantity Decision. This table shows the mean, median and variance of quantity. The statistics are calculated at market level. The top panel is the statistics of the LtO treatment, and the bottom panel is statistics of the mixed treatment. Each statistic is calculated for the 50 periods (overall), period 1-25 and period 26-50.

	LtO								
		Mean			Median			Variance	
	Period 1-50	Period 1-25	Period 26-50	Period 1-50	Period 1-25	Period 26-50	Period 1-50	Period 1-25	Period 26-50
Market 1	0.1226	0.2102	0.0351	0.0625	0.1500	0	0.9137	1.3328	0.5127
Market 2	0.0257	-0.0013	0.0527	0	0	0	1.2140	1.9937	0.4824
Market 3	0.1326	0.3227	-0.0574	0.0418	0.6000	-0.4250	1.7939	2.6091	0.8552
Market 4	0.1884	0.1743	0.2025	0.0050	0	0.1150	1.2192	1.5792	0.8646
Market 5	0.1297	0.1899	0.0695	0	0.1250	0	0.4217	0.6236	0.1939
Market 6	0.1137	0.1821	0.0452	0	0	0	0.9504	1.7812	0.1411
Market 7	0.1286	0.4645	-0.2073	0	0.0750	-0.2000	0.8684	1.3844	0.1213
Market 8	0.1659	0.2107	0.1211	0	0	0	0.9080	1.4957	0.3220
Average	0.1259	0.2191	0.0327	0.0137	0.1188	-0.0638	1.0362	1.6000	0.4366
	mixed								
		Mean			Median			Variance	
	Period 1-50	Period 1-25	Period 26-50	Period 1-50	Period 1-25	Period 26-50	Period 1-50	Period 1-25	Period 26-50
Market 1	0.1421	0.2537	0.0305	0	-0.1250	0	1.3195	2.5209	0.1291
Market 2	0.0683	0.2067	-0.0702	0	0	0	3.0443	4.1895	1.8675
Market 3	0.1213	0.2019	0.0407	0.0750	0.2500	0	2.4415	2.3640	2.4773
Market 4	0.2266	0.2273	0.2260	0.7125	1	0.5000	2.9712	4.4101	1.6070
Market 5	0.1038	0.1600	0.0477	0	0.2250	0	0.9099	1.6660	0.1841
Market 6	0.0054	0.0517	-0.0410	0	0	0	0.5437	0.9278	0.1638
Market 7	0.1165	0.0047	0.2283	0.0000	0	0	1.6847	2.7472	0.5579
Market 8	0.5642	0.7919	0.3366	1.1250	1	1.2500	9.0092	5.8308	11.8394
Average	0.1685	0.2372	0.0998	0.2391	0.2938	0.2188	2.7405	3.0820	2.3532

The variances of the quantity decision are 1.04 and 2.74 over 50 periods in the LtO and mixed treatments, respectively. The variance of the actual quantity decision in the mixed treatment is larger than that in the LtO treatment on average. The variances of the quantity decision are 1.60 and 3.08 (in period 1 to 25), 0.44 and 2.35 (in period 26 to 50) in the LtO and mixed treatments, respectively. The variances of the quantity decision in most markets of both treatments decrease in period 26 to 50 compared with the former 25 periods. It implies the variances of actual quantity decision decline as time increases in the LtO and mixed treatments. Figure 3 and Figure 4 plot the average quantity decisions (top panel) and the average quantity of eight markets (bottom panel) in the LtO and mixed treatments, respectively.

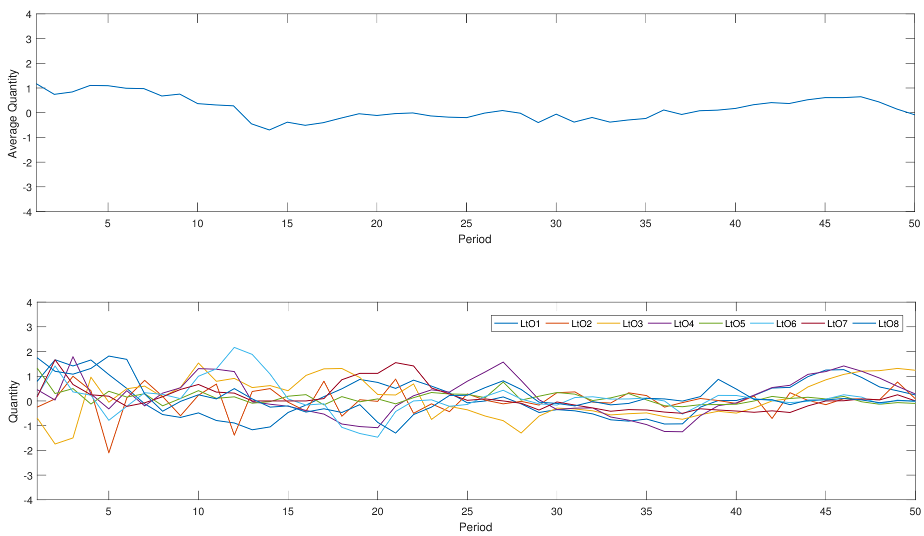

Figure 3: The average quantity decision of the LtO treatment (top panel) and the average quantity decision in each of the eight markets in the LtO treatment (bottom panel); the x-axis is the period, and the y-axis is the quantity.

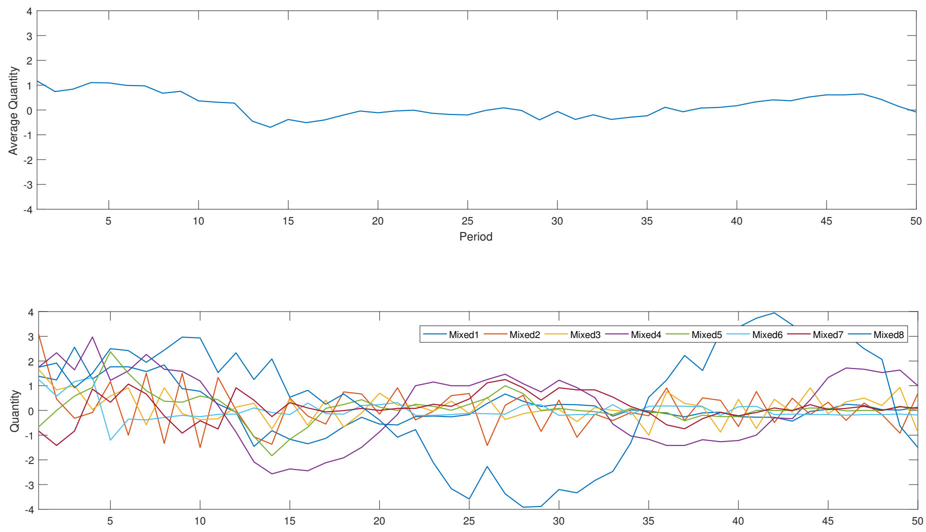

Figure 4: The average quantity decision of the mixed treatment (top panel) and the average quantity decision of each of the eight markets in the mixed treatment (bottom panel); the x-axis is the period, and the y-axis is the quantity.

In general, the magnitude of the fluctuation of quantities tends to decrease over time in both the LtO and mixed treatments. There is a larger fluctuation in market 1, 2, 3 and 6 in the first 20 periods, and it exhibits a sudden increase from period 25 to 30 in market 4 of the LtO treatment. The quantity in all other markets of the LtO treatment moves smoothly during the experimental period. After period 30, the magnitude of the fluctuation of quantities tends to decrease in all markets of the LtO treatment.

The average quantity of each market in the mixed treatment exhibits greater volatility than in the LtO treatment. The quantity of market 1 and 4 in the mixed treatment seems non-stationary in the 50 periods. In the first 10 periods, the actual quantity decisions in most markets of the mixed treatment depart from the average quantity. As in Figure 4, after period 20, the quantity decisions in some markets (market 5 to 8) of the mixed treatment gradually converge toward zero, and some of them (market 1 to 4) continue to fluctuate. The greater volatility of the quantity decisions in the mixed treatment may be due to the high cognitive cost incurred by the subjects to perform both price prediction and trading in this treatment.

Due to the greater fluctuation in the mixed treatment, we will focus on the quantity decision in the mixed treatment.The following three subsections are organized as follows: First, we introduce how to derive the conditionally optimal level of quantity. Second, we show the plots of DQ, the difference between the actual quantity decision and the conditionally optimal level in the mixed treatment. Finally, we conduct ordinary least squares (OLS) regression on the actual quantity decision and the conditionally optimal level to test whether the actual quantity converges to the conditionally optimal level in the mixed treatment.

5.1 Derivation of Conditionally Optimal Level of Quantity

Following Brock and Hommes (1998), agents allocate their wealth between one risky asset with a fixed dividend y and one risk-free bond with a fixed gross $R = 1 + r$. The wealth of agent i is defined as follows:

$$W_{i,t+1} = RW_{i,t} + q_{i,t}(p_{t+1} + y - Rp_t) \tag{12}$$

where $q_{i,t}$ denotes the demand for the risky asset by agent i at period t and p_t and p_{t+1} denote the risky asset price at period t and $t+1$. Assume that $E_{i,t}$ and $V_{i,t}$ are the forecasts of agent i regarding the conditional expectation and the conditional variance derived from publicly available information at period t. The agents myopically maximize the mean-variance utility of the wealth in the next period:

$$\max_{q_{i,t}}\{E_{i,t}W_{i,t+1} - \frac{a}{2}V_{i,t}(W_{i,t+1})\} = \max_{q_{i,t}}\{q_{i,t}E_{i,t}\rho_{t+1} - \frac{a}{2}{q_{i,t}}^2 V_{i,t}(\rho_{t+1})\}$$

where a denotes the risk-aversion parameter and ρ_{t+1} is the excess return of the risky asset, defined as follows:

$$\rho_{t+1} = p_{t+1} + Y - Rp_t$$

Let $V_{i,t}(\rho_{t+1}) = \sigma^2$, The optimal demand for the asset by agent i is defined as follows:

$$q^*_{i,t} = \frac{E_{i,t}(\rho_{t+1})}{aV_{i,t}(\rho_{t+1})} = \frac{p^e_{i,t+1} + y - Rp_t}{a\sigma^2}$$

where $p^e_{i,t+1}$ is the price expectation by individual i at period $t+1$. $R = 1 + r = 21/20$ and $a\sigma^2 = 6$, and the dividend of risk asset y is 3.3. The optimal demand of agent i at period t, $q^*_{i,t}$, is a function of the one-period ahead price prediction $p^e_{i,t+1}$:

$$q^*_{i,t} = \frac{p^e_{i,t+1} + y - Rp_t}{a\sigma^2} = \frac{p^e_{i,t+1} + 3.3 - 1.05p_t}{6} \tag{13}$$

We can derive the conditionally optimal level for any given price expectation $p^e_{i,t}$ from equation (13).

5.2 Deviation of Quantity Decision

According to Beja and Goldman (1980), the market price is set by a market maker using a simple price adjustment mechanism in response to excess demand in the experiment, as shown in equation (14):

$$p_{t+1} = p_t + \lambda(Z^D_t - Z^S_t) + \epsilon_t \tag{14}$$

where $\epsilon_t \sim N(0,1)$ is a small iid shock, $\lambda > 0$ is a scaling factor, Z^S_t is the exogenous supply and $Z^D_t$is the total demand. Additionally, in Bao et al. (2017), the exogenous supply Z^S_t is normalized to 0 in all periods.

We find that the deviation of the actual quantity from the conditionally optimal level will contribute to the deviation of price from the equation above; thus, we define the $DQ_{i,t}$ and the $ADQ_{i,t}$ of individual i at period t as follows:

$$DQ_{i,t} = q_{i,t} - q^*_{i,t} \tag{15}$$

$$ADQ_{i,t} = \left| q_{i,t} - q^*_{i,t} \right| \tag{16}$$

where $q_{i,t}$ is the actual quantity decision of individual i at period t and $q^*_{i,t}$ is the conditionally optimal level of individual i at period t. We define the average $DQ_{i,t}$ and $ADQ_{i,t}$ at market level as DQ_t, ADQ_t:

$$DQ_t = \frac{1}{6}\sum_i (DQ_{i,t})$$

$$ADQ_t = \frac{1}{6}\sum_i (ADQ_{i,t})$$

DQ measures the deviation of the actual quantity from the conditionally optimal level, and ADQ measures the absolute deviation of the actual quantity from the conditionally optimal level. Our definition is similar to the definition of Relative Deviation (RD) and Absolute Relative Deviation (ARD) in Stöckl et al. (2010).

Table 4
The numbers reported in this table are average values and calculated at market level. The second column and third column are the average actual quantity decision and conditionally optimal level in each market of the mixed treatment, $\overline{q}$ and $\overline{q^*}$, respectively, where $\overline{q}=\frac{1}{50}\sum_t(\frac{1}{6}\sum_i q_{i,t})$ and $\overline{q^*}=\frac{1}{50}\sum_t(\frac{1}{6}\sum_i q^*_{i,t})$. The third column and the fourth column are the average DQ_t and ADQ_t over the period, $\overline{DQ}$ and $\overline{ADQ}$, respectively, where $\overline{DQ}=\frac{1}{50}\sum_t DQ_t$ and $\overline{ADQ}=\frac{1}{50}\sum_t ADQ_t$. The bottom row is the $\overline{q}$, $\overline{q^*}$, $\overline{DQ}$ and $\overline{ADQ}$ over the entire mixed treatment.

	$\overline{q}$	$\overline{q^*}$	$\overline{DQ}$	$\overline{ADQ}$
mixed 1	0.1421	-0.1234	0.2658	0.5734
mixed 2	0.0683	-0.0184	0.0739	1.3853
mixed 3	0.1213	-0.0087	0.1504	1.2959
mixed 4	0.2266	-0.0352	0.2461	0.8299
mixed 5	0.1038	-0.0060	0.1120	0.5720
mixed 6	0.0054	0.1306	-0.1214	0.4578
mixed 7	0.1165	0.0838	0.0333	0.8010
mixed 8	0.5642	0.0995	0.5069	1.9007
Average	0.1685	0.0153	0.1584	0.9770

The last row of Table 4 above shows the $\overline{q}$, $\overline{q^*}$, $\overline{DQ}$ and $\overline{ADQ}$ over the entire mixed treatment. They are 0.1685, 0.0153, 0.1584 and 0.9770, respectively. We can observe from Table 4 that the actual quantity decision is not equal to the conditionally optimal level, the DQ and ADQ are far from 0. Figure 5 below shows the fluctuation of the average DQ_t over individuals of the entire mixed treatment (top panel), the DQ_t in each market of the mixed treatment (middle panel) and the $DQ_{i,t}$ of individual i in one market of the mixed treatment (bottom panel). The average DQ of the entire treatment in the top panel of Figure 5 fluctuates around zero, and the average DQ of the eight markets does not show convergence. There are great fluctuations in the market 2 and 8 of the mixed treatment. In all other markets of the mixed treatment (Figure A5 in Appendix A), the average DQ is also volatile. The results of DQ illustrate that there is no convergence between the actual quantity decision and the conditionally optimal level in the mixed treatment.

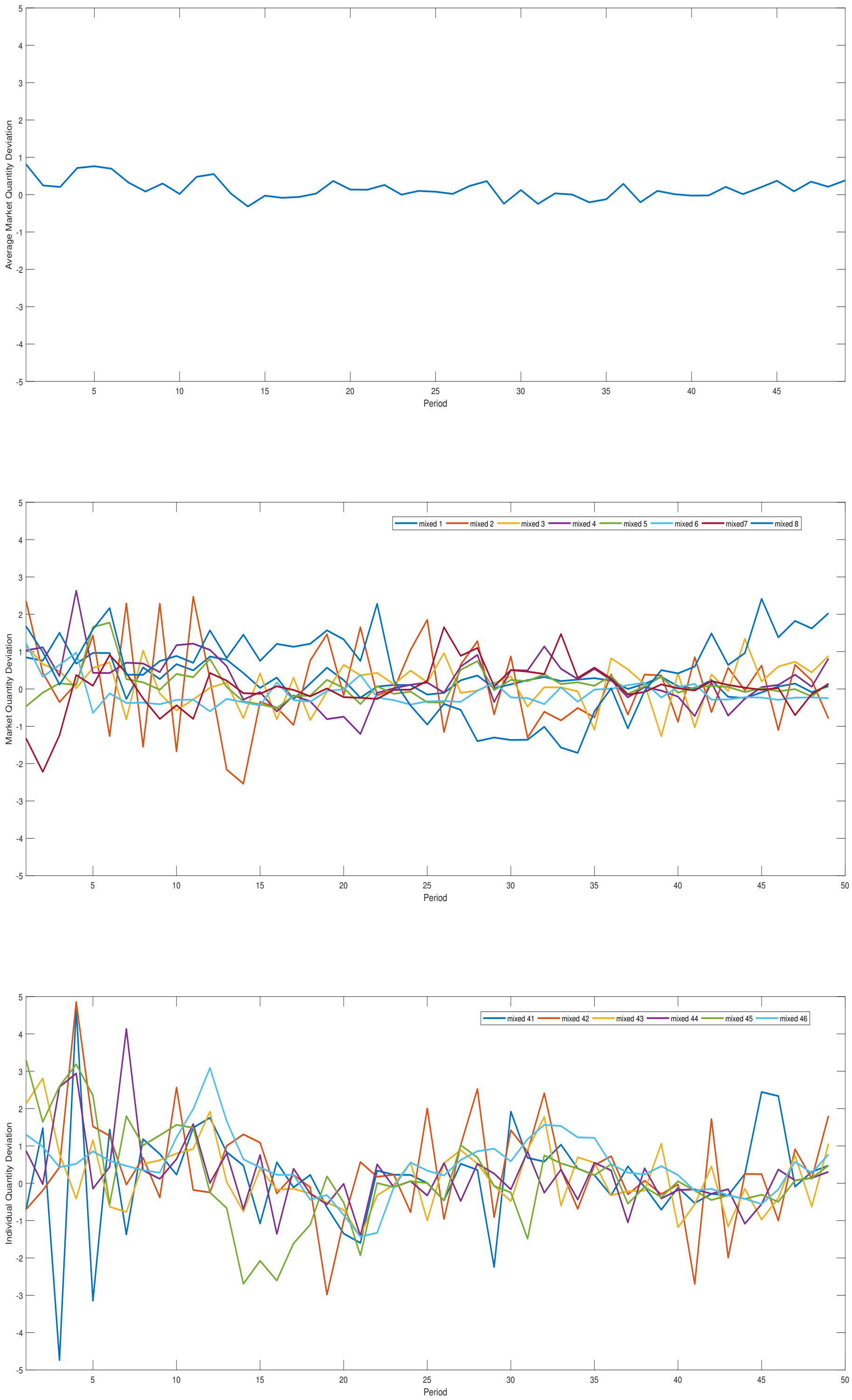

Figure 5: The average DQ of the entire mixed treatment (top panel), the market average DQ of the different markets in the mixed treatment (middle panel) and the individual DQ in market 4 of the mixed treatment (bottom panel); the x-axis is the number of the period, and the y-axis is the quantity.

5.3 Convergence of Actual Quantity to the Optimal Level

In this part, we run the regression on the actual quantity decision and the conditionally optimal level to investigate whether there is a tendency of the former to converge towards the latter in the long run. Similar to Bao et al. (2013), we estimate a linear equation on the actual quantity and examine whether the long-run equilibrium of the equation is equal to the conditionally optimal level. We tested the following equation:

$$q_{i,t} = c + a_1 q_{i,t-1} + a_2 q^*_{i,t}$$

$q_{i,t}$ is the actual quantity decision of individual i at period t, $q_{i,t-1}$ is the one-period lagged actual quantity decision of individual i, and $q^*_{i,t}$ is the conditionally optimal level of individual i at period t. The rational benchmark is that c, a_1 are 0 and a_2 is 1, which indicates that actual quantity decision equals to the conditionally optimal level. It is easy to observe that the long-run steady state of this equation is $q^a_e = \frac{c}{1-a_1} + \frac{a_2}{1-a_1} q^*$. If the intercept $\frac{c}{1-a_1}$ is 0 and $\frac{a_2}{1-a_1}$ is approximately equal to 1, then the actual quantity decision will converge towards the conditionally optimal level.

We estimate the equation for each of the 48 subjects, and the results are reported in Table 5, in which the first column is the subject number from market 1 to market 8 of the mixed treatment, the second and third columns are the intercept c with its p-value, respectively, and the fourth and fifth columns are the coefficient a_1 with its p-value, respectively, and the sixth and seventh columns are the coefficient a_2 with its p-value, respectively. The last two columns are $c/(1-a_1)$ and $a_2/(1-a_1)$. We report the coefficients that are significantly different from 0 at 5% level.

c, a_1 and a_2 are significant in 9 , 26 and 43 out of 48 subjects, respectively. The means of c, a_1 and a_2 are 0.06, 0.47 and 1.46, respectively. Since a_1 is not near 0 and a_2 is not 1, so our result shows that actual quantity decision does not equal the conditionally optimal level. If we look at the long run equilibrium of the estimated equations, the mean and median of $c/(1-a_1)$ are 0.85 and 0.51, respectively. Moreover, the mean and median of $a_2/(1-a_1)$ are 2.72 and 3.06, respectively. Since $c/(1-a_1)$ is not close to 0 and $a_2/(1-a_1)$ is far from 1, we can conclude that the long-run equilibrium of the actual quantity decision is not equal to conditionally optimal level in the mixed treatment either. This result indicates that there is a persistent difference between the actual quantity and the conditionally optimal level in the mixed treatment.

To summarize, our findings suggest that in the mixed treatment, while the actual quantity decision converges toward the conditionally optimal level for some individuals, the deviation persists for others. This persistence contributes to the larger mispricing in the mixed treatment than in the other two treatments, particularly the LtF treatment where the computer algorithm always chooses the conditionally optimal level for the subject.

Table 5
The first column is the subject numbers of the individuals in the mixed treatment, and the second and third columns are the estimation results of the constant c and its p–value, respectively. The fourth and fifth columns are the estimation results of a_1 and its p–value, respectively. The sixth and seventh columns are the coefficient a_2 with its p-value. The last two columns are the values of $c/(1 - a_1)$ and $a_2/(1 - a_1)$.

No.	Cons	p-value	a_1	p-value	a_2	p–value	$c/(1 - a_1)$	$a_2/(1 - a_1)$
11			0.2579	0.0020	1.5671	0.0000		2.1116
12					1.8557	0.0000		
13					2.8100	0.0000		
14			0.5373	0.0000	1.5918	0.0000		3.4402
15	0.1344	0.0310	0.7337	0.0000	1.1060	0.0000	0.5046	4.1530
16			0.7180	0.0000	1.0064	0.0000		3.5686
21					1.0324	0.0000		
22			0.3149	0.0170	1.0381	0.0020		1.5153
23					1.2878	0.0000		
24								
25			-0.4549	0.0020				
26					1.0008	0.0000		
31	0.8357	0.0190						
32	0.5230	0.0050			1.0118	0.0270		
33	0.3711	0.0000			1.2066	0.0000		
34	-1.6583	0.0000						
35			-0.3167	0.0310	0.9769	0.0250		0.7420
36			0.6677	0.0000	1.6232	0.0000		4.8850
41					1.8349	0.0000		
42			0.6486	0.0000	1.3075	0.0000		3.7208
43			0.4888	0.0000	1.5467	0.0000		3.0252
44			0.2993	0.0240	1.7889	0.0000		2.5530
45			0.4936	0.0000	1.7893	0.0000		3.5338
46	0.1700	0.0010	0.6599	0.0000	1.4494	0.0000	0.4998	4.2613
51			0.2933	0.0480	1.1997	0.0000		1.6975
52			0.6321	0.0000	1.0054	0.0000		2.7324
53					1.3804	0.0000		
54					1.7377	0.0000		
55			1.4941	0.0000	0.3752	0.0000		-0.7593
56			0.3113	0.0260	2.2171	0.0060		3.2191
61					1.3493	0.0000		
62			0.5066	0.0000	1.0037	0.0000		2.0343
63			0.3141	0.0330	1.1151	0.0060		1.6256
64	0.1216	0.0030			0.6887	0.0000		
65					1.0264	0.0000		
66	-0.6466	0.0000			6.6755	0.0000		
71					1.2526	0.0000		
72					1.1329	0.0110		
73			0.3551	0.0090	1.0616	0.0000		1.6460
74					0.9173	0.0030		
75					0.9988	0.0000		
76			0.4816	0.0010				
81			0.4661	0.0010	0.9672	0.0000		1.8115
82			0.5718	0.0000	1.3409	0.0000		3.1315
83			0.5372	0.0000	1.4838	0.0000		3.2062
84			0.6045	0.0000	1.6666	0.0000		4.2144
85					1.9658	0.0000		
86	0.6559	0.0060	0.5736	0.0000	1.3223	0.0000	1.5380	3.1009

6 Conclusion

This paper aims to find a possible explanation for why bubbles are more likely and tend to be larger when people make quantity decisions than price forecasts. We apply the HSM to simulate the price and the quantity in these treatments and find that the extended HSM fits the quantity decisions in the LtO treatment very well. Our paper provides two explanations of this difference. First, the LtO treatment is usually associated with a high intensity of choice parameter and a small inertia parameter in the HSM, which causes a larger fraction of the population to choose the destabilizing strong trend-following rule. The intensity of choice parameter is also higher in the mixed treatment, which leads to individuals switch faster to the destabilizing strong trend-following rule as well. Second, we find that the actual quantity decision in the mixed treatment may deviate from the conditionally optimal level substantially and persistently, which amplifies the price deviation from the rational expectation equilibrium.

Our findings suggest that people are more likely to switch between strategies and join the crowd to become trend followers when they make a quantity decision rather than a price forecast. This may be because the fluctuation of subjects' emotion tends to be larger when they receive feedbacks in terms of how much profit they made than how accurate their price forecast is. The role of emotion in bubble formation is also highlighted in recent research in experimental finance, e.g., Andrade et al.(2015) and Breaban and Noussair (2017).

One possible policy recommendation would be to provide robot advisors or mobile applications for individual investors to help them calculate their optimal asset demand for their price forecast. This calculator may reduce their tendency to chase the trend and enhance the stability of financial markets.

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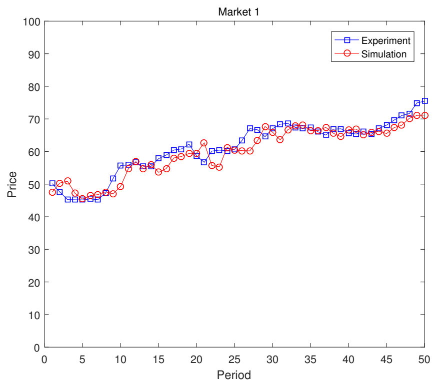
Appendix A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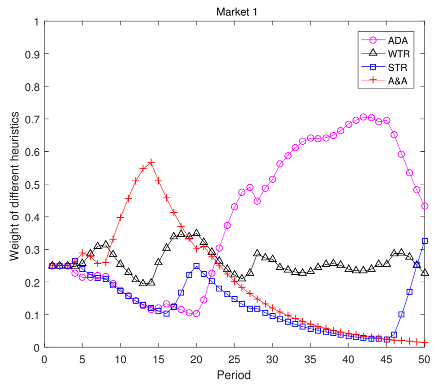
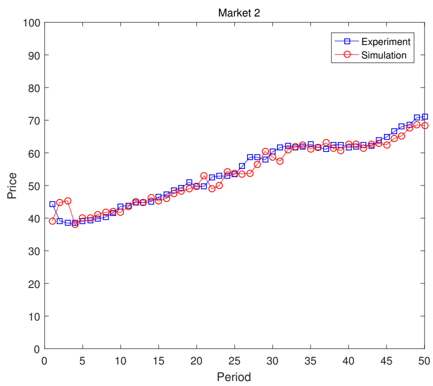
Experiment
Simulation
Price
Period


Market 1
ADA
WTR
STR
A&A
Weight of different heuristics
Period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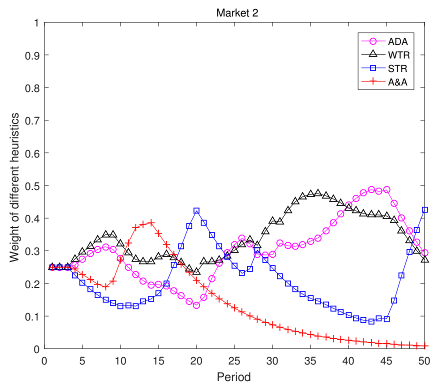
Experiment
Simulation
Price
Period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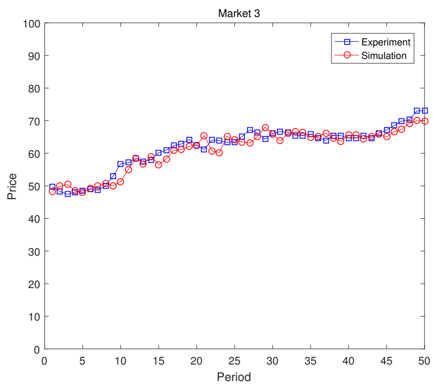
ADA
WTR
STR
A&A
Weight of different heuristics
Period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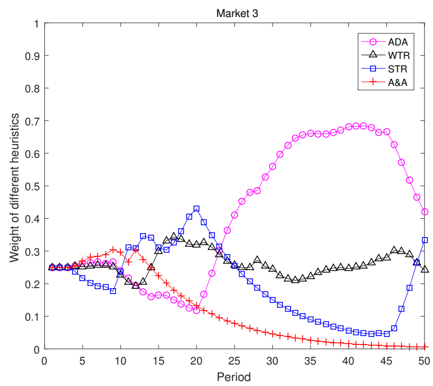
Experiment
Simulation
Price
Period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WTR
STR
A&A
Weight of different heuristics
Period

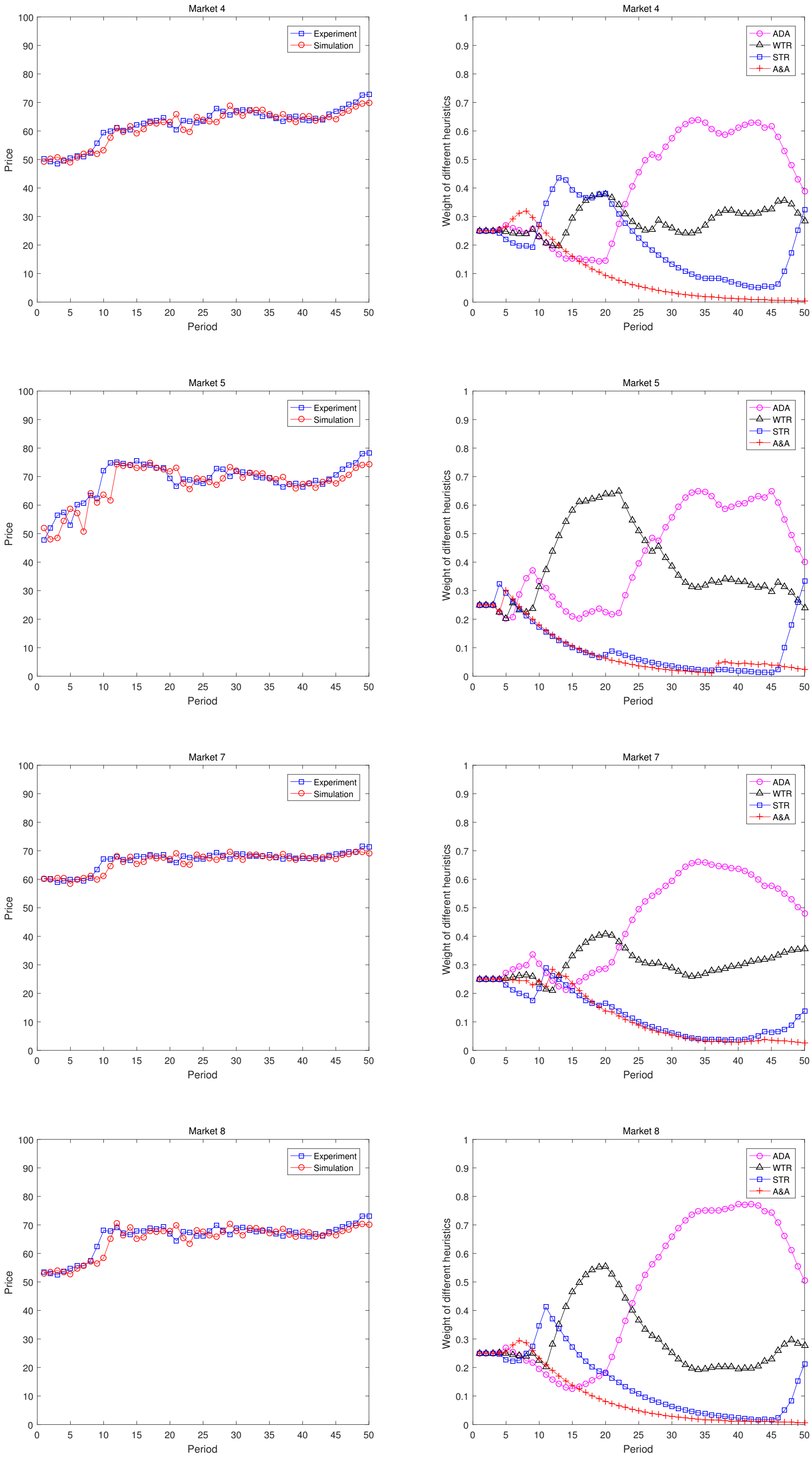
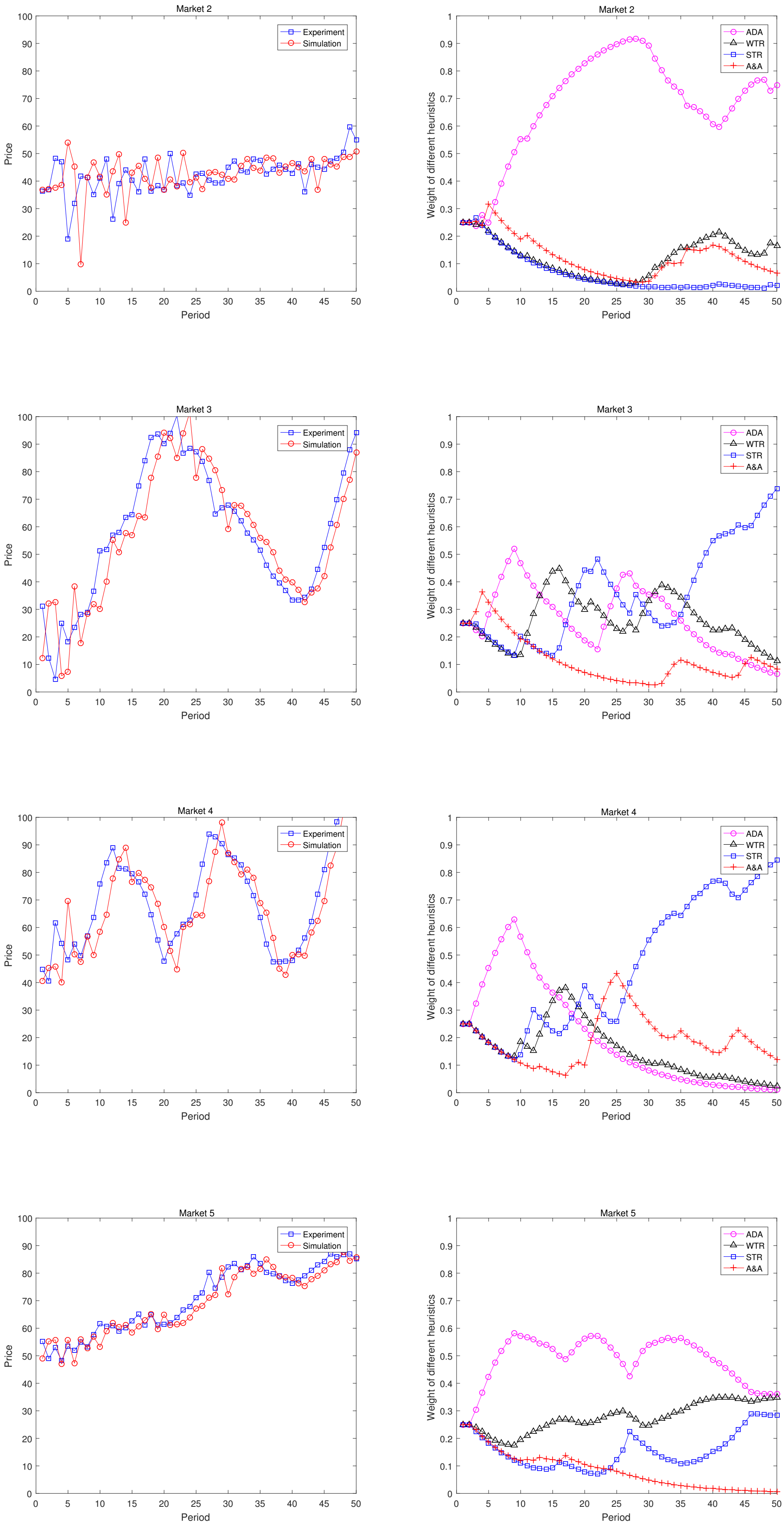


Figure A1: Experimental data (blue line with squares) and simulated asset price (red line with circles) using the HSM (left panel) and the weights of the different heuristics (right panel) in the LtF treatment. The x-axis is the period, and the y-axis is the price (left panel) and the weight of the heuristics (right panel).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Market 3
Market 4
Market 5
Experiment
Simulation
Price
Period
ADA
WTR
STR
A&A
Weight of different heuristics

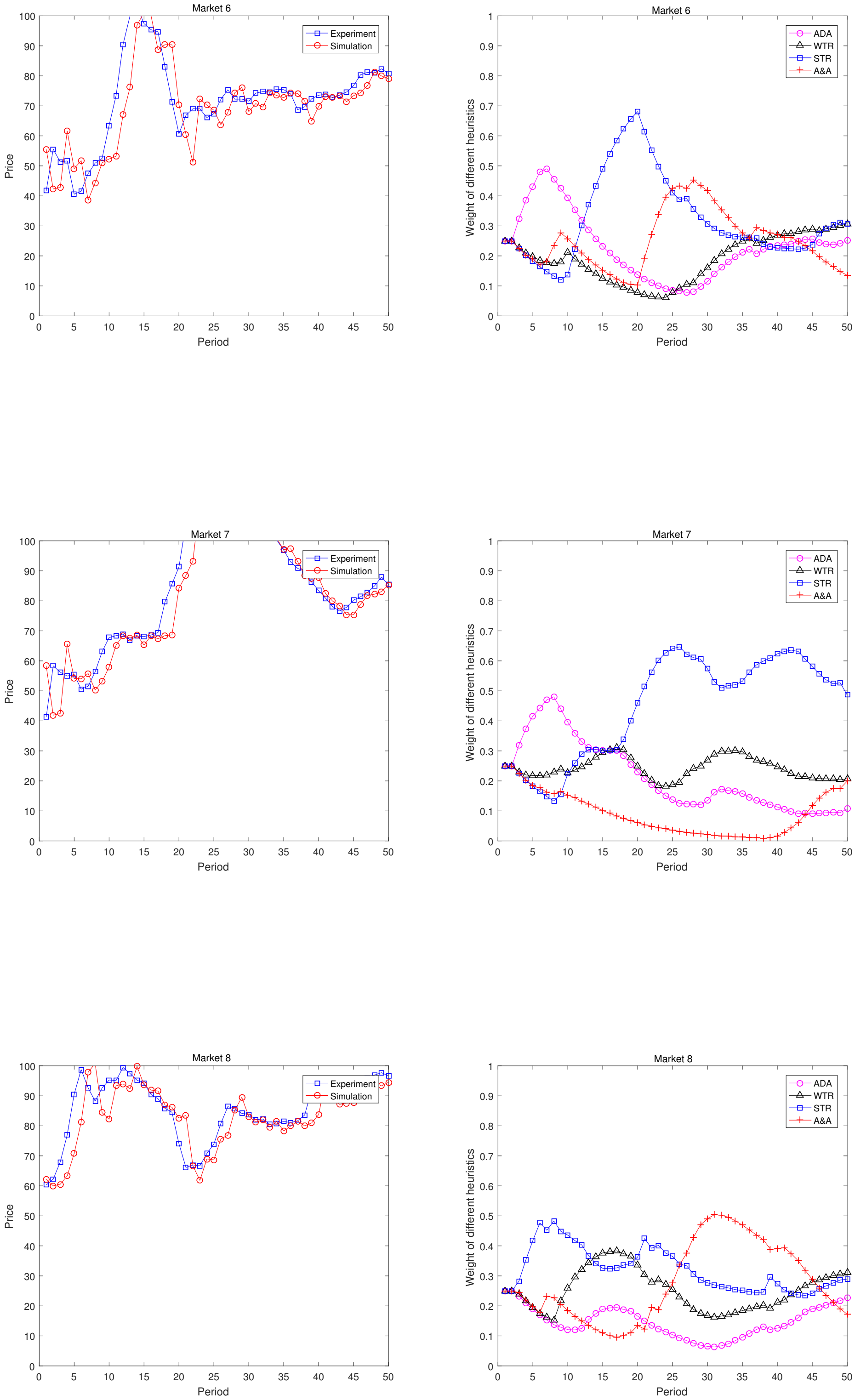
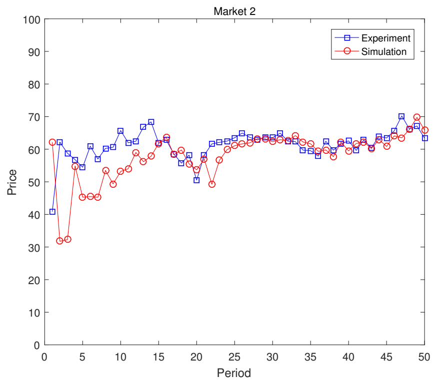


Figure A2: Experimental data (blue line with squares) and simulated asset price (red line with circles) using the HSM (left panel) and the weights of the different heuristics (right panel) in the LtO treatment. The x-axis is the period, and the y-axis is the price (left panel) and the weight of the heuristics (right panel).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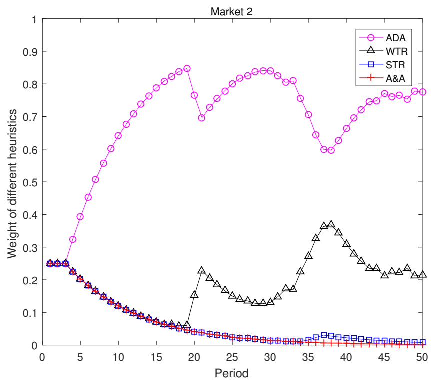
Experiment
Simulation
Price
Period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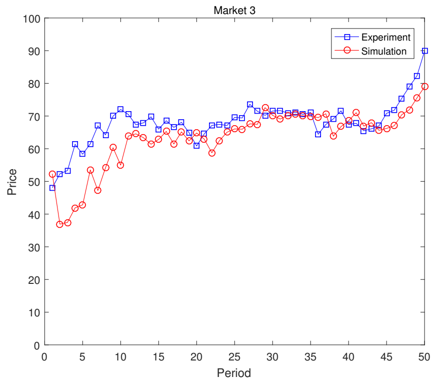
ADA
WTR
STR
A&A
Weight of different heuristics
Period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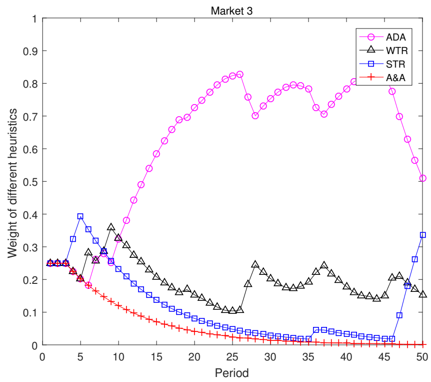
Experiment
Simulation
Price
Period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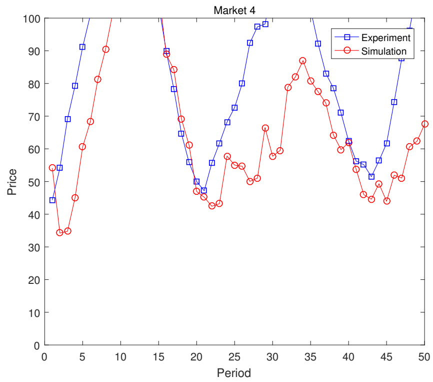
STR
A&A
Weight of different heuristics
Period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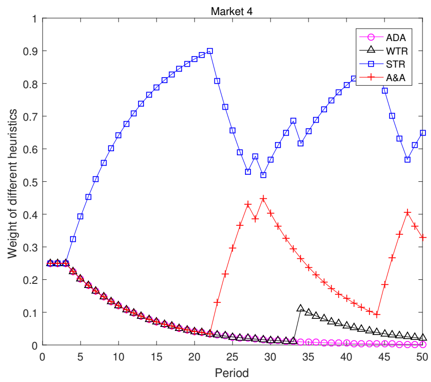
Experiment
Simulation
Price
Period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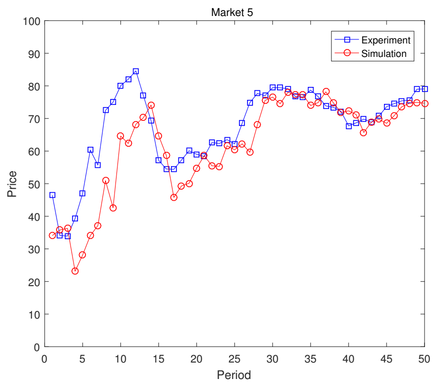
WTR
STR
A&A
Weight of different heuristics
Period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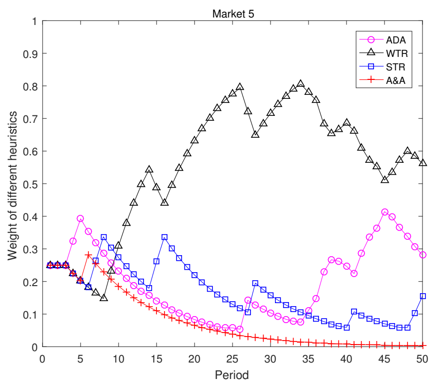
Experiment
Simulation
Price
Period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WTR
STR
A&A
Weight of different heuristics
Period

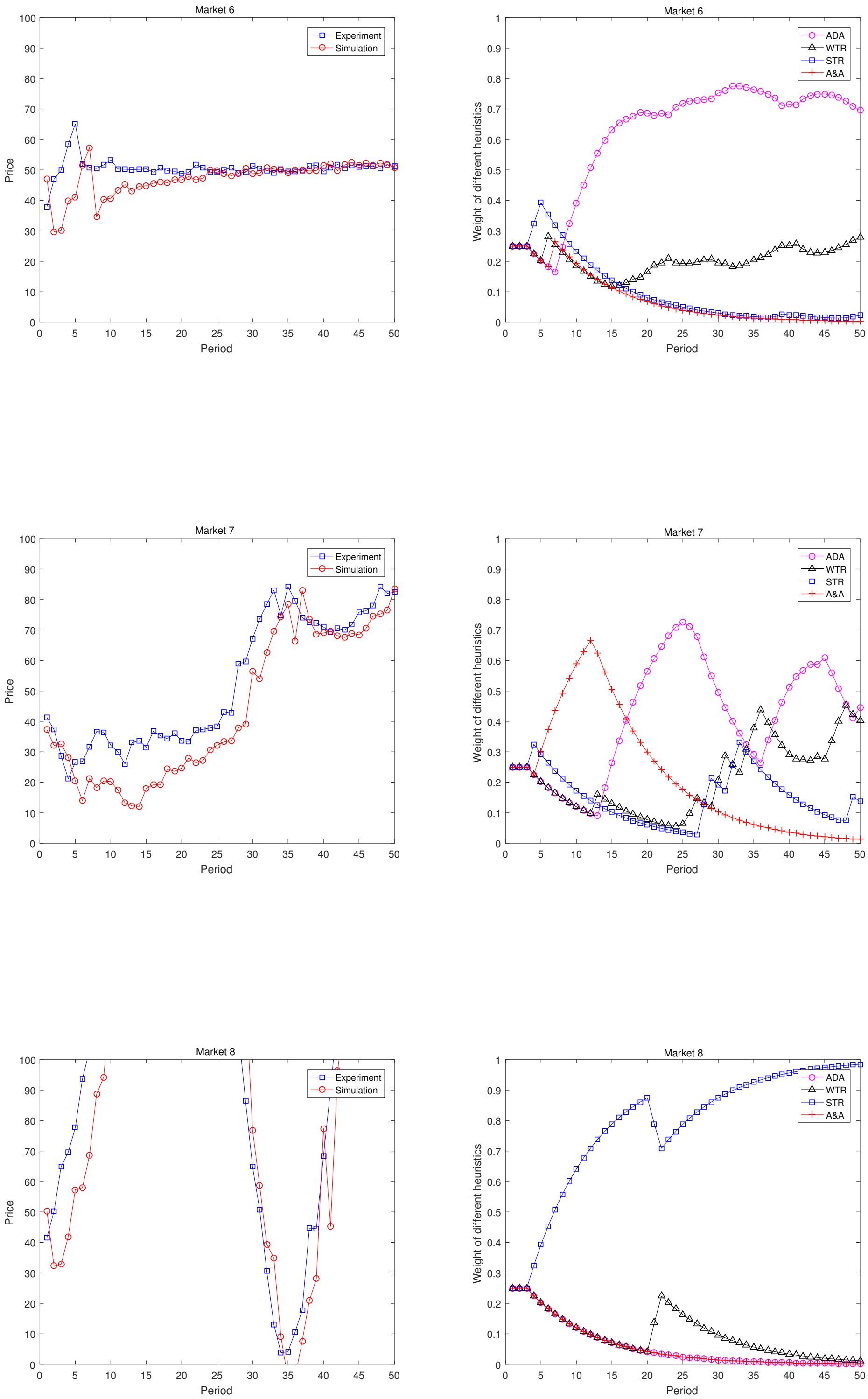
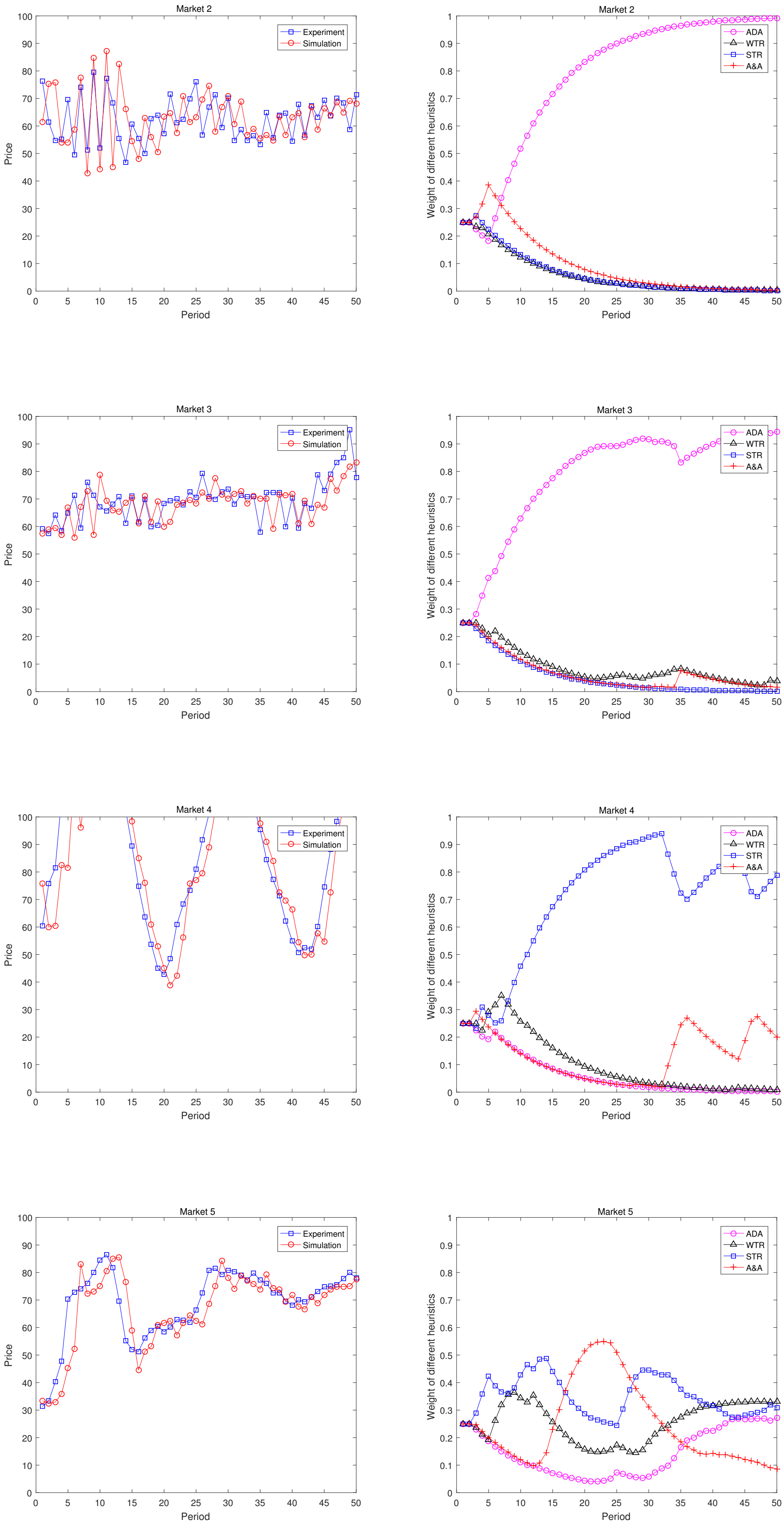


Figure A3: Experimental data (blue line with squares) and simulated asset price (red line with circles) using the HSM (left panel) and the weights of the different heuristics (right panel) in the mixed-F of the mixed treatment. The x-axis is the period, and the y-axis is the price (left panel) and the weight of the heuristics (right panel).


Market 2
Market 3
Market 4
Market 5
Price
Period
Weight of different heuristics
Experiment
Simulation
ADA
WTR
STR
A&A

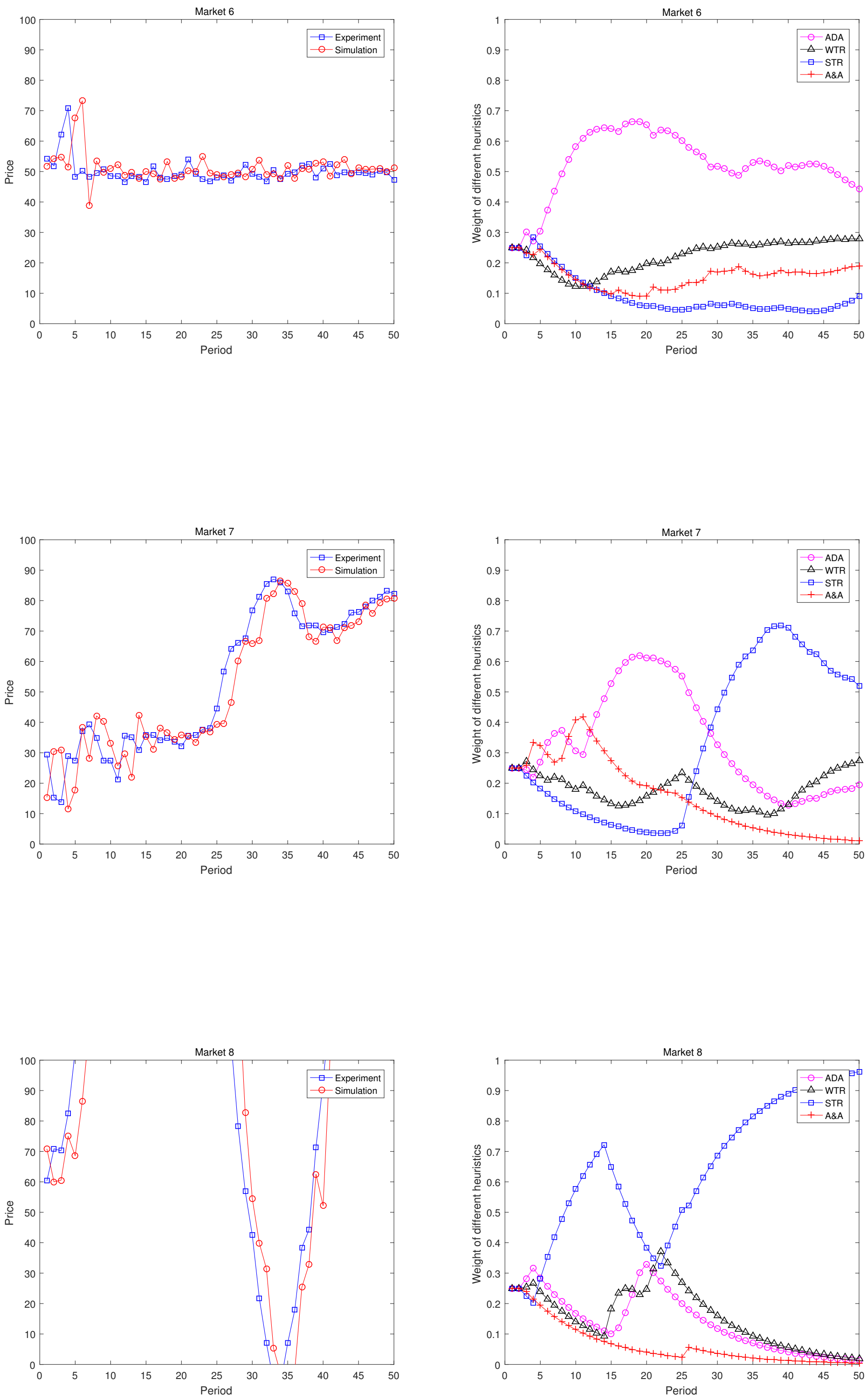
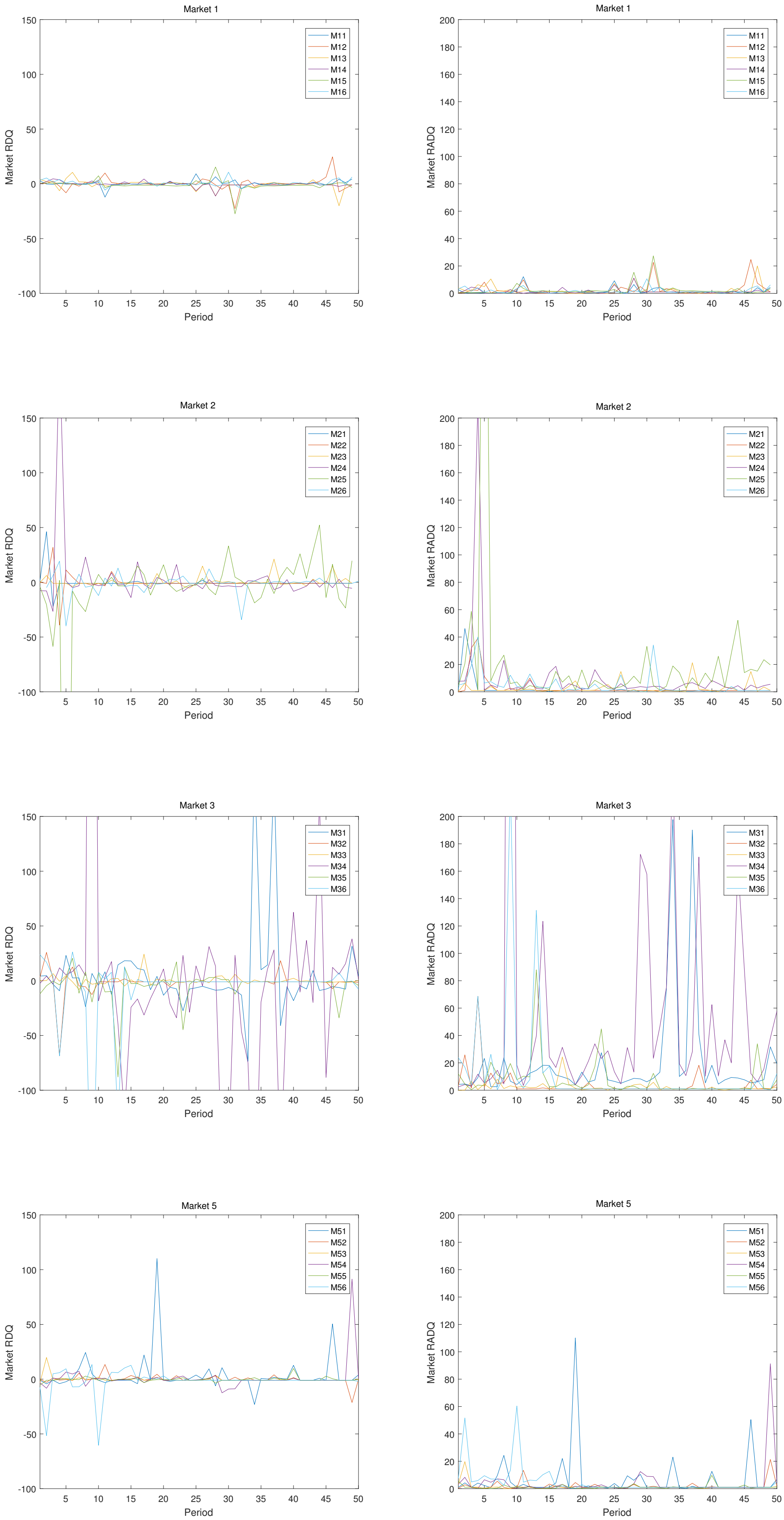


Figure A4: Experimental data (blue line with squares) and simulated asset price (red line with circles) using the HSM (left panel) and the weights of the different heuristics (right panel) in the mixed-Q of the mixed treatment. The x-axis is the period, and the y-axis is the price (left panel) and the weight of the heuristics (right panel).


Market 1
Market RDQ
Period
M11
M12
M13
M14
M15
M16
Market 1
Market RADQ
Period
Market 2
Market RDQ
Period
M21
M22
M23
M24
M25
M26
Market 2
Market RADQ
Period
Market 3
Market RDQ
Period
M31
M32
M33
M34
M35
M36
Market 3
Market RADQ
Period
Market 5
Market RDQ
Period
M51
M52
M53
M54
M55
M56
Market 5
Market RADQ
Period

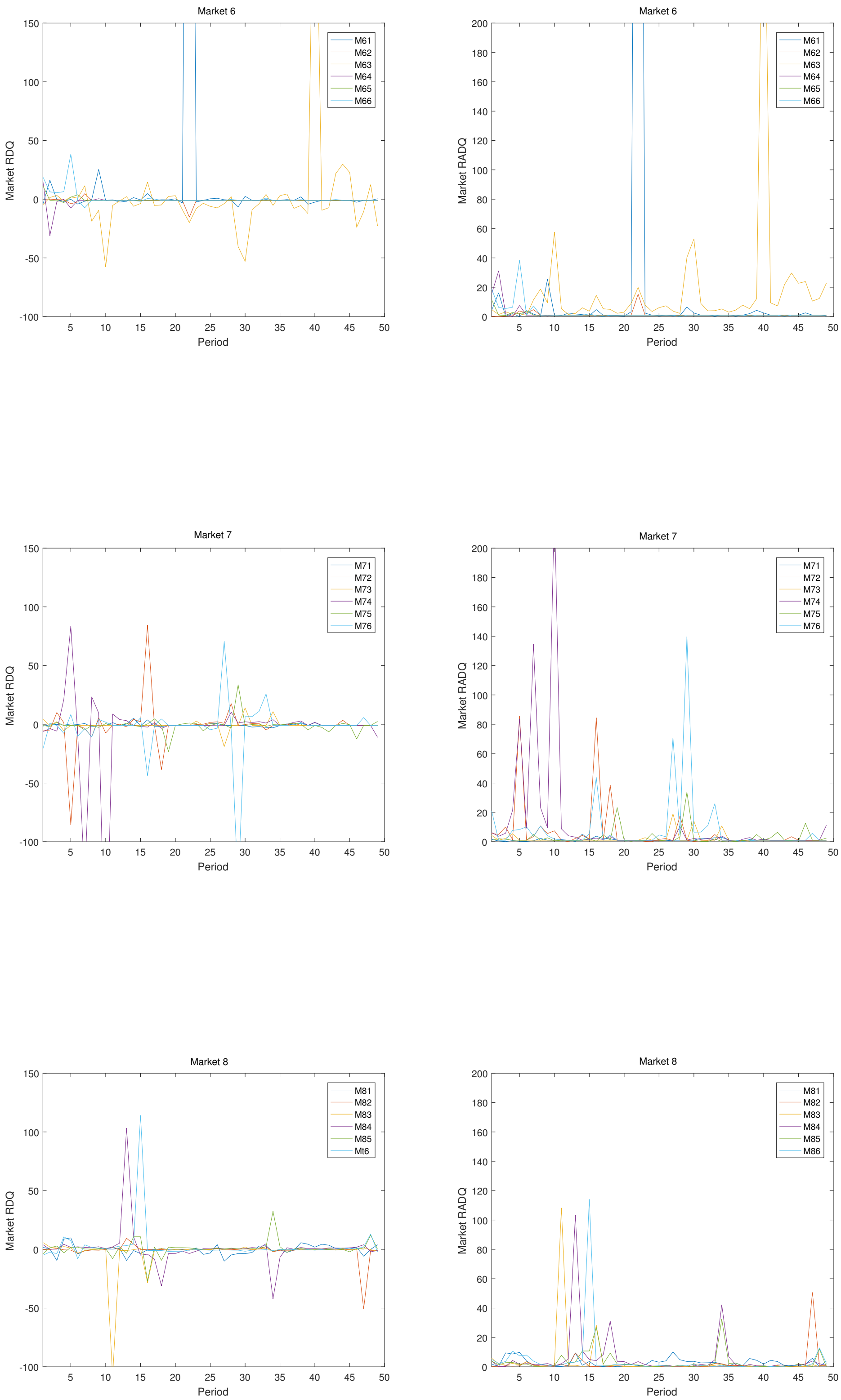
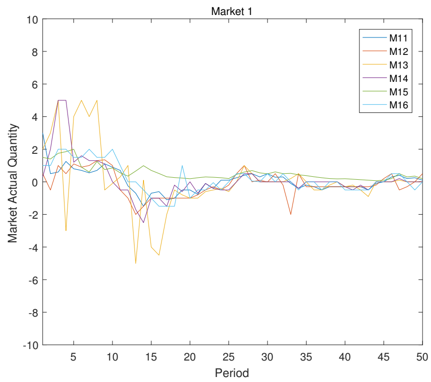
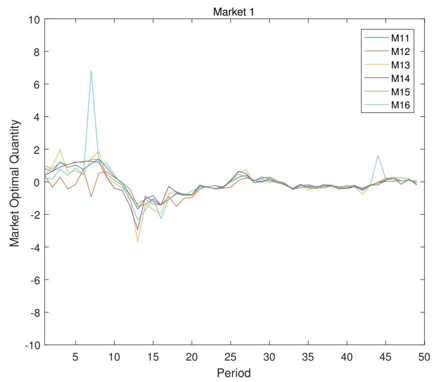


Figure A5: The individual DQ in each market of the mixed treatment (left panel) and individual ADQ in each market of the mixed treatment (right panel), the x-axis is the experimental period, and the y-axis is the percentage.


Market 1
Market Actual Quantity
Period
M11
M12
M13
M14
M15
M16


Market 1
Market Optimal Quantity
Period
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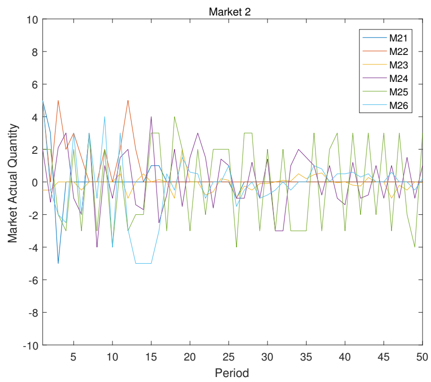
M13
M14
M15
M16


Market 2
Market Actual Quantity
Period
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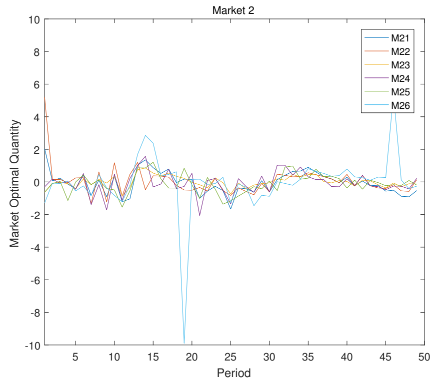
M22
M23
M24
M25
M26


Market 2
Market Optimal Quantity
Period
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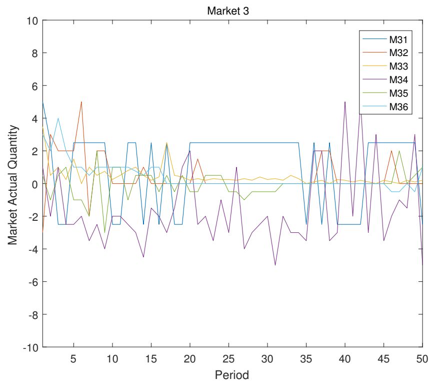
M22
M23
M24
M25
M26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Market Actual Quantity
Period
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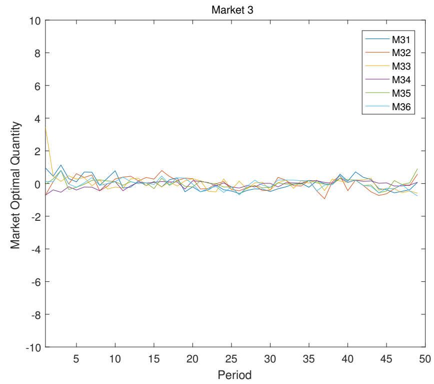
M32
M33
M34
M35
M36


Market 3
Market Optimal Quantity
Period
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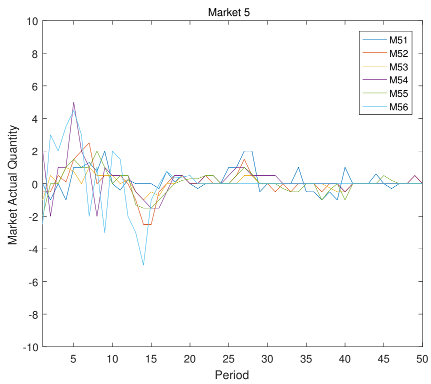
M32
M33
M34
M35
M36


Market 5
Market Actual Quantity
Period
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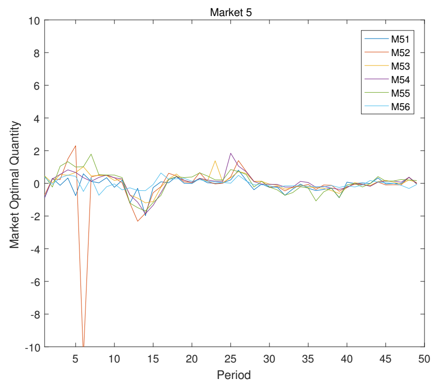
M52
M53
M54
M55
M56


Market 5
Market Optimal Quantity
Period
M51
M52
M53
M54
M55
M56

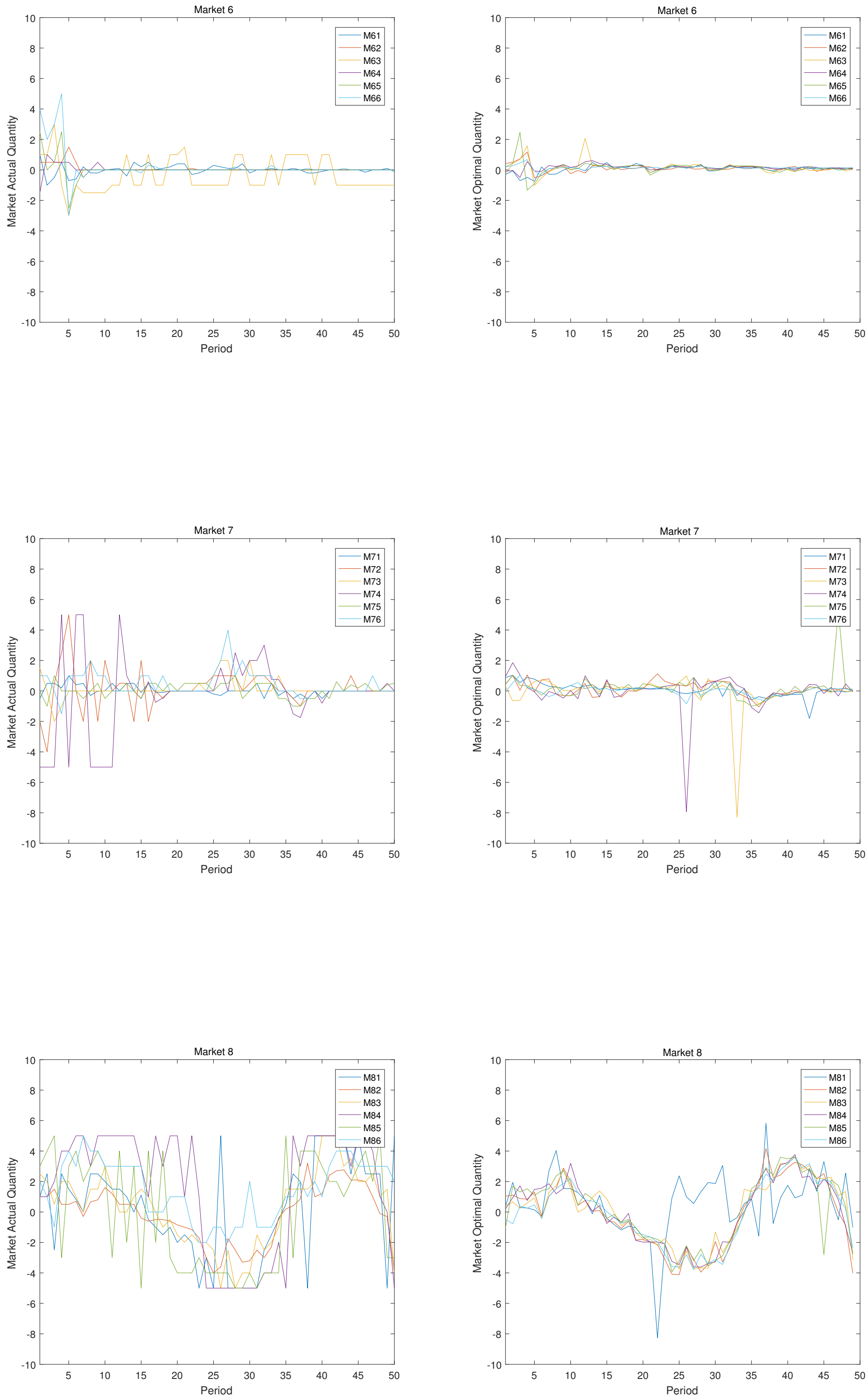


Figure A6: The actual quantity decision of individuals in each market of the mixed treatment (left panel) and conditionally optimal level of individuals in each market of the mixed treatment (right panel). The x-axis is the experimental period, and the y-axis is the actual quantity (left panel) and market conditionally optimal level (right panel).

Appendix B

Table B1
The result is for the estimation of $p^e_{i,t} = \alpha_i p_{t-1} + \beta_i p^e_{i,t-1} + \gamma_i(p_{t-1} - p_{t-2})$ for the LtF treatment. The first column is the subject number. The second to the fifth columns are the estimated coefficients, constant c, P_{t-1}, P^e_{t-1} and P_{t-1}-P_{t-2}, respectively. We drop all the coefficients that are not significant at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The sixth column is the R^2 of the regression.

No.	Cons	P_{t-1}	P^e_{t-1}	P_{t-1}-P_{t-2}	R^2	MSE
11		0.2880	0.7560	0.6800	0.9950	0.3770
12	-1.9520		1.0900	0.4480	0.9960	0.2370
13		1.0000		0.7440	0.7340	0.3104
14	-1.3490		0.9820	0.4270	0.9980	0.1857
15	-2.0800	0.3070	0.7250	0.3620	0.9970	0.2326
16		1.0000		0.7700	0.6480	0.5064
21			1.0140		0.9980	0.5941
22		0.6260	0.3470	0.5190	0.9980	0.2944
23	-2.1100	0.3460	0.6970		0.9960	0.4809
24			1.0130		0.9920	0.7847
25			1.0130		0.9970	0.2629
26	-1.8570	0.4750	0.5610	0.3910	0.9960	0.5100
31		0.4630	0.5220	0.7070	0.9930	0.2309
32		0.5130	0.4950	0.6550	0.9940	0.2181
33		0.4760	0.6600	0.3950	0.9930	0.2699
34		1.0000		0.3020	0.3100	0.1968
35		1.0000		0.3640	0.3900	0.2710
36		0.4710	0.5440	0.5790	0.9980	0.0861
41		0.5960	0.5680	0.4820	0.9880	0.3820
42		1.0000		0.6790	0.3200	1.2562
43		1.0000		0.1610	0.0250	0.3208
44	-2.5530	0.4180	0.6210	0.4050	0.9920	0.2654
45		0.3890	0.6080	0.5390	0.9960	0.0945
46		1.0000		0.3410	0.3850	0.2014
51		0.2600	0.7150	0.7290	0.9900	0.2521
52			1.0210		0.8950	2.1217
53	-53.0680	-0.3690	2.1250	-1.5910	0.6550	35.3252
54		0.1780	0.9020	0.8360	0.9800	1.1334
55		0.4520	0.5870	0.7910	0.9930	0.1690
56		0.2810	0.7190	1.2450	0.9850	0.3251
61			0.9930		0.8800	8.2432
62		1.0000		0.9210	0.5070	2.5087
63		1.0000		0.7120	0.7610	0.7262
64		1.0000		0.8270	0.8040	0.5871
65		0.4520	0.4110	0.9770	0.9860	0.8208
66		1.0000		0.8040	0.8090	0.4060
71	6.9140		0.9020		0.9100	0.6423
72			1.0100		0.9980	0.0845
73			0.9260		0.9240	0.5544
74		0.3590	0.5900	0.3990	0.9660	0.2648
75			0.9900		0.9730	0.1621
76		0.3080	0.5360	0.5450	0.9600	0.2947
81		1.0000		0.4510	0.2930	0.8352
82		1.0000		0.3700	0.5020	0.2326
83	2.7780		0.8220	0.4700	0.9840	0.2958
84	7.9580		0.8840	0.7830	0.9110	1.3398
85		0.3160	0.7010	0.4710	0.9920	0.1346
86		1.0000		0.3420	0.0810	2.0595

Source: Bao et al. (2017)

Table B2
The result is for the estimation of $p^e_{i,t} = \alpha_i p_{t-1} + \beta_i p^e_{i,t-1} + \gamma_i(p_{t-1} - p_{t-2})$ for the mixed-F in the mixed treatment. The first column is the subject number. The second to the fifth columns are the estimated coefficients, constant c, P_{t-1}, P^e_{t-1} and P_{t-1}-P_{t-2}, respectively. We drop all the coefficients that are not significant at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The sixth column is the R^2 of the regression.

No.	Cons	P_{t-1}	P^e_{t-1}	P_{t-1}-P_{t-2}	R^2	MSE
11		0.8020	0.2092	0.8497	0.9974	0.7404
12		0.7164	0.3086	0.6650	0.9835	4.7611
13		0.9877		0.9634	0.9817	4.6682
14		0.8418		0.8158	0.9853	3.7006
15		0.7051	0.2878	0.8909	0.9976	0.6497
16		2.8554		10.2985	0.1701	15913.8225
21	27.2758	0.3181	0.2342		0.4556	3.0436
22	13.2259	0.7787		-0.3235	0.6278	5.8826
23	10.1961	0.5606	0.2757		0.8558	1.9544
24		0.6430	0.2249	-0.5214	0.7139	4.4745
25		0.5512			0.4811	10.7833
26					0.0340	948987.7056
31		0.5655	0.3576	0.3945	0.8664	4.3310
32		0.6501	0.3221		0.8755	4.6829
33	13.4894	0.9260			0.9387	1.9061
34	-4.3367	0.6970	0.3664		0.9774	1.0533
35		0.7942			0.9323	3.0005
36	5.5762	0.7423			0.9402	1.8608
41	6.3453	0.6811		0.8810	0.9738	21.9314
42	7.5877	0.9703		0.6659	0.9375	50.0769
43	3.7344	1.1754		0.9699	0.9940	5.1388
44		0.9082		0.6503	0.9935	5.6254
45		0.9354		0.9604	0.9949	4.6794
46	3.0289	0.5235	0.4398	0.9887	0.9969	2.8315
51		1.2070			0.9568	5.9146
52		1.1287			0.5411	107.1846
53		0.8207		0.7374	0.9797	2.7238
54		0.6435	0.3263	0.8395	0.9701	4.1767
55		0.7887		0.9957	0.9657	4.4720
56		1.0567			0.9850	1.8461
61	24.3493	0.6301			0.7177	0.9342
62		0.8435	0.1760	0.7672	0.9664	0.4467
63		0.7504		0.6095	0.5874	6.1251
64		0.8142			0.8420	1.1247
65	28.1617	0.9250	-0.4796	0.5197	0.5181	4.8009
66		0.7383	0.2739	0.5424	0.9680	0.3081
71		0.8013			0.9897	4.7716
72		0.7412		0.5765	0.9891	5.4648
73		1.0226			0.8872	54.9466
74		1.1005			0.8932	61.1696
75		1.9462			0.1316	10999.8144
76		0.4481	0.5606	0.4170	0.9961	1.9410
81		0.5932	0.3680		0.5747	3835.2010
82	2.7979	0.8578		0.9327	0.9974	14.4294
83		0.8543		0.8849	0.9965	20.0498
84	2.8015	0.7624		0.9173	0.9980	11.0603
85		0.9886		0.8201	0.9873	71.0329
86		0.5018	0.4830	0.9747	0.9982	10.6322

Source: Bao et al. (2017)

Table B3

The result is for the estimation of $p^e_{i,t} = p^e_{t-1} + w(p_{t-1} - p^e_{t-1})$ for the LtO treatment. The first column is the subject number. The second and third columns are the estimated coefficients, P^e_{t-1} and P_{t-1}-P^e_{t-1}, respectively. We drop all the coefficients that are means insignificance at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The fourth and fifth columns are the R^2 and the MSE of the regression. The sixth and seventh columns show whether we reject the null hypothesis that there is no breakpoint in the Chow test. The last two columns show the result of AC test.

No.	P^e_{t-1}	P_{t-1}-P^e_{t-1}	R^2	MSE	Chow	p-value	AC	p-value
11	1.0599	-0.5427	0.9940	19.2905	N	0.3419	Y	0.0412
12	1.0052		0.9797	68.7307	Y	0.0102	Y	0.0000
13	1.0269		0.9887	36.7272	N	0.2387	Y	0.0053
14	1.0178		0.9927	23.6293	N	0.0830	Y	0.0267
15	1.0051		0.9910	29.9198	Y	0.0135	N	0.1150
16	1.0490	-0.3924	0.9925	24.1661	N	0.1577	Y	0.0159
21	0.8494	0.9888	0.9629	54.1402	N	0.7903	N	0.0925
22	0.8560	1.3068	0.9474	84.0669	N	0.7894	N	0.2991
23	0.8784	0.8474	0.9003	157.1262	N	0.5094	N	0.4825
24	0.8808	1.2104	0.9794	32.6932	N	0.9413	N	0.9787
25	0.8948	0.7283	0.9884	16.6350	N	0.0771	Y	0.0448
26	0.8557	0.9996	0.9434	85.0195	N	0.2836	N	0.1091
31	0.9890		0.9699	96.2557	Y	0.0003	N	0.1472
32	0.9678	0.5128	0.9606	132.6874	N	0.0646	N	0.3138
33	0.9948		0.9734	84.0357	Y	0.0214	N	0.3014
34	0.9298	0.8858	0.9445	186.7869	Y	0.0272	N	0.3847
35	1.0294		0.9886	38.6859	Y	0.0041	Y	0.0140
36	1.0024		0.9770	77.7183	Y	0.0001	N	0.1783
41	1.0384		0.9909	36.5856	N	0.0984	Y	0.0038
42	0.9989		0.9783	99.2753	Y	0.0001	N	0.1288
43	1.0127		0.9881	51.2456	Y	0.0001	Y	0.0021
44	0.9957		0.9832	72.1973	Y	0.0001	Y	0.0027
45	0.9648	0.5541	0.9737	114.3189	Y	0.0000	Y	0.0008
46	0.9861		0.9785	94.4512	Y	0.0222	Y	0.0402
51	0.9268	0.8027	0.9906	39.1325	N	0.5178	N	0.6900
52	0.8927	1.2342	0.9975	10.4445	N	0.7705	N	0.1781
53	0.9831	0.3643	0.9986	6.1375	N	0.5405	N	0.4083
54	0.9442	0.6177	0.9963	15.2537	N	0.4076	N	0.5064
55	0.9247	0.9115	0.9988	4.9609	N	0.6141	N	0.5676
56	0.9342	0.7835	0.9974	10.7086	N	0.7455	N	0.1297
61	0.9670	0.4267	0.9883	51.7954	N	0.3289	N	0.1482
62	0.9826		0.9909	40.6623	Y	0.0279	Y	0.0128
63	0.9775		0.9893	47.1763	N	0.2505	Y	0.0001
64	1.0025		0.9890	49.5151	N	0.8391	Y	0.0033
65	0.9436	0.6787	0.9805	86.7543	N	0.3554	N	0.4128
66	0.9684		0.9833	71.9477	N	0.4209	N	0.0677
71	1.0093		0.9974	15.3962	Y	0.0000	Y	0.0119
72	0.9681	0.5428	0.9812	119.0717	N	0.5315	N	0.1998
73	0.9775		0.9957	25.5035	Y	0.0000	Y	0.0021
74	0.9935		0.9963	22.1568	Y	0.0018	Y	0.0227
75	0.9890		0.9943	35.7640	Y	0.0018	N	0.7376
76	1.0058		0.9962	22.7062	Y	0.0004	N	0.1571
81	0.9698	0.5132	0.9869	83.3587	N	0.6689	N	0.9890
82	0.9737		0.9969	18.3732	N	0.0561	Y	0.0018
83	1.0009		0.9950	30.7703	Y	0.0012	Y	0.0326
84	1.0367	-0.3672	0.9978	13.2919	N	0.1004	N	0.1622
85	0.9768	0.3906	0.9878	76.0297	N	0.0873	N	0.1139
86	0.9653	0.4182	0.9959	24.5510	N	0.1985	N	0.0990

Table B4

The result is for the estimation of $p^e_{i,t} = p^e_{t-1} + w(p_{t-1} - p^e_{t-1})$ for the mixed-Q of the mixed treatment. The first column is the subject number. The second and third columns are the estimated coefficients, P^e_{t-1} and P_{t-1}-P^e_{t-1}, respectively. We drop all the coefficients that are not significant at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The fourth and fifth columns are the R^2 and the MSE of the regression. The sixth and seventh columns show whether we reject the null hypothesis that there is no breakpoint in the Chow test. The last two columns show the result of AC test.

No.	P^e_{t-1}	P_{t-1}-P^e_{t-1}	R^2	MSE	Chow	p-value	AC	p-value
11	1.0227		0.9961	28.0826	N	0.1370	N	0.1581
12	1.0182		0.9935	45.7869	N	0.1313	Y	0.0021
13	0.9664	0.3539	0.9724	202.6068	N	0.4424	N	0.1466
14	1.0161		0.9929	51.4562	N	0.4999	N	0.4420
15	1.0404	-0.7436	0.9975	19.5470	Y	0.0317	N	0.1235
16	1.0237		0.9948	38.6424	N	0.3594	N	0.2538
21	0.8971	0.9012	0.9948	50.7257	N	0.4439	Y	0.0265
22	0.9536	0.7469	0.9801	70.1909	N	0.2717	N	0.1846
23	0.8691	1.0896	0.9908	28.8863	N	0.9885	N	0.1388
24	0.8753	1.2599	0.9509	165.7141	N	0.8151	N	0.5166
25	0.8198	1.4082	0.9092	310.2178	N	0.9262	N	0.1594
26	0.8621	0.8609	0.9314	212.0810	N	0.4090	N	0.0795
31	0.9967	0.8283	0.9499	247.4014	N	0.0717	N	0.8736
32	0.9472	1.0269	0.9832	73.0324	N	0.6009	N	0.4869
33	0.9503	0.8477	0.9959	17.2399	N	0.2308	N	0.2710
34	0.7266	0.8949	0.9170	249.1662	Y	0.0131	N	0.2723
35	0.8782	1.1953	0.9907	36.7309	N	0.6954	N	0.6930
36	0.9900		0.9954	19.4710	N	0.2262	N	0.4755
41	0.9860		0.9678	253.9242	Y	0.0208	Y	0.0004
42	1.0300	-0.5075	0.9898	81.1855	N	0.1415	N	0.0834
43	1.0332	-0.4610	0.9896	80.4214	N	0.0890	N	0.2020
44	1.0277		0.9840	121.3082	N	0.0731	Y	0.0327
45	1.0177	-0.2894	0.9863	105.0625	N	0.1389	N	0.2484
46	1.0319	-0.5787	0.9906	75.9042	N	0.0532	Y	0.0006
51	0.9651	0.5026	0.9905	39.3142	N	0.8026	Y	0.0356
52	1.0009		0.9902	39.7946	N	0.5504	Y	0.0016
53	1.0146		0.9952	19.3248	N	0.2979	Y	0.0027
54	0.9615	0.5105	0.9826	72.8070	N	0.3333	Y	0.0010
55	1.0046		0.9924	30.9503	N	0.0776	Y	0.0043
56	0.9662	0.3894	0.9746	103.6935	N	0.2597	N	0.0638
61	0.8390	1.2564	0.9954	9.2799	N	0.6162	N	0.4890
62	0.9404	0.5063	0.9972	5.7879	N	0.3679	Y	0.0329
63	0.9071	0.4594	0.9683	59.7390	Y	0.0335	Y	0.0303
64	0.8884	0.9462	0.9965	7.1862	N	0.8801	N	0.1450
65	0.8691	1.0165	0.9880	24.5590	N	0.9889	N	0.6542
66	0.9235	0.6884	0.9736	57.2353	N	0.9891	N	0.9179
71	0.9551	0.5379	0.9956	12.0152	Y	0.0054	N	0.1237
72	0.9449	0.7402	0.9680	92.5598	N	0.1055	N	0.1638
73	0.9622	0.5396	0.9882	33.4165	N	0.1027	Y	0.0143
74	0.9358	0.6891	0.8985	305.9351	N	0.2958	N	0.3899
75	0.9749		0.9920	22.0318	Y	0.0001	N	0.5585
76	0.9876	0.3993	0.9866	40.3784	Y	0.0481	Y	0.0222
81	1.0038		0.9664	674.9604	N	0.2246	Y	0.0007
82	1.0658	-0.8177	0.9929	135.4198	Y	0.0066	Y	0.0073
83	1.0340	-0.5850	0.9904	190.6609	N	0.0655	N	0.0640
84	0.9869	-0.3555	0.9829	397.2846	N	0.4116	N	0.0986
85	0.9828		0.9570	839.9563	Y	0.0489	Y	0.0022
86	1.0150	-0.7024	0.9917	182.7904	Y	0.0002	N	0.2171

Table B5
The result is for the estimation of $p^e_{i,t} = p^e_{t-1} + \gamma(p_{t-1} - p_{t-2})$ for the LtO treatment. The first column is the subject number. The second and third columns are the estimated coefficients, P_{t-1} and P_{t-1}-P_{t-2}, respectively. We drop all the coefficients that are not significant at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The fourth and fifth columns are the R^2 and the MSE of the regression. The last two columns show whether we reject the null hypothesis that there is no breakpoint in the Chow test.

No.	P_{t-1}	P_{t-1} -P_{t-2}	R^2	MSE	Chow	p-value
11	0.8955	0.8991	0.9993	2.2070	Y	0.0289
12	0.8988	1.6064	0.9953	15.7561	Y	0.0287
13	0.8941	1.0337	0.9984	5.2436	N	0.7307
14	0.9030	0.5470	0.9989	3.6005	Y	0.0047
15	0.8984	1.3173	0.9952	15.7935	N	0.1861
16	0.8898	0.9064	0.9984	5.1670	N	0.1978
21	0.8576	0.9473	0.9891	15.7339	N	0.8865
22	0.8868	1.4742	0.9821	28.3482	N	0.7581
23	0.8557	1.7519	0.9509	75.9565	N	0.7887
24	0.9060		0.9825	27.2307	N	0.9252
25	0.8687	0.2449	0.9988	1.6638	N	0.7297
26	0.8621	1.2932	0.9794	30.6517	N	0.9637
31	0.8804	1.1131	0.9896	32.1387	N	0.4863
32	0.9103	0.8832	0.9787	70.3250	N	0.8814
33	0.8781	1.0692	0.9906	29.0392	N	0.9815
34	0.9008	0.9833	0.9700	98.6248	N	0.9581
35	0.9206	0.7246	0.9953	15.5402	N	0.8493
36	0.9122	1.0495	0.9951	16.1114	N	0.1404
41	0.8734	0.8895	0.9957	16.8625	N	0.4893
42	0.9266	1.2789	0.9934	29.8171	N	0.6465
43	0.9087	0.6504	0.9972	11.8247	N	0.2161
44	0.9027	0.9509	0.9969	12.9434	N	0.8434
45	0.9041	1.1179	0.9942	24.7486	N	0.2320
46	0.9112	1.0201	0.9927	31.4586	N	0.3959
51	0.8834	2.1974	0.9954	18.9564	N	0.2671
52	0.9068	0.5887	0.9985	6.4120	N	0.9326
53	0.9297		0.9991	3.7126	N	0.3892
54	0.9063		0.9961	16.1210	N	0.7312
55	0.9173		0.9990	3.9569	N	0.6015
56	0.9086		0.9981	7.9987	N	0.8320
61	0.9098	0.7549	0.9961	17.2009	N	0.9521
62	0.9159	0.7309	0.9979	9.2064	N	0.4462
63	0.9041	0.9238	0.9985	6.3499	N	0.7406
64	0.9064	1.3676	0.9964	15.9664	N	0.6174
65	0.9076	0.9292	0.9910	39.8224	N	0.9459
66	0.8892	1.1943	0.9943	24.5659	N	0.8394
71	0.9087	0.4019	0.9993	4.4306	Y	0.0000
72	0.9177	2.0313	0.9918	52.3221	N	0.1163
73	0.9063	0.6006	0.9987	7.7012	Y	0.0023
74	0.9112	0.6874	0.9983	10.4465	Y	0.0001
75	0.9254	0.9208	0.9971	17.9708	N	0.6802
76	0.9104	0.8463	0.9989	6.5628	Y	0.0071
81	0.9210	1.5971	0.9941	37.2906	Y	0.0500
82	0.9050	0.3490	0.9991	5.5319	N	0.1152
83	0.9074	1.1217	0.9985	9.3593	N	0.3803
84	0.9175	0.7623	0.9994	3.7620	Y	0.0497
85	0.9111	1.6936	0.9953	29.3276	N	0.6837
86	0.9047	0.7834	0.9992	4.8603	N	0.8168

Table B6

The result is for the estimation of $p^e_{i,t} = p^e_{t-1} + \gamma(p_{t-1} - p_{t-2})$ for the mixed-Q of the mixed treatment. The first column is the subject number. The second and third columns are the estimated coefficients, P_{t-1} and P_{t-1}-P_{t-2}, respectively. We drop all the coefficients that are not significant at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The fourth and fifth columns are the R^2 and the MSE of the regression. The last two columns show whether we reject the null hypothesis that there is no breakpoint in the Chow test.

No.	P_{t-1}	P_{t-1} -P_{t-2}	R^2	MSE	Chow	p-value
11	0.9125	0.5696	0.9993	5.2556	Y	0.0437
12	0.8994	0.7937	0.9988	8.2277	N	0.8251
13	0.9005	2.0594	0.9929	52.1356	N	0.7870
14	0.9103	1.2588	0.9971	20.9975	N	0.1441
15	0.9486	0.3566	0.9994	4.4449	Y	0.0001
16	0.9214	0.9323	0.9985	10.7663	N	0.1900
21	0.8971		0.9910	28.5583	N	0.4330
22	0.9445		0.9853	52.0317	Y	0.0089
23	0.8925		0.9973	8.4001	N	0.4713
24	0.9062	1.2746	0.9740	87.0638	N	0.5443
25	0.8769	2.8475	0.9650	117.6791	N	0.2321
26	0.8612	1.6905	0.9739	80.3013	N	0.1141
31	0.9769	2.0032	0.9696	151.1424	N	0.1404
32	0.9357	0.8834	0.9908	39.7555	N	0.5582
33	0.9365		0.9984	6.8152	N	0.1517
34	0.7411	2.2788	0.9480	157.1513	Y	0.0071
35	0.8967		0.9932	26.2851	N	0.9478
36	0.9292		0.9949	21.1067	Y	0.0001
41	0.9215	0.9923	0.9938	48.8112	N	0.2567
42	0.9301	0.9225	0.9970	23.6109	N	0.2567
43	0.9105	1.0593	0.9980	15.5567	N	0.4258
44	0.9068	0.8655	0.9970	22.2784	N	0.0705
45	0.8951	1.4577	0.9962	28.7167	N	0.1417
46	0.9372	0.8531	0.9976	19.0628	Y	0.0338
51	0.9172	0.5119	0.9959	16.9225	N	0.3738
52	0.8990	1.1242	0.9979	8.6742	N	0.4199
53	0.9041	0.4491	0.9993	2.6903	N	0.2240
54	0.9085	1.2891	0.9957	17.7275	N	0.7260
55	0.9005	0.9535	0.9984	6.3479	N	0.1117
56	0.8889	1.6410	0.9876	50.2724	N	0.1084
61	0.8859	0.2881	0.9986	2.8160	N	0.5547
62	0.8962		0.9986	2.8214	N	0.1982
63	0.8396	1.9381	0.9841	30.1489	N	0.0888
64	0.8951		0.9993	1.4706	N	0.2038
65	0.8847	1.0929	0.9976	4.8470	N	0.3128
66	0.9038	2.0696	0.9933	14.5802	N	0.6179
71	0.8982		0.9988	3.0674	Y	0.0464
72	0.8971	1.0910	0.9816	52.3684	N	0.7617
73	0.9056	0.5256	0.9950	13.9487	N	0.1842
74	0.8467	3.2960	0.9549	133.6336	N	0.6374
75	0.8968	0.3542	0.9971	7.8126	Y	0.0027
76	0.9335	0.6051	0.9921	23.4895	N	0.2081
81	0.9057	1.1760	0.9929	137.3584	N	0.5458
82	0.9098	0.7216	0.9987	24.7855	Y	0.0232
83	0.9197	0.9578	0.9978	43.3952	Y	0.0115
84	0.9833	1.3937	0.9932	157.8290	N	0.3737
85	0.8956	1.2939	0.9903	186.9783	N	0.7604
86	0.9729	0.6934	0.9977	50.2171	Y	0.0342

Table B7

The result is for the estimation of $p^e_{h,t} = c + \sum_{i=1}^{3} o_i p_{t-i} + \sum_{i=1}^{3} s_i p^e_{h,t-i} + \nu_t$ for the LtF treatment. The first column is the subject number. The second to the eighth columns are the estimated coefficients, constant c, P_{t-1}, P_{t-2}, P_{t-3}, P^e_{t-1}, P^e_{t-2} and P^e_{t-3}, respectively. We drop all the coefficients that are not significant at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The ninth and tenth columns are the R^2 and the MSE of the regression. The last two columns show whether we reject the null hypothesis that there is no breakpoint in the Chow test.

No.	Cons	P_{t-1}	P_{t-2}	P_{t-3}	P^e_{t-1}	P^e_{t-2}	P^e_{t-3}	R^2	MSE	Chow	p-value
11		1.4722	-0.5795					0.9945	0.3302	N	0.1329
12	-2.2026	1.5519	-0.7818					0.9964	0.2213	Y	0.0500
13		1.8507				-0.2290		0.9947	0.3107	N	0.1228
14	-1.2911	1.4068						0.9975	0.1464	N	0.9992
15	-2.2117	1.1437	-0.6562		0.4095			0.9968	0.1975	Y	0.0421
16		1.8357	-1.3635	0.5628				0.9930	0.4171	N	0.2062
21	-1.5988	1.0230	0.3541					0.9949	0.4568	Y	0.0314
22	-0.8903	0.8733	-0.6731		0.7609			0.9979	0.1836	Y	0.0229
23		0.8301		-0.3740	0.3442	0.4223		0.9974	0.2561	Y	0.0482
24		0.8633						0.9913	0.7354	Y	0.0182
25		0.9560			0.2922			0.9972	0.2370	N	0.4807
26	-1.9888	0.9908	-0.4720		0.6213			0.9956	0.4081	N	0.3343
31		1.1902						0.9934	0.2313	N	0.5918
32		1.1555	-0.8048		0.6095			0.9946	0.2158	N	0.5575
33		1.0294			0.3538			0.9938	0.2477	Y	0.0009
34		1.2590						0.9949	0.1923	N	0.5888
35		1.3828						0.9927	0.2681	N	0.6491
36	-1.2208	1.1197	-0.4507		0.3787			0.9979	0.0833	N	0.1233
41		1.0337			0.4918			0.9884	0.3092	Y	0.0228
42		1.5756						0.9555	1.2065	N	0.6806
43		1.0926			-0.3910			0.9900	0.3023	Y	0.0409
44	-2.3981	1.0432			0.3361			0.9922	0.2447	N	0.9930
45		1.1426	-0.4721		0.3523			0.9225	1.6030	Y	0.0152
46		1.3457					-0.1258	0.9934	0.1929	N	0.2868
51	2.2729	1.3989				-0.1463		0.9928	0.1524	N	0.2126
52		0.8969	0.8093		-0.3535			0.9194	2.0667	Y	0.0011
53	30.6105							0.6191	32.5676	N	0.3996
54		1.6121		-0.4233		0.7938		0.9836	0.3591	N	0.1579
55	1.9947	1.3423	-0.4206	-0.2920				0.9939	0.1244	Y	0.0073
56		1.9928	-1.7045		0.4851			0.9857	0.3019	N	0.1677
61		0.9361						0.8866	8.9832	N	0.1795
62		2.0109						0.9577	2.6108	N	0.2299
63		1.6156	-0.7633					0.9929	0.4638	N	0.8819
64	-3.0548	1.9196	-0.6962					0.9921	0.5661	Y	0.0457
65		1.4683	-1.5142		0.7181			0.9885	0.7664	N	0.3964
66		1.6867	-0.8804					0.9939	0.4106	N	0.2648
71		0.9450						0.9137	0.6969	Y	0.0280
72		1.0074					-0.0181	0.9987	0.0119	N	0.2339
73								0.9279	0.6035	N	0.3022
74		0.9833			0.3296			0.9682	0.2558	N	0.1631
75		0.7924						0.9830	0.1509	N	0.1004
76		1.0764	-0.6958		0.4022			0.9621	0.2781	Y	0.0447
81		1.3079						0.9617	0.7590	N	0.1030
82		1.2823						0.9904	0.1972	N	0.3832
83		1.2591	-0.7670		0.3098			0.9873	0.2404	Y	0.0033
84	9.6149	1.5315	-0.8086					0.9194	1.3458	Y	0.0464
85		1.1549	-0.6669		0.4827			0.9932	0.1331	Y	0.0272
86		1.4543			-0.3862			0.8944	2.1141	N	0.3889

Table B8
The result is for the estimation of $p^e_{h,t} = c + \sum_{i=1}^{3} o_i p_{t-i} + \sum_{i=1}^{3} s_i p^e_{h,t-i} + \nu_t$ for the LtO treatment. The first column is the subject number. The second to the eighth columns are the estimated coefficients, constant c, P_{t-1}, P_{t-2}, P_{t-3}, P^e_{t-1}, P^e_{t-2} and P^e_{t-3}, respectively. We drop all the coefficients that are not significant at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The ninth and tenth columns are the R^2 and the MSE of the regression. The last two columns show whether we reject the null hypothesis that there is no breakpoint in the Chow test.

No.	Cons	P_{t-1}	P_{t-2}	P_{t-3}	P^e_{t-1}	P^e_{t-2}	P^e_{t-3}	R^2	MSE	Chow	p-value
11	7.0550	3.3838	-2.8501					0.9829	3.3838	N	0.1100
12	9.3340	1.8087						0.9453	13.8555	Y	0.0440
13	6.2512	2.5525	-2.7386		0.3997			0.9745	5.3764	N	0.1641
14	4.8199	2.0638	-2.6764	0.6291	0.5559		0.1877	0.9877	2.3691	N	0.0792
15		3.1195	-2.9013					0.9784	5.2258	N	0.4521
16	6.2715	2.8940	-2.7724					0.9791	4.4054	Y	0.0342
21						-0.5961		0.2636	38.8715	N	0.4164
22			-2.1659	2.1889	-0.4990			0.2619	58.2673	N	0.6892
23								0.0947	114.8970	N	0.3606
24		1.2772						0.3103	35.8813	N	0.9789
25			-1.1587	1.2319		0.9397		0.4488	10.6309	N	0.8393
26								0.2171	76.1850	N	0.4464
31		3.0847	-2.0005					0.9359	28.5103	Y	0.0489
32	10.4882			-1.1566				0.7721	103.8239	N	0.8781
33	3.0563							0.9437	23.9238	N	0.8641
34		2.3837			-0.5542			0.8166	103.3272	N	0.4242
35	4.8582	0.9103			0.8022			0.9526	21.8697	Y	0.0361
36	7.3229	2.5778	-1.6832					0.9088	38.0270	N	0.0911
41	8.2352	1.2445	-1.2777		0.9057			0.9190	20.6598	N	0.5159
42		2.4448		-0.9901		-0.5631		0.8695	41.7536	Y	0.0031
43	11.7626	1.7952		-1.0934				0.9457	13.7418	Y	0.0412
44		3.8267	-1.8904	-0.7671				0.9304	19.2475	Y	0.0014
45		3.0289						0.9054	28.0455	Y	0.0402
46		2.1490						0.7661	60.3325	Y	0.0000
51	-13.3100	2.3887						0.8012	32.2954	N	0.4314
52		1.8919						0.9273	8.3984	N	0.6327
53		0.8087			0.4673			0.9433	5.9317	N	0.3634
54	7.3581							0.8696	12.8910	N	0.1653
55		91.0000						0.9641	3.9573	N	0.9383
56		1.2204					-0.3423	0.9390	6.4384	N	0.8680
61	13.6081	1.6943						0.7786	32.2351	N	0.9267
62		2.2322	-1.9073					0.8955	17.5905	N	0.9718
63		3.1473	-1.7277					0.9355	10.1321	N	0.7290
64		2.0872			0.5169			0.8178	32.5573	N	0.9337
65	13.9434	2.6770	-1.6841					0.7082	43.9768	N	0.9987
66		3.4704	-2.2277					0.7715	49.5095	Y	0.0088
71		2.0753	-1.8185					0.9793	6.2400	Y	0.0159
72					1.1325			0.8551	47.6749	N	0.6854
73		3.1295	-2.6223					0.9781	6.1708	Y	0.0061
74		2.2626	-2.3550			0.4787		0.9678	9.8345	Y	0.0402
75		1.4903						0.9684	9.3391	Y	0.0197
76		2.9621	-2.5485					0.9803	5.6544	N	0.9529
81		5.1497	-6.4662	2.3246				0.5307	50.7286	N	0.0765
82		2.3266	-2.1617	0.6530				0.9069	6.3142	N	0.0902
83	10.7291	2.8818	-1.8896			-0.3840		0.9173	6.2996	Y	0.0342
84	6.7746	2.1664	-2.7903	0.9024				0.9524	2.8311	Y	0.0410
85								0.4883	52.6408	N	0.3236
86		2.9228	-2.6472					0.9573	3.1039	N	0.1861

Table B9

The result is for the estimation of $p^e_{h,t} = c + \sum_{i=1}^{3} o_i p_{t-i} + \sum_{i=1}^{3} s_i p^e_{h,t-i} + \nu_t$ for the mixed-F of the mixed treatment. The first column is the subject number. The second to the eighth columns are the estimated coefficients, constant c, P_{t-1}, P_{t-2}, P_{t-3}, P^e_{t-1}, P^e_{t-2} and P^e_{t-3}, respectively. We drop all the coefficients that are not significant at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The ninth and tenth columns are the R^2 and the MSE of the regression. The last two columns show whether we reject the null hypothesis that there is no breakpoint in the Chow test.

No.	Cons	P_{t-1}	P_{t-2}	P_{t-3}	P^e_{t-1}	P^e_{t-2}	P^e_{t-3}	R^2	MSE	Chow	p-value
11		1.6805						0.9970	0.7213	Y	0.0000
12		1.3072						0.9815	4.4758	Y	0.0489
13		1.3247		-0.7764				0.9805	4.3094	Y	0.0000
14								0.9829	3.6634	Y	0.0267
15		-0.6236	0.6095		1.7980	-0.9342		0.9971	0.6766	N	0.8422
16								0.1080	16299.6289	N	0.8595
21	21.9476	0.1995			0.3414			0.4807	2.7034	N	0.4299
22	18.7384	0.4652	0.4095					0.5928	6.1118	Y	0.0392
23	9.6204	0.6723					0.1382	0.8525	1.8605	N	0.6657
24			0.5259					0.7282	4.0433	N	0.4102
25		0.7546						0.4580	10.6269	Y	0.0485
26								-0.1012	1034289.0000	N	0.7500
31		0.9545						0.8354	4.4121	N	0.1450
32		0.7426			0.4385			0.8427	4.7672	Y	0.0382
33	14.4651	0.9812		0.2065				0.9324	1.7276	N	0.5208
34		0.9998					0.1290	0.9765	0.8660	Y	0.0470
35		1.0141						0.9165	3.1311	N	0.4918
36	6.7868	0.6546						0.9176	2.0025	N	0.7478
41		1.7894						0.9729	21.3056	N	0.5405
42								0.9309	52.5422	N	0.5217
43	3.3959	2.2598	-0.8404					0.9943	4.6345	N	0.1282
44		1.5817		-0.6835		0.3644		0.9943	4.6298	Y	0.0371
45		1.8265						0.9944	4.8088	Y	0.0053
46								0.9972	2.4339	Y	0.0068
51		1.4158						0.9426	6.1222	Y	0.0033
52	-26.2005	4.3369	-5.9537	3.2957				0.6596	67.9586	Y	0.0099
53		1.4700						0.9708	2.9258	Y	0.0494
54		1.7183	-1.5997	0.5258	0.5486			0.9653	3.7438	N	0.6226
55		1.6348	-0.7648					0.9530	4.4218	N	0.3816
56		1.2615						0.9826	1.5590	Y	0.0026
61	18.4254	0.6639						0.7393	0.7893	N	0.8882
62		1.6328						0.9666	0.4251	N	0.6331
63		1.2774						0.5414	6.5122	Y	0.0240
64		1.0160					0.1479	0.8445	1.0280	Y	0.0189
65	28.5211	1.1476		-0.5956			0.4753	0.5444	4.3422	Y	0.0196
66		1.2499						0.9766	0.2148	N	0.3141
71		1.0888						0.9899	4.3945	N	0.2595
72		1.7794	-1.3234					0.9925	3.5134	N	0.2488
73		1.2946						0.8661	59.3316	Y	0.0363
74								0.8789	65.5128	N	0.5958
75								0.0156	11894.0836	N	0.9927
76		0.8827	-0.4715		0.5518		-0.1811	0.9961	1.7766	N	0.8065
81					0.3953			0.5142	4142.3383	Y	0.0249
82		2.0385	-2.0153	0.6081	0.4962			0.9976	12.2528	N	0.4604
83		1.8873	-1.4467					0.9962	20.3067	Y	0.0177
84		1.7964	-1.0375					0.9979	11.0350	N	0.2772
85		1.6417						0.9858	74.9679	N	0.4714
86		1.6073	-1.3200	0.4468				0.9984	8.6607	N	0.6813

Table B10

The result is for the estimation of $p^e_{h,t} = c + \sum_{i=1}^{3} o_i p_{t-i} + \sum_{i=1}^{3} s_i p^e_{h,t-i} + \nu_t$ for the mixed-Q of the mixed treatment. The first column is the subject number. The second to the eighth columns are the estimated coefficients, constant c, P_{t-1}, P_{t-2}, P_{t-3}, P^e_{t-1}, P^e_{t-2} and P^e_{t-3}, respectively. We drop all the coefficients that are not significant at 5% level. All the blank spaces means coefficients are insignificant at 5% level. The ninth and tenth columns are the R^2 and the MSE of the regression. The last two columns show whether we reject the null hypothesis that there is no breakpoint in the Chow test.

No.	Cons	P_{t-1}	P_{t-2}	P_{t-3}	P^e_{t-1}	P^e_{t-2}	P^e_{t-3}	R^2	MSE	Chow	p-value
11	5.2109	1.7380	-0.9548				-0.2897	0.9815	3.8487	N	0.7202
12		1.7151						0.9112	18.3227	N	0.7324
13	30.7815	0	4.5252	-3.3543				0.6880	101.9090	N	0.8067
14	10.5848	2.1122	-2.0541					0.9617	7.3479	N	0.1786
15	9.9001		0.8524	-1.3111	0.6378		0.7816	0.9805	4.1465	N	0.1676
16		2.3138		-0.6827				0.9542	11.6465	Y	0.0463
21	21.6461		0.5003					0.2191	13.8153	N	0.7676
22								0.1092	55.7188	Y	0.0057
23	42.4634							0.1297	18.2209	N	0.2525
24								0.0443	147.3796	N	0.3420
25								0.1913	285.7452	N	0.9786
26	83.3113					0.6576		0.3154	128.7317	N	0.1007
31								0.0384	265.5270	Y	0.0352
32	55.9280	1.8280		-0.9959	-0.4745			0.2209	49.7180	N	0.8808
33	24.2772	0.6010						0.4805	14.7902	Y	0.0234
34						0.4158		0.1344	213.2184	N	0.6156
35								0.4504	36.1249	N	0.8039
36								0.5644	11.4935	N	0.4202
41	20.3982	2.5648						0.9113	70.7567	Y	0.0420
42	14.9017	1.2459			0.5836			0.9493	39.6321	N	0.4076
43	11.1973	3.2407	-1.7176					0.9820	14.6406	N	0.6358
44	19.8359	1.7996						0.9506	40.6228	N	0.3281
45	19.1666	2.3913						0.9614	36.2103	N	0.1990
46	10.6538	1.6879						0.9880	11.3771	N	0.5168
51		1.7618						0.7643	22.0111	N	0.7719
52		3.4780	-1.5164		-0.5118		-0.4445	0.8815	11.4021	Y	0.0125
53	9.6459	1.4493						0.8937	7.8691	N	0.6784
54	14.4537	2.9877					-0.5038	0.7780	21.1784	N	0.8777
55	17.2568	1.9935				-0.4400	0.3677	0.8759	10.6230	Y	0.0094
56	23.4038	2.9542	-3.5176					0.3920	63.9104	N	0.2916
61	58.6584	1.2638			-0.8494	-0.4901		0.3715	4.5148	N	0.5705
62	42.8874			-0.9568	0.9141		0.7468	0.7779	2.4951	N	0.2442
63	93.6821	-2.0807			0.4530			0.3014	27.3153	N	0.9832
64			-0.8833	0.7613			-0.6044	0.7538	2.0272	N	0.7320
65	62.4087	1.6319			-0.6434		0.3721	0.3050	13.6974	Y	0.0408
66	110.9434		-2.6755			0.5011	0.5004	0.2550	32.4307	Y	0.0398
71		1.3615	-1.4900	0.9131	0.5159		-0.6962	0.9887	4.5203	N	0.5282
72		2.9255	-2.5888	1.0641			-0.3160	0.8640	54.8755	N	0.1236
73		1.4908						0.9586	17.3806	N	0.3595
74		3.9976						0.5927	267.8787	N	0.5076
75		1.5676						0.7650	3.7002	Y	0.0068
76		2.2354	-1.3461					0.9466	21.6718	N	0.9521
81				-1.6581				0.9382	314.0693	N	0.7731
82		1.8691	-1.6390					0.9911	41.9593	N	0.8234
83	8.2116	2.3817	-1.8069					0.9874	59.9664	N	0.6778
84	13.7960	2.3840	-2.8516		0.4506			0.9676	197.8242	N	0.6447
85		3.8592			-0.5257			0.9492	258.5986	N	0.6433
86	13.2219	1.1872		-0.6197	0.4785			0.9870	64.3220	Y	0.0461

Appendix C

Estimation of Linear Prediction Rules

The rule that we employed is from Bao et al. (2012); they use the rule to measure the price prediction in a positive and negative feedback system. We estimated the following linear prediction rule:

$$p^e_{h,t} = c + \sum_{i=1}^{3} o_i p_{t-i} + \sum_{i=1}^{3} s_i p^e_{h,t-i} + v_t \tag{17}$$

where $p^e_{h,t}$ is the price forecast in period t in market h and p_{t-i} is the i period lagged market price ($i = 1, 2, 3$). We estimate the linear prediction rule in the LtF, LtO, and mixed treatments. As described in section 3, the subject will make both a price forecast and a trading quantity decision in the mixed treatment. We investigate in the data of the price prediction (mixed-F) and trading quantity decision (mixed-Q) in the mixed treatment separately. We estimate both the mixed-F and the mixed-Q of the mixed treatment. There are48 regressions in each treatment. We find that the prediction behaviors of most subjects can be well captured by these simple rules, especially for the LtF and LtO treatment. As shown in the tables in Appendix B from Table B7 to Table B10, all the blank spaces in these tables imply that the coefficients are insignificant at the 5% level.

The mean adjusted R^2 is 0.9701 in the LtF treatment, 0.8113 in the LtO treatment, 0.8266 in the mixed-F of the mixed treatment and 0.6751 in the mixed-Q of the mixed treatment. The average mean squared error (MSE) is 1.36 in the LtF treatment, 27.82 in the LtO treatment, 22231.94 in the mixed-F of the mixed treatment and 65.15 in the mixed-Q of the mixed treatment. The mean adjusted R^2 is greatest in the LtF treatment and smallest in the mixed-Q of the mixed treatment. Moreover, the average MSE is smallest in the LtF treatment and largest in the mixed-F of the mixed treatment. In general, the average MSE of the regression in the mixed treatment is much higher than those in the LtF or LtO treatments. Additionally, we find that there is at least one significant coefficient (47 in the LtF treatment, 46 in the LtO treatment, 42 in the mixed treatment out of 48, respectively). Furthermore, we embed the Chow test in the regression to estimate whether there are any structural breaks. The results are presented in the last two columns in Table B7 to Table B10 in Appendix B. Y means that we reject the null hypothesis that there is no breakpoint. The results show that almost half of the subjects changed their rules in the LtF treatment, 16 out of 48 subjects changed their rules in the LtO treatment, half of the subjects changed their rules in the mixed-F of the mixed treatment and 11 out of 48 subjects changed their rules in the mixed-Q of the mixed treatment. These results imply that the subjects do have heterogeneity when using the simple linear rule.

Estimation of Simple Heuristic in the LtF treatment

In this subsection, we estimate individual forecasting dynamics using the first-order heuristic (Heemeijer et al., 2009) and investigate whether there are significant differences between the three treatments. The First-Order Heuristic is as follows:

$$p^e_{i,t} = \alpha_i p_{t-1} + \beta_i p^e_{i,t-1} + \gamma_i (p_{t-1} - p_{t-2}) \tag{18}$$

This rule is an anchor and adjustment rule (Tversky and Kahneman, 1974), as it extrapolates a price change (the last term) from an anchor (the first two terms). We apply this rule because the simple trend-following rule uses an anchor to give all weight to the last observed price while in the general rule (18), the anchor gives weight to the last observed price as well as the last forecast. In this sense, the general rule is more cautious and extrapolates the trend from a more gradually evolving anchor, while the pure trend-following rule is more aggressive in extrapolating the trend from the last price observation. We use this equation to estimate the forecasting strategies of the subjects who are in the LtF treatment and mixed-F in the mixed treatment and report the results in Table B1 and B2 in Appendix B.