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**ESSAYS ON BEHAVIORAL AND
EXPERIMENTAL FINANCE**

JIAHUA ZHU

SCHOOL OF SOCIAL SCIENCES

2020

ESSAYS ON BEHAVIORAL AND EXPERIMENTAL FINANCE

JIAHUA ZHU

SCHOOL OF SOCIAL SCIENCES

**A thesis submitted to the Nanyang Technological University
in partial fulfilment of the requirement for the degree of
Doctor of Philosophy**

2020

Statement of Originality

I certify that all work submitted for this thesis is my original work. I declare that no other person's work has been used without due acknowledgement. Except where it is clearly stated that I have used some of this material elsewhere, this work has not been presented by me for assessment in any other institution or University. I certify that the data collected for this project are authentic and the investigations were conducted in accordance with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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June 1, 2020

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Date

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Bao Te

Authorship Attribution Statement

This thesis contains material from one paper published in the following peer-reviewed journal in which I am listed as an author.

Chapter 1 is published as Zhu, J., Bao, T., & Chia, W. M. (2019). Evolutionary selection of forecasting and quantity decision rules in experimental asset markets. Journal of Economic Behavior & Organization.

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The contributions of the co-authors are as follows:

- I made the initial design of the project. Asst Prof Bao Te and Assoc Prof. Chia Wai Mun provided comments and feedback to refine the design.
- I designed the model together with Asst Prof. Bao Te, and I also analyzed the data.
- I prepared the manuscript drafts. The manuscript was then edited by Asst Prof. Bao Te, and revised by Assoc Prof Chia Wai Mun.

05-29-2020

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Date

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Executive Summary

Behavioral finance has become a prevalent research area to investigate the bounded rationality of investors and inefficiency of the financial market, which is different from the traditional economic and financial theory that assumes the agents are rational, self-controlled, and are not confused by behavioral bias or information processing errors. This thesis contains three essays that revolve around the topic of behavioral and experimental financial, which aims to provide new insight to the ongoing growth of behavioral finance literature and possible policies to maintain the stability of the market.

Chapter 1 provides two explanations for the findings found by Bao et al. (2017) 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). 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.

Chapter 2 explores how ambiguous signals and ambiguity aversion influence individuals' expectations and the pricing of asset in experimental financial markets. In line with the theory of Epstein and Schneider (2008) we find that subjects' degree of ambiguity aversion is positively correlated with their expectations about the variance of ambiguous signals. These signals matter for the determination of asset prices. We find that the distribution of the excess return of the asset exhibits negative skewness, and that price volatility is significantly larger under ambiguous signals. Our findings provide evidence in support of the idea that ambiguous information and ambiguity aversion may be a source of negative skewness and excess volatility in financial markets.

Chapter 3, following Bloomfield and Hales (2002), investigates how individuals use measures of apparent predictability from the price chart to predict future market prices. Our findings are as follows: first, we confirm the experimental findings by Bloomfield and Hales (2002) that people use the number of rever-

sals as a proxy for predictability. Their predicted price changes are smaller when there are fewer reversals. Second, people also use the volatility of the price as a measure of predictability. Third, social intelligence and cognitive ability do not seem to influence people's predicting ability or their perceived predictability of the asset prices.

In summary, these three chapters investigate expectation formation and belief updating in financial markets, find that behavioral bias affects individuals' expectations and market efficiency. These findings provide informative suggestions for designing financial education and regulation program to stabilize the financial market.

Chapter 1

Evolutionary Selection of Forecasting and Quantity Decision Rules in Experimental Asset Markets

1.1 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 the 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, 2008, 2017), Bao et al. (2012), Bao and Hommes (2019). 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 are 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 deviation of quantity (DQ) and absolute deviation of quantity (ADQ), 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 is 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 the result, we speculated that a robot advisor based on AI technology that provides optimal trading quantity based on investor's expectations may be helpful for market stability if it can reduce the irrationality of quantity decision made by human traders.

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, experimental design and economy. 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.

1.2 Literature Review

This paper is related to previous studies on the LtF and LtO experiments. Marimon et al. (1993), Adam (2007) and Pfajfar and Zakelj (2018) study the interaction between individual forecasts and aggregate market prices in macroeconomic models¹. 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 to the fundamental value 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. They estimated the simple forecasting rules, but did not capture the evolution of the fraction of the forecasting rules over time. They did not provide a unified model to fully explain the mechanism in their paper. Different from their papers, we provide a computational micro-foundation to explain the sharp difference in the LtF treatment with the LtO and mixed treatments in Bao et al. (2017). 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 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. Recently, researchers also apply genetic algorithm learning models to experimental data (Anufriev et al., 2019, Hommes et al., 2017). In particular, Anufriev et al., (2019) apply genetic algorithm learning model to the same dataset as our paper and propose that the median of the distribution of GA forecasting heuristics can be used in designing or validating the

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

Heuristic Switching Model. This paper contributes to the literature on HSM by extending the HSM to the Learning to Optimize experiments.

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 to the fundamental value. On the other hand, if trend rules are the dominant rules, the price will diverge from the fundamental value. 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 modeling approach, e.g. Anufriev et al. (2019), Chen and Yeh (2001), Chiarella and He (2002,2003), Dawid and Delli Gatti (2018), Gaunersdorfer (2000), van der Hoog and Dawid (2019), Huang et al. (2010, 2013), Jawadi et al. (2018), Westerhoff (2003). For a comprehensive survey of applying agent-based modeling to experimental economics, see Arifovic and Duffy (2018).

1.3 Experimental Data

1.3.1 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.

1.3.2 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 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.²

1.3.3 Experimental Economy

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 interest rate $R = 1 + r$. The wealth of agent i evolves as follows:

$$W_{i,t+1} = RW_{i,t} + q_{i,t}(p_{t+1} + y - Rp_t) \quad (1.1)$$

where $q_{i,t}$ denotes the demand for the risky asset by agent i at period t , 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:

$$\max_{q_{i,t}} \{E_{i,t}W_{i,t+1} - \frac{a}{2}V_{i,t}(W_{i,t+1})\} = \max_{q_{i,t}} \{q_{i,t}E_{i,t}\rho_{t+1} - \frac{a}{2}q_{i,t}^2V_{i,t}(\rho_{t+1})\} \quad (1.2)$$

where a denotes the risk-aversion parameter and ρ_{t+1} is the excess return of the risky asset, defined by equation (1.3):

$$\rho_{t+1} = p_{t+1} + y - Rp_t \quad (1.3)$$

Let $V_{i,t}(\rho_{t+1}) = \sigma^2$, the optimal demand for the asset by agent i at period t is

²The payoff in the LtF treatment is $Payoff_{i,t} = \max\{0, [1300 - \frac{1300}{49}(p_{i,t}^e - p_t)^2]\}$, in the LtO is $Payoff_{i,t} = \max\{0, 800 + 40[q_{i,t}(p_t + 3.3 - 1.05p_{t-1}) - 3q_{i,t}^2]\}$. The payoff in the mixed treatment is either the payoff in the LtF treatment or in the LtO treatment with equal probability.

defined as follows³:

$$q_{i,t}^* = \frac{E_{i,t}(\rho_{t+1})}{aV_{i,t}(\rho_{t+1})} = \frac{p_{i,t+1}^e + y - Rp_t}{a\sigma^2} \quad (1.4)$$

where $p_{i,t+1}^e$ 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 3.3.⁴ The optimal demand of agent i at period t , $q_{i,t}^*$, is a function of the one-period ahead price prediction $p_{i,t+1}^e$:

$$q_{i,t}^* = \frac{p_{i,t+1}^e + y - Rp_t}{a\sigma^2} = \frac{p_{i,t+1}^e + 3.3 - 1.05p_t}{6} \quad (1.5)$$

The price determination function in this experiment is given by equation (1.6), where is the average prediction of the price p_{t+1} by six subjects in each market. Equation (1.6) means that the price determination process is a function of the average individual forecast in the LtF treatment.⁵ This experimental asset market is a positive feedback system, and the realized price is higher when the average forecast is higher⁶.

$$p_{t+1} = 66 + \frac{20}{21}(\bar{p}_{t+1}^e - 66) + \varepsilon_t \quad (1.6)$$

The rational expectations condition is $\bar{p}_{t+1}^e = p^f = E_t(p_{t+1})$. 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 $p_t = p^f + \varepsilon_t = 66 + \varepsilon_t$.

Under the assumption of price-taking behavior, the optimal demand for the asset is a function of the price forecast as shown in equation (1.5). The price determination function of the LtO treatment is based on the aggregate excess demand:

³ $V_{i,t}(\rho_{t+1}) = \sigma^2$ follows from a simplifying assumption made by Brock and Hommes (1998) that all agents have homogeneous and constant beliefs about the conditional variance. See Hommes (2013a), chapter 6, for a more detailed discussion.

⁴Our results are not very sensitive to the choice of parameters. The value of y is different in different experiments in the previous literature, and the value of y does not matter for the qualitative result of the studies. There are several options of y according to the literature. For example, $y = 3.3$ in Bao et al. (2017), $y = 3$ in Anufriev and Hommes (2012), Heemeijer et al. (2009), Bao et al. (2020), Bao and Zong (2019). The only exception is that the results depend on the value of R . The market system is more stable when $1/R < 0.75$ and unstable when $1/R \approx 1$. The reason we use the experimental data of Bao et al. (2017) is that they chose $1/R \approx 0.95$ so that it generates richer patterns in the price of the experimental markets, i.e. convergence, persistent oscillation and dampened oscillation, and also contains the data from both LtFE and LtOE treatments.

⁵The price adjustment is the same as Heemeijer et al. (2009). The only difference is the fundamental value is 60 in Heemeijer et al. (2009), and 66 in Bao et al. (2017).

⁶In the learning to forecast experiments on asset markets, the slope α is typically $1/(1+r)$, where r is the risk free interest rate. In Bao et al. (2017), the interest rate is 0.05, and the slope is thus 20/21.

$$p_{t+1} = p_t + \frac{20}{21} \sum_{i=1}^6 q_{i,t} + \varepsilon_t \quad (1.7)$$

where $q_{i,t}$ is the quantity decision by individual i in period t , and the shocks ε_t are the same iid shocks in the LtF treatment. Under the assumption of price-taking behavior, when the price is p^f , that is $p_t = p^f = 66$, the expected excess return of the risky asset is 0, and the optimal demand for the risky asset by each agent is also 0. The law of motion of the mixed treatment is decided by equation (1.7), which is same as the LtO treatment.

1.4 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 the 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 the HSM to explain the difference among the three treatments. This section is organized as follows: Section 4.1 derives the fitted price in the LtO and mixed treatments. Section 4.2 shows the result of the estimation of simple forecasting heuristics that can be used in the HSM. Section 4.3 describes the HSM in the LtF treatment, Section 4.4 presents the extended HSM in the LtO treatment, and Section 4.5 reports the results of the simulation.

1.4.1 Derivation of Fitted Price in the LtO and Mixed Treatment

As discussed in Section 3.3, the optimal demand for the asset by agent i is given by equation (1.5). Let recall equation (1.5):

$$q_{i,t}^* = \frac{p_{i,t+1}^e + y - Rp_t}{a\sigma^2} = \frac{p_{i,t+1}^e + 3.3 - 1.05p_t}{6}$$

To investigate the price forecast and quantity decision in the mixed treatment, we separate the two tasks in the mixed treatment. Mixed-F is the price forecast and mixed-Q is the quantity decision in the mixed treatment. We rewrite equation (1.5) and obtain the fitted price prediction based on the subject's quantity decision for the LtO treatment and the mixed-Q in the mixed treatment:⁷

$$p_{i,t+1}^e = 6q_{i,t} + 1.05p_t - 3.3 \quad (1.8)$$

⁷See Bao et al. (2017) for more details.

1.4.2 Estimation of Simple Forecasting Heuristics

We estimate the simple heuristics to check whether the simple heuristics 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:

$$p_{ADA,t+1}^e = p_t^e - w(p_t^e - p_t) \quad (1.9)$$

which describes the relationship between the price prediction and the observed price in the last period. The parameter w captures the strength of individuals' correction of their expectations based on their previous forecasting errors. The larger the w , the stronger the correction. Equation (1.9) describes the relationship between the price forecast in the current period, the last period market price, and the last period price forecast. This means that individuals will adjust their price prediction upwards/downwards when they made negative/positive prediction error in the last period. According to results in the previous literature, this rule will lead to convergence of price to the REE. All results are shown in Table B3 and Table B4 in Appendix B. The value of w is near 1 for all subjects in the LtF treatment and the mixed-F of the mixed treatment⁸, between 0.3 and 1 in the LtO treatment and the mixed-Q of the mixed treatment. w is significant at the 5% level for almost all subjects in the LtF treatment, for half of the subjects in the LtO treatment and the mixed-Q of the mixed treatment. The adjusted R^2 is 0.9995 in the LtF treatment, 0.9831 in the LtO treatment, 0.8363 in the mixed-F, and 0.9792 in the mixed-Q of the mixed treatment. The MSE is 1.42 in the LtF treatment, 54.96 in the LtO treatment, 20422.50 in the mixed-F, and 124.62 in the mixed-Q. 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, more than half of the subjects pass the AC test in the LtO treatment and the mixed-F of the mixed treatment. 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:

$$p_{TRF,t+1}^e = p_t + \gamma(p_t - p_{t-1}) \quad (1.10)$$

If γ is positive, it implies that when the price in the last period increased, 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 sign implies that when the price

⁸We use the estimation result of First Order Heuristic, $p_{i,t}^e = \alpha_i p_{t-1} + \beta_i p_{i,t-1}^e + \gamma_i (p_{t-1} - p_{t-2})$, 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.

in the last period increased, the subjects will expect the price to decrease in the future. Tables B5 and B6 in Appendix B show the results of the trend rule.

To summarize, the parameter γ is positive and in the range between 0 and 1.24 in the LtF treatment, positive and in the range between 0.2 and 2.03 in the LtO treatment, and positive in the mixed treatment. γ is significantly different from 0 at 5% level for all subjects in the LtF treatment, significantly different from 0 for 43 out of 48 subjects in the LtO treatment, significantly different from 0 for 29 out of 48 subjects in the mixed-F, and 39 out of 48 subjects in the mixed-Q. The mean of γ is 0.4 in the LtF treatment, 1.02 in the LtO treatment, 0.82 in the mixed-F, and 1.02 in the mixed-Q. The median of γ is 0.4 in the LtF treatment, 0.94 in the LtO treatment, 0.57 in the mixed-F, and 0.62 in the mixed-Q. The adjusted R^2 is 0.9995 in the LtF treatment, 0.9935 in the LtO treatment, 0.8363 in the mixed-F, and 0.9913 in the mixed-Q. The MSE is 1.42 in the LtF treatment, 20.35 in the LtO treatment, 20422.50 in the mixed-F, and 42.30 in the mixed-Q. More than half of the subjects failed to pass the AC test means 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.

1.4.3 The Heuristic Switching Model with Benchmark Parameter Settings

According to Anufriev and Hommes (2012), the typical assumptions of the HSM are: agents choose from a menu of 4 forecasting heuristics, and switch from one heuristic to another based on their past performance. Let $p_{h,t+1}^e$ denote that participants use h heuristic for price prediction for the price at period $t + 1$, where $h \in \{1, 2, 3, 4\}$. There are four heuristics (or rules) in this model:

The adaptive expectation rule (ADA) is as follows:

$$p_{1,t+1}^e = wp_t + (1 - w)p_{1,t}^e \quad (1.11)$$

The weak-trend rule (WTR) is given by:

$$p_{2,t+1}^e = p_t + \gamma_w(p_t - p_{t-1}) \quad (1.12)$$

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

$$p_{3,t+1}^e = p_t + \gamma_s(p_t - p_{t-1}) \quad (1.13)$$

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

$$p_{4,t+1}^e = \frac{(p^f + p_t)}{2} + (p_t - p_{t-1}) \quad (1.14)$$

The values of the parameters used in the first three rules are the medians of the successful (with a significant coefficient, 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 $\gamma_s = 1.3$, which are also widely used by the literature, e.g., Anufriev and Hommes (2012), Bao et al. (2013), Hommes (2011), etc. 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. This means that individuals will adjust their price prediction upwards/downwards when they made negative/positive prediction error in the last period. According to results in the previous literature, this rule will lead to convergence of price to the REE. The parameter w captures the strength of individuals' correction. The larger the w , the stronger the correction. The second rule (WTR) and the third rule (STR) are the trend rules, which means 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 parameter γ captures the strength with which subjects extrapolate the past trend. Both WTR and STR are trend-following rules. The main difference between the WTR and STR is the value of γ . If $\gamma = 0.3$, the rule is WTR. If $\gamma = 1.3$, the rule is STR. The higher the γ , the more the subjects chase the past price trend, and the larger the deviation from the fundamental value. The weak trend rule helps to explain the pattern of slow convergence or dampened oscillation, while the strong trend rule leads to large bubbles and crashes. 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.

In the model, the subjects use different heuristics to make price forecast. As a consequence, the average price expectations in equation (1.6) becomes a population-weighted average of the different heuristics:

$$\bar{p}_{t+1}^e = \sum_{i=1}^H n_{h,t} p_{h,t+1}^e \quad (1.15)$$

where $\bar{p}_{t+1}^e$ is defined in equation (1.6), and H is the number of heuristics, in our case, $H = 4$. $n_{h,t}$ is the impact of the heuristic h at period t , and depends on the past performance of the heuristic.

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

$$U_{h,t} = -(p_t - p_{h,t}^e)^2 + \eta U_{h,t-1} \quad (1.16)$$

The first term in equation (1.16) is the squared error of prediction. The agents in the LtF treatment will make their price forecast, their payoff depends on the accuracy of their prediction. The payoff function of the subjects in the LtF treatment

is a decreasing function of the squared error of prediction, that is $(p_t - p_{h,t}^e)^2$. Hence, the lower the mean squared error, the higher their payoff. 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 gives 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 h at period t is defined as $n_{h,t}$, which is determined by a discrete choice model with asynchronous updating (Hommes et al., 2005. Diks and Van der Weide, 2005).

$$n_{h,t} = \delta n_{h,t-1} + (1 - \delta) \frac{\exp(\beta U_{h,t-1})}{\sum_{h=1}^4 \exp(\beta U_{h,t-1})} \quad (1.17)$$

The parameter $\delta \in [0, 1]$ reflects the inertia of agents. In other words, it measures the inertia for subjects to stick 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 update the information will switch to the most successful rule.

1.4.4 Modeling Switching Behavior in the LtO Treatment

Our extended HSM in the LtO treatment uses the same four heuristics defined by equation (1.11), (1.12), (1.13), and (1.14). Hence, the average price prediction in equation (1.6) is also a weighted average of the heuristics as shown in equation (1.15).

In contrast to the LtF treatment, in the LtO treatment, the agents' payoff is not determined by the accuracy of the price prediction, but the trading profit. Therefore, the performance of the agent is measured by the profit from trading instead of prediction error. As discussed in Section 3.3, agents will myopically maximize the mean-variance utility of wealth. The profit in the LtO treatment is defined by the mean-variance wealth, the performance of the agent in the LtO treatment is measured as follows:

$$\pi_t = W_t - \frac{1}{2} \text{Var}(W_t)^2 \quad (1.18)$$

where π_t is the profit that the agent earned in the LtO treatment and W_t equals the return of the asset multiplied by the quantity of asset. The return of the asset is $\rho_t = p_t + y - Rp_{t-1}$, where p_t is the market price at period t , y and R are defined in the Section 3.3, y is the dividend of the risky asset, and $R = 1 + r$ is the gross interest rate of risk free bond. q_t is the quantity demand for the risky asset at period t . For simplicity, Bao et al. (2017) assumes that the expected variance of the price of a unit of the asset is 6. We substitute them to equation (1.18), we can rewrite the performance in the following manner:

$$\pi_t = (p_t + y - Rp_{t-1})q_t - 3q_t^2 \quad (1.19)$$

Thus, in the LtO treatment, the performance of heuristic h , $i \in \{1, 2, 3, 4\}$ is given by equation (1.20). Subjects in the LtO treatment seek to maximize their total profit. For this reason, the sign of the first term π_t in equation (1.20) is positive:

$$U_{h,t} = \pi_t + \eta U_{h,t-1} = (p_t + y - Rp_{t-1})q_t - 3q_t^2 + \eta U_{h,t-1} \quad (1.20)$$

The weight $n_{i,t}$ is defined by equation (1.17). All the other parameters, such as β , η and δ , are the same as the HSM in the LtF treatment.

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 their utility is forecasting accuracy in mixed-F (defined by equation (1.16)) and profit defined by equation (1.20) in mixed-Q. The weight assigned to the heuristics $n_{h,t}$ is the same as that in the LtF treatment.

1.4.5 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 1.1 and Figure 1.2 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 1.1 and 1.2 (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 dynamics of the experimental data and the simulated asset price, 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 1.1. 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 1.1 illustrates the simulation results of the LtO treatment. The STR is the dominant rule in the LtO treatment.

The top panel of Figure 1.2 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 1.2 illustrates the STR dominates 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 1.1: 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) from the LtF treatment (top panel), and one one typical market (market 1) from the LtO treatment (bottom panel). The x-axis is the period. The y-axis is the price in the left panel, and the weight of the heuristics in the right panel.

Figure 1.2: 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. The x-axis is the period. The y-axis is the price in the left panel, and the weight of the heuristics in the right panel. The default upper bound of y-axis is 100 for comparison. The upper bound of y-axis is 200 in this figure since the average price forecast is beyond 100 for some period.

Table 1.1 shows the MSE of the simulation in all markets in each treatment. The MSE is chosen as a criterion to measure the fitness of the model. In the real market, a trader/investor also tends to earn more when his/her forecast is more accurate. When the forecasts are more accurate, their trading decisions based on their forecasts are in general more profitable. E.g., if you can forecast a big boom/bust of stock prices before the other traders, you stand a much larger chance to gain from trading. 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. The average MSE is 160.2 in the mixed-F, and 125.4 in the mixed-Q. 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, 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 1.1 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 (The 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, there is a higher β and lower δ 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 that individuals in the LtO and mixed treatments may make their decisions more flexible than those in the LtF treatment.

In summary, among the simple heuristics, the 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. We observe some heterogeneity of the best rules in the LtO and mixed treatment, i.e., ADA fits the data best in some markets of LtO and mixed treatment, it implies that some markets are stable within the LtO or the mixed treatment. However, these markets are stable only when compared with other markets in the LtO treatment or the mixed treatment. If compared with the markets in the LtF treatment, the markets are more stable in the LtF treatment than the other two treatments. Both the variance of the price and the retreat (the maximum price-the minimum price) are smallest in the LtF treatment (Refer to Table B11 for more details), which provides the support that the markets are more stable in the LtF treatment than in the LtO and mixed treatment. The average of the variance of the price is 53.71 in the LtF treatment, 247.67 in the LtO treatment, 1058.48 in the mixed-F, and 1001.98 in the mixed-Q. The average of the retreat of the price is 26.50 in the LtF treatment, 57.12 in the LtO treatment, 123.11 in the mixed-F, and 83.09 in the mixed-Q. Additionally, the MSE is quite

Table 1.1: 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	<u>7.4563</u>	<u>4.1856</u>	<u>3.8692</u>	<u>4.2674</u>	<u>13.5770</u>	<u>9.0967</u>	<u>2.7013</u>	<u>5.5272</u>
$\beta \in [0, 10]$	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	<u>27.4231</u>	<u>57.8884</u>	<u>66.2478</u>	<u>47.7612</u>	<u>7.5233</u>	<u>39.9163</u>	<u>33.9680</u>	<u>33.6557</u>
$\beta \in [0, 10]$	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	<u>56.2114</u>	<u>25.6583</u>	<u>16.2143</u>	<u>80.2756</u>	<u>47.6096</u>	<u>17.9525</u>	<u>38.6626</u>	<u>240.5224</u>
$\beta \in [0, 10]$	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	<u>46.1489</u>	<u>72.9935</u>	<u>36.0537</u>	<u>89.9091</u>	<u>47.6096</u>	<u>28.7006</u>	<u>44.4057</u>	<u>228.2831</u>
$\beta \in [0, 10]$	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

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.

Besides, compared to all other models, the HSM optimal fits the data best in terms of generating the smallest MSE. MSE alone may not be a fair measure to compare big and small models. To make our findings robust, we also calculate the AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) for all the models. According to Anufriev et al. (2013), AIC and BIC punish larger models and provide a fairer ground for comparison⁹ The average AIC is 5151.92

⁹ $AIC = 2n + kG \ln MSE_{kG}(\hat{\theta}) - 2C$, and $BIC = n \ln(kG) + kG \ln MSE_{kG}(\hat{\theta}) - 2C$, where n is the number of parameters in the model, k is the periods of the model's prediction, G is the number of markets, and $C = -kG(1 + \ln(2\pi))/2$ depends on the number of observation. Refer to Anufriev

for the HSM optimal, 5269.26 for the ADA, 5264.26 for the WTR, 5287.98 for the STR, 5326.80 for the A&A, and 5301.83 for the HSM benchmark in the LtF treatment. The average AIC is 7183.93 for the HSM optimal, 7734.86 for the ADA, 7734.85 for the WTR, 7741.89 for the STR, 7773.32 for the A&A, and 7734.70 for the HSM benchmark in the LtO treatment. The average AIC is 7488.19 for the HSM optimal, 8234.67 for the ADA, 8229.73 for the WTR, 8228.42 for the STR, 8262.12 for the A&A, and 8243.15 for the HSM benchmark in the mixed-F. The average AIC is 7814.77 for the HSM optimal, 8255.18 for the ADA, 8265.61 for the WTR, 8303.25 for the STR, 8288.15 for the A&A, and 8251.28 for the HSM benchmark in the mixed-Q. Based on the criteria of AIC, the small the value, the better the model that fits the data. The AIC value for the HSM optimal is always the smallest. Therefore, HSM always fits the data best. The result also holds for BIC. (refer to Table: B12 for more details)

Table 1.2 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 ($p = 0.0002$ for the test on the difference between the weight of ADA and the other three rules in the LtF treatment) and the STR is the dominant rule in the LtO treatment ($p = 0.0002$ for the test on the difference between the weight of STR and the other three rules in the LtO treatment). On average, the STR is the dominant rule in the mixed treatment ($p = 0.0002$ for the test on the difference between the weight of STR and the other three rules in the mixed treatment). 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 ($p = 0.0000$ for the test on the difference between the weight of ADA or STR between the LtF treatment and the other two treatments). These results are in line with the conclusion from the graphs of the simulation.

Table 1.2: 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. 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.

	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

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

et al. (2013) for more details.

treatment. Since, as described in section 4.1, the ADA illustrates that individuals will be reflective by correcting their predictions concerning the one-period lagged price prediction error. 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 and contributes to large bubbles and crashes. Bao et al. (2012) argue that if the adaptive expectation strategy dominates the market, then the price will tend to converge to the fundamental. 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 and mixed treatments than in the LtF treatment in Bao et al. (2017).

1.5 Conditional Optimality of the Quantity Decision in the Mixed Treatment

This section addresses the second question in the introduction. Bao et al. (2017) analyzed the quantity decision in the mixed treatment and found that there is a persistent deviation from the optimal quantity in the mixed treatment, and found that the deviation of the market price from the fundamental value. The price deviation is the greatest in the mixed treatment and they speculated that it is due to the inconsistency between the quantity decision and the conditionally optimal level given the price forecast. However, they did not check the dynamic pattern of the quantity decision. In a way, their paper did a pooled treatment level comparison, which made it impossible for them to check whether decisions converge to the REE over time. 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 1.3. Table 1.3 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. The statistics are mean (left panel), median (middle panel) and variance (right panel). For each statistic, we calculate the value for period 1 to 50, period 1 to 25 and period 26 to 50.

Table 1.3: Summary Statistics of Quantity Decision. This table shows the mean, median and variance of quantity. The statistics are calculated at the 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 average variance of the quantity decision over 50 periods is 1.04 in the LtO treatment, and 2.74 in the mixed treatment. 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 in the LtO treatment and 3.08 in the mixed treatment (in period 1 to 25), 0.44 in the LtO treatment and 2.35 in the mixed treatment (in period 26 to 50). 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 1.3 and Figure 1.4 plot the average quantity decisions (top panel) and the average quantity of eight markets (bottom panel) in the LtO and mixed treatments.

Figure 1.3: The average quantity decision of the LtO treatment (top panel) and the average quantity decision of 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 1.4: 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 1.4, after period 20, the quantity decisions in some markets (market 5 to 8) of the mixed treatment gradually converge to 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 (Bao et al., 2017).

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.

1.5.1 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 (1.21):

$$p_{t+1} = p_t + \lambda(Z_t^D - Z_t^S) + \varepsilon_t \quad (1.21)$$

where p_t and p_{t+1} is the market price at period t and $t + 1$. $\varepsilon_t \sim N(0, 1)$ is a small iid shock, $\lambda > 0$ is a scaling factor, Z_t^S is the exogenous supply and Z_t^D is the total demand (Z_t in Bao et al. (2017) is the aggregate quantity decision, which is the aggregation of $q_{i,t}$. $q_{i,t}$ is the individual's quantity decision as mentioned in Section 3.3). Additionally, in Bao et al. (2017), the exogenous supply Z_t^S 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:

$$DQ_{i,t} = q_{i,t} - q_{i,t}^* \quad (1.22)$$

$$ADQ_{i,t} = |q_{i,t} - q_{i,t}^*| \quad (1.23)$$

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 and is defined by equation (1.5). We define the average $DQ_{i,t}$ and $ADQ_{i,t}$ at market level as DQ_t , ADQ_t :

$$DQ_t = \frac{1}{6} \sum_i (DQ_{i,t}) \quad (1.24)$$

$$ADQ_t = \frac{1}{6} \sum_i (ADQ_{i,t}) \quad (1.25)$$

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 Relative Absolute Deviation (RAD) in Stöckl et al. (?). We use the DQ or ADQ rather than the relative DQ or ADQ to measure the deviation of the actual quantity decision from the conditionally optimal level, considering the optimal level of quantity decision is 0 under REE, and conditionally optimal level varies among subjects in the mixed treatment.

Table 1.4: The numbers reported in this table are average values and calculated at the market level. The second column and third column are the average actual quantity decision ($\bar{q}$) and conditionally optimal level ($\bar{q}^*$) in each market of the mixed treatment, where $\bar{q} = \frac{1}{50} \sum_t (\frac{1}{6} \sum_i q_{i,t})$ and $\bar{q}^* = \frac{1}{50} \sum_t (\frac{1}{6} \sum_i q_{i,t}^*)$. The third column and the fourth column are the average DQ_t ($\overline{DQ}$) and ADQ_t ($\overline{ADQ}$) over the period, 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 $\bar{q}$, $\bar{q}^*$, $\overline{DQ}$ and $\overline{ADQ}$ over the entire mixed treatment.

	$\bar{q}$	$\bar{q}^*$	$\overline{DQ}$	$\overline{ADQ}$
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 1.4 above shows the $\bar{q}$, $\bar{q}^*$, $\overline{DQ}$ and $\overline{ADQ}$ over the entire mixed treatment. The average actual quantity decision of the mixed treatment ($\bar{q}$) is 0.1685, the average conditionally optimal level ($\bar{q}^*$) is 0.0153, average DQ_t ($\overline{DQ}$) is 0.1584, and the average ADQ_t ($\overline{ADQ}$) is 0.9770. We can observe from Table 1.4 that the actual quantity decision is not equal to the conditionally optimal level, the DQ and ADQ are far from 0. Figure 1.5 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 1.5 fluctuates around zero, and the average DQ of the eight markets does not show convergence. There are great fluctuations in 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 show that there is no convergence of the actual quantity decision to the conditionally optimal level in the mixed treatment.

Figure 1.5: 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.

1.5.2 Convergence of Actual Quantity to the Optimal Level

In this subsection, 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 to 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 implies 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 $q_e^a = \frac{c}{1-a_1} + \frac{a_2}{1-a_1} q^*$. 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 to the conditionally optimal level.

We estimate the equation for each of the 48 subjects, and the results are reported in Table 3.3, 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, and the fourth and fifth columns are the parameter a_1 with its p -value, and the sixth and seventh columns are the parameter a_2 with its p -value. 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 is significant in 9 out of 48 subjects, a_1 is significant in 26 out of 48 subjects, and a_2 is significant in 43 out of 48 subjects. The mean of c is 0.06, a_1 is 0.47, and a_2 is 1.46. 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 equation, the mean of $c/(1-a_1)$ is 0.85, and the median is 0.51. Moreover, the mean of $a_2/(1-a_1)$ is 2.72, and the median is 3.06. 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 shows that there is a persistent difference between the actual quantity and the conditionally optimal level in the mixed treatment. This result is a stronger version of Bao et al. (2017) that the quantity does not only deviate from the optimal level, but also shows no tendency to converge to it over time.

To summarize, our findings suggest that in the mixed treatment, while the actual quantity decision converges to 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

Table 1.5: 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. The fourth and fifth columns are the estimation results of a_1 and its p -value. The sixth and seventh columns are the parameter 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

optimal level for the subject.

1.6 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 for 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 individuals to 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. (2016) and Breaban and Noussair (2018).

One possible policy recommendation would be to provide robot advisors or mobile applications that always give the suggestion of the optimal trading quantity based on the investor's expectation, to help improving the quality of individual investment decisions. This calculator may reduce their tendency to chase the trend and enhance the stability of financial markets.

1.7 Appendix A

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. The y-axis is the price in the left panel, and the weight of the heuristics in the right panel.

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. The y-axis is the price in the left panel, and the weight of the heuristics in the right panel.

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. The y-axis is the price in the left panel, and the weight of the heuristics in the right panel.

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. The y-axis is the price in the left panel, and the weight of the heuristics in the right panel.

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 period. The y-axis is the value of DQ in the left panel, and value of ADQ in the right panel.

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 period. The y-axis is the actual quantity decision in the left panel, and market conditionally optimal level in the right panel.

1.8 Appendix B

Table B1: The result is for the estimation of $p_{i,t}^e = \alpha_i p_{t-1} + \beta_i p_{i,t-1}^e + \gamma_i (p_{t-1} - p_{t-2})$ for the LtF treatment. The first column is the subject number. The estimated coefficient of constant c is reported in the second column, P_{t-1} in the third column, P_{t-1}^e in the fourth column, and $P_{t-1} - P_{t-2}$ in the fifth column. 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_{t-1}^e	$P_{t-1} - P_{t-2}$	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 $p_{i,t}^e = \alpha_i p_{t-1} + \beta_i p_{i,t-1}^e + \gamma_i (p_{t-1} - p_{t-2})$ for the mixed-F in the mixed treatment. The first column is the subject number. The estimated coefficient of constant c is reported in the second column, P_{t-1} in the third column, P_{t-1}^e in the fourth column, and $P_{t-1}-P_{t-2}$ in the fifth column. 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_{t-1}^e	$P_{t-1}-P_{t-2}$	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 $p_{i,t}^e = p_{t-1}^e + w(p_{t-1} - p_{t-1}^e)$ for the LtO treatment. The first column is the subject number. The second column is the estimated coefficients P_{t-1}^e , and third column is $P_{t-1} - P_{t-1}^e$. 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 null hypothesis of Chow test is that there is no structural break of the forecast during the 50 periods of the experiment. The last two columns show the result of AC test.

No.	P_{t-1}^e	$P_{t-1} - P_{t-1}^e$	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 $p_{i,t}^e = p_{t-1}^e + w(p_{t-1} - p_{t-1}^e)$ for the mixed-Q of the mixed treatment. The first column is the subject number. The second column is the estimated coefficients P_{t-1}^e , and third column is $P_{t-1} - P_{t-1}^e$. 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 null hypothesis of Chow test is that there is no structural break of the forecast during the 50 periods of the experiment. The last two columns show the result of AC test.

No.	P_{t-1}^e	$P_{t-1} - P_{t-1}^e$	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 $p_{i,t}^e = p_{t-1}^e + \gamma(p_{t-1} - p_{t-2})$ for the LtO treatment. The first column is the subject number. The second column is the estimated coefficients P_{t-1}^e , and third column is $P_{t-1} - P_{t-2}^e$. 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. The null hypothesis of Chow test is that there is no structural break of the forecast during the 50 periods of the experiment.

No.	P_{t-1}	$P_{t-1} - P_{t-2}^e$	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 $p_{i,t}^e = p_{t-1}^e + \gamma(p_{t-1} - p_{t-2})$ for the mixed-Q of the mixed treatment. The first column is the subject number. The second column is the estimated coefficients P_{t-1}^e , and third column is $P_{t-1} - P_{t-1}^e$. 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. The null hypothesis of Chow test is that there is no structural break of the forecast during the 50 periods of the experiment.

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 $p_{h,t}^e = c + \sum_{i=1}^3 o_i p_{t-i} + \sum_{i=1}^3 s_i p_{h,t-i}^e + v_t$ for the LtF treatment. The first column is the subject number. The estimated coefficient of constant c is reported in the second column, P_{t-1} in the third column, P_{t-2} in the fourth column, P_{t-3} in the fifth column, P_{t-1}^e in the sixth column, P_{t-2}^e in the seventh column, and P_{t-3}^e in the eighth column. 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. The null hypothesis of Chow test is that there is no structural break of the forecast during the 50 periods of the experiment.

No.	Cons	P_{t-1}	P_{t-2}	P_{t-3}	P_{t-1}^e	P_{t-2}^e	P_{t-3}^e	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 $p_{h,t}^e = c + \sum_{i=1}^3 o_i p_{t-i} + \sum_{i=1}^3 s_i p_{h,t-i}^e + v_t$ for the LtO treatment. The first column is the subject number. The estimated coefficient of constant c is reported in the second column, P_{t-1} in the third column, P_{t-2} in the fourth column, P_{t-3} in the fifth column, P_{t-1}^e in the sixth column, P_{t-2}^e in the seventh column, and P_{t-3}^e in the eighth column. 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. The null hypothesis of Chow test is that there is no structural break of the forecast during the 50 periods of the experiment.

No.	Cons	P_{t-1}	P_{t-2}	P_{t-3}	P_{t-1}^e	P_{t-2}^e	P_{t-3}^e	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 $p_{h,t}^e = c + \sum_{i=1}^3 o_i p_{t-i} + \sum_{i=1}^3 s_i p_{h,t-i}^e + v_t$ for the mixed-F of the mixed treatment. The first column is the subject number. The estimated coefficient of constant c is reported in the second column, P_{t-1} in the third column, P_{t-2} in the fourth column, P_{t-3} in the fifth column, P_{t-1}^e in the sixth column, P_{t-2}^e in the seventh column, and P_{t-3}^e in the eighth column. 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. The null hypothesis of Chow test is that there is no structural break of the forecast during the 50 periods of the experiment.

No.	Cons	P_{t-1}	P_{t-2}	P_{t-3}	P_{t-1}^e	P_{t-2}^e	P_{t-3}^e	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 $p_{h,t}^e = c + \sum_{i=1}^3 o_i p_{t-i} + \sum_{i=1}^3 s_i p_{h,t-i}^e + v_t$ for the mixed-Q of the mixed treatment. The first column is the subject number. The estimated coefficient of constant c is reported in the second column, P_{t-1} in the third column, P_{t-2} in the fourth column, P_{t-3} in the fifth column, P_{t-1}^e in the sixth column, P_{t-2}^e in the seventh column, and P_{t-3}^e in the eighth column. 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. The null hypothesis of Chow test is that there is no structural break of the forecast during the the 50 periods of the experiment.

No.	Cons	P_{t-1}	P_{t-2}	P_{t-3}	P_{t-1}^e	P_{t-2}^e	P_{t-3}^e	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

Table B11: This table reports the variance of price and the retreat of price in each market of LtF treatment (top panel), LtO treatment (middle panel) and mixed treatment (bottom panel). The retreat of price is defined as $price_{max} - price_{min}$.

	LtF1	LtF2	LtF3	LtF4	LtF5	LtF6	LtF7	LtF8
Variance	67.7382	96.4943	47.0794	37.7095	42.8265	99.0999	10.7541	28.0108
Retreat	30.2617	32.6600	25.6367	24.2467	30.6567	35.1333	12.7050	20.6733
	LtO1	LtO2	LtO3	LtO4	LtO5	LtO6	LtO7	LtO8
Variance	241.3853	45.8468	607.0985	322.8269	147.0175	206.5831	323.6839	86.8904
Retreat	53.0545	40.6780	95.6430	65.7000	38.7785	62.4610	65.7667	34.8476
mixed								
	mixed-F1	mixed-F2	mixed-F3	mixed-F4	mixed-F5	mixed-F6	mixed-F7	mixed-F8
Variance	894.9806	862.8085	44.7682	832.1891	151.5439	9.9713	495.3864	5176.1950
Retreat	215.9083	226.3417	41.7500	105.1700	50.6533	27.1783	89.3017	228.5500
	mixed-Q1	mixed-Q2	mixed-Q3	mixed-Q4	mixed-Q5	mixed-Q6	mixed-Q7	mixed-Q8
Variance	291.2490	65.3393	56.6281	950.6947	160.7399	15.8051	532.4385	5942.9665
Retreat	79.1425	32.7505	37.8120	113.8220	55.1940	24.4400	73.2975	248.2770

Table B12: This table shows the AIC and BIC of the four heuristics and HSM models in the LtF, LtO and mixed treatment. The bold numbers are the smallest value of AIC and BIC for each group among all the models. The smaller the value of AIC or BIC, the better the model.

		LtF1	LtF2	LtF3	LtF4	LtF5	LtF6	LtF7	LtF8
AIC	ADA	5607.0489	4958.4956	4874.4367	4932.6370	6165.0207	6018.4075	4343.8201	5254.1966
	WTR	5599.3179	4952.0694	4868.5988	4925.5920	6160.8949	6017.4578	4339.8067	5250.3737
	STR	5620.5967	4967.5913	4904.8843	4951.1003	6174.8469	6035.4579	4374.3106	5275.0681
	A&A	5673.2843	5169.5421	4944.4450	4991.5375	6177.9617	6042.0403	4349.6022	5265.9773
	HSM Benchmark	5647.3762	4986.2840	4917.9313	4968.5416	6187.7584	6033.3970	4387.1005	5286.2181
	HSM Optimal	5477.3477	4826.0337	4737.3661	4847.8642	6153.3725	5701.6525	4332.0666	5139.6512
BIC	ADA	5632.1899	4983.6366	4899.5777	4957.7780	6190.1618	6043.5485	4368.9611	5279.3376
	WTR	5624.4589	4977.2104	4893.7398	4950.7330	6186.0359	6042.5988	4364.9477	5275.5147
	STR	5645.7378	4992.7323	4930.0253	4976.2413	6199.9879	6060.5989	4399.4516	5300.2091
	A&A	5698.4253	5194.6831	4969.5860	5016.6785	6203.1028	6067.1813	4374.7432	5291.1183
	HSM Benchmark	5672.5172	5011.4250	4943.0723	4993.6826	6212.8994	6058.5380	4412.2415	5311.3591
	HSM Optimal	5502.4887	4851.1747	4762.5071	4873.0052	6178.5135	5726.7935	4357.2076	5164.7922
		LtO1	LtO2	LtO3	LtO4	LtO5	LtO6	LtO7	LtO8
AIC	ADA	7482.0520	8341.3694	8526.0823	8219.1525	6124.5331	8066.7570	7538.6638	7580.2582
	WTR	7481.5778	8351.2532	8515.1248	8218.6966	6124.7192	8066.9724	7540.4250	7580.0369
	STR	7482.6955	8397.7414	8512.6238	8218.9986	6125.1665	8068.1582	7549.7757	7579.9676
	A&A	7543.7876	8344.9123	8552.7748	8302.7125	6227.7448	8073.2039	7538.5619	7602.8835
	HSM Benchmark	7481.7212	8343.0910	8520.4253	8219.6087	6124.7489	8067.6233	7538.4182	7581.9946
	HSM Optimal	6946.3687	7789.1326	7941.2836	7572.2136	5487.4289	7369.8197	7187.7974	7177.3804
BIC	ADA	7507.1930	8366.5104	8551.2233	8244.2935	6149.6741	8091.8980	7563.8048	7605.3992
	WTR	7506.7189	8376.3942	8540.2658	8243.8376	6149.8602	8092.1134	7565.5660	7605.1779
	STR	7507.8365	8422.8824	8537.7649	8244.1396	6150.3075	8093.2992	7574.9187	7605.1087
	A&A	7568.9287	8370.0533	8577.9158	8327.8536	6252.8858	8098.3449	7563.7029	7628.0245
	HSM Benchmark	7506.8622	8368.2320	8545.5664	8244.7497	6149.8899	8092.7643	7563.5592	7607.1356
	HSM Optimal	6971.5097	7814.2736	7966.4246	7597.3546	5512.5699	7394.9608	7212.9384	7202.5214
mixed									
		mixed-F1	mixed-F2	mixed-F3	mixed-F4	mixed-F5	mixed-F6	mixed-F7	mixed-F8
AIC	ADA	9566.2244	7825.4252	6438.6797	8727.1434	7707.4366	6565.6557	8633.2692	10413.5154
	WTR	9566.1262	7826.2656	6405.6484	8712.5919	7706.5157	6566.7020	8633.7610	10420.1939
	STR	9566.7308	7828.9299	6353.6329	8717.2793	7710.7332	6571.0488	8636.1604	10442.8736
	A&A	9567.5594	7821.3799	6546.1859	8718.4808	7714.7551	6567.9077	8718.4135	10442.2840
	HSM Benchmark	9570.1818	7823.4418	6484.5875	8744.5169	7714.6871	6565.1391	8634.1717	10408.4685
	HSM Optimal	7755.9715	6871.3364	6353.6134	8157.9300	7568.6273	6468.4858	7333.8216	9395.7386
BIC	ADA	9591.3654	7850.5662	6463.8207	8752.2844	7732.5776	6590.7967	8658.4102	10438.6564
	WTR	9591.2672	7851.4066	6430.7894	8737.7329	7731.6567	6591.8431	8658.9020	10445.3350
	STR	9591.8719	7854.0709	6378.7739	8742.4203	7735.8742	6596.1898	8661.3014	10468.0146
	A&A	9592.7004	7846.5209	6571.3269	8743.6219	7739.8961	6593.0487	8743.5545	10467.4250
	HSM Benchmark	9595.3228	7848.5828	6509.7285	8769.6579	7739.8281	6590.2801	8659.3127	10433.6095
	HSM Optimal	7781.1125	6896.4774	6378.7545	8183.0710	7593.7684	6493.6268	7358.9626	9420.8796
		mixed-Q1	mixed-Q2	mixed-Q3	mixed-Q4	mixed-Q5	mixed-Q6	mixed-Q7	mixed-Q8
AIC	ADA	8171.0552	8387.7425	7546.2137	9018.2097	7818.2499	7236.5471	7825.3340	10038.0644
	WTR	8170.9261	8413.3677	7613.6103	9013.9266	7819.1541	7235.7230	7825.2929	10032.9094
	STR	8170.7398	8494.7957	7802.9866	9024.6533	7823.5029	7233.9981	7827.2172	10048.0829
	A&A	8170.7605	8448.0332	7523.9471	9024.2385	7822.0330	7236.8763	7890.0074	10189.2980
	HSM Benchmark	8170.3411	8360.6510	7462.0802	9015.9805	7818.1046	7240.5416	7825.9902	10116.5145
	HSM Optimal	7533.4772	8050.6635	7255.0155	8285.7705	7568.6282	6997.7270	7490.0432	9336.8271
BIC	ADA	8196.1962	8412.8835	7571.3547	9043.3507	7843.3909	7261.6881	7850.4750	10063.2054
	WTR	8196.0671	8438.5087	7638.7514	9039.0676	7844.2951	7260.8640	7850.4339	10058.0504
	STR	8195.8808	8519.9367	7828.1276	9049.7943	7848.6440	7259.1391	7852.3582	10073.2239
	A&A	8195.9015	8473.1742	7549.0881	9049.3795	7847.1741	7262.0173	7915.1485	10214.4390
	HSM Benchmark	8195.4821	8385.7920	7487.2212	9041.1215	7843.2456	7265.6826	7851.1313	10141.6555
	HSM Optimal	7558.6182	8075.8045	7280.1565	8310.9115	7593.7692	7022.8680	7515.1842	9361.9681

1.9 Appendix C

Estimation of Linear Prediction Rules

We estimate the following forecast rule following Bao et al. (2012). We estimated the following linear equation for each individual:

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

where $p_{h,t}^e$ 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 are 48 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 the coefficient is significant for 7 out of 48 in the LtF treatment, 46 out of 48 in the LtO treatment, 42 out of 48 in the mixed treatment.

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 rules 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:

$$p_{i,t}^e = \alpha_i p_{t-1} + \beta_i p_{i,t-1}^e + \gamma_i (p_{t-1} - p_{t-2}) \quad (\text{c.1})$$

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 (c.1), 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.

Chapter 2

Asset Pricing with Ambiguous Signals: An Experiment

2.1 Introduction

Participants in financial markets confront many signals about market fundamentals every day. How should they process these signals? According to Epstein and Schneider (2008), agents take the quality of the signals they receive into account when processing the information. They assign more weight to signals from a reliable source and less weight to signals from obscure sources. The variance of a signal serves as a measure of its quality. The quality of a signal is good (bad) when the variance of that signal is small (large). While the variance of a signal can be considered as known when it comes from a source with a track record, there are also *ambiguous* signals from previously unknown sources for which the variance may be unknown. Epstein and Schneider (2008) suggest that when faced with such ambiguous information, ambiguity-averse investors maximize expected utility under a worst-case belief as in Gilboa and Schmeidler (1989) about the quality of the ambiguous signal. Thus, if there are ambiguity-averse investors, there will be an asymmetric reaction to ambiguous signals: bad signals will be treated as if they are more accurate (have smaller variance) than good signals, and agents will allocate higher weight to bad signals when making decisions. Since signals matter for asset price determination, if there are ambiguity-averse investors pricing assets they will require higher excess returns when signals are ambiguous, and the volatility of prices will also be greater under ambiguous signals.

In this paper, we report the results of an experimental study that tests these implications of Epstein and Schneider's theory (2008). In our view, the theoretical predictions of Epstein and Schneider (2008) are four-fold. (1) Ambiguity averse participants' perceived variance of an ambiguous signal is smaller when it conveys bad news than when it conveys good news. (2) Ambiguity averse participants allocate a larger weight to such signals when they convey bad news than when they convey good news. (3) The response of ambiguity-averse investors to

ambiguous information implies that there will be negative skewness in measured excess returns. (4) The volatility of prices is greater when the signal is ambiguous than when it is unambiguous.

To test these hypotheses, we design a two-stage experiment. In the first stage, participants' attitude towards ambiguity is measured, along with measures for their risk aversion. Then, in the second stage they participate in a simplified version of an experimental asset market.

In the first stage, we measure the participants' ambiguity attitudes using a classic two-color Ellsberg urn according to Ellsberg (1961), which is widely used in the previous literature, e.g. Trautmann et al. (2008), Kocher and Trautmann (2013), Trautmann and Van de Kuilen (2015). Specifically, participants are asked to make a number of choices between pairs of boxes. The K (known) box in each pair has a known number (or fraction) of purple balls and orange balls. The U (unknown) box in each pair has an unknown number (or fraction) of purple balls and orange balls. Subjects are instructed that if a purple ball is drawn from the box they chose, they will win a positive money amount, and 0 otherwise. Using this task we find that 66.67% of our participants are ambiguity averse, 22.22% are ambiguity neutral, and 11.11% are ambiguity seeking. The degree of ambiguity aversion is heterogeneous across participants.

In the second stage, participants need to predict the fundamental value of an asset based on two signals: a public signal and a private signal. The public signal is the known-to-all information that the fundamental value of the asset is a random variable drawn from a normal distribution having a mean of 3 and a variance of 1. The private signal s_t is equal to the actual realization of the fundamental value of the asset, plus some mean zero, normally distributed noise. Thus, the private signal is normally distributed with a mean equal to the realization of the fundamental value in each period and a variance that varies every 5 periods. The private signal is *unambiguous* in the first 15 periods. The variance of the private signal is 1 in periods 1 – 5, 0.25 in periods 6 – 10, and 4 in periods 11 – 15. The signal becomes *ambiguous* in the last 5 periods. In those final periods, 16 – 20, the variance of the signal lies somewhere between 0.25 and 4, inclusive, but the actual value is unknown to participants¹. We face the subjects with unambiguous private signals first because forming expectations with unambiguous signals is easier, and this also provides them an opportunity to learn a practice how to form expectations with two signals.

In this second stage of the experiment, participants are first shown their private signal and are asked to make an implicit prediction of the fundamental value of the asset by choosing the weight they wish to assign to their private signal. The remaining weight is given to the publicly known mean realization of the public signal, which is fixed across all rounds at 3. In addition, prior the last five

¹The ambiguity in our paper is not strictly following the definition of ambiguity (unknown probability distribution, Knight, 1921). The ambiguity in our paper is a compound lottery (Attanasi et al., 2014; Miao and Song, 2012; Ergin and Gul, 2009) or higher order risk (Deck and Schlesinger, 2010; Trautmann and van de Kuilen, 2018). To make it consistent with the theoretical work of Epstein and Schneider (2008), we keep using ambiguity in this paper.

periods, subjects are asked to forecast what they think will be the variance of the signal in those last 5 periods. Differently from Bleaney and Humphrey (2006), Halevy (2007), Bossaerts et al. (2010), etc., our experiment uses the variance of the signal to characterize the ambiguity of the signal information rather than different probabilities in the returns to the asset. To the best of our knowledge, this is the first work on financial ambiguity in terms of the *variance* of signals instead of the probabilities of outcomes. After the subjects choose the weight between the two signals, their implied prediction for the fundamental value of the asset is calculated. Using these forecasts, the asset is then traded using a call market mechanism. Subjects' payoffs are determined by the profitability of their asset market trade outcome, which in turn depends on their use of the public and private signals, or their forecast of the fundamental value of the asset.

Our experimental results confirm some of the theoretical predictions of Epstein and Schneider (2008). We find that ambiguity averse subjects predict a higher variance for the ambiguous signal. Additionally, ambiguity averse individuals overestimate the variance of good news relative to bad news when the signal is ambiguous. However, they do not assign significantly more weight to bad news than to good news. The distribution of the excess returns of the asset under ambiguous signals is negatively skewed. We also find a significantly larger price deviation and price volatility when the signal is ambiguous than when it is unambiguous.

Asparouhova et al. (2015) present a theory of asset trading with symmetric information but asymmetric reasoning. Based on asymmetric reasoning, there are two kinds of agents. Price-sensitive agents are confident in their reasoning to calculate the possible outcomes and regard asset payoffs as risky (rather than ambiguous). While price-insensitive agents who observe prices that cannot be reconciled with their reasoning perceives the prices as ambiguous. Both theory and experimental results confirm that without aggregate risk, mispricing decreases as the fraction of price-sensitive agents increases. With aggregate risk, price-insensitive agents trade to more balanced portfolios. Recently, Epstein and Halevy (2019) investigate the implications of hard-to-interpret signals on individuals' belief updating behavior. In their paper, they also differentiate between risky signals, for which the accuracy is known, and ambiguous signals, for which the accuracy is uncertain, i.e., subject to two-point ambiguity. They find that compared to the case of risky signals, individuals have more difficulty updating their beliefs following Bayes rule under ambiguous signals, which is called information ambiguity aversion in their paper. The main difference between their papers and ours is that although both studies are based on Epstein and Schneider (2007; 2008), the uncertainty on the accuracy of the signals in their experiment is generated by the probability of realization of the state of the world (red asset or black asset) in Asparouhova et al. (2015), the number of red and black balls to be added to the payoff urn to form the signal urn in Epstein and Halevy (2019). Hence, the uncertainty with the accuracy of the signal is related to the first moment of the signal in their experiments, and to the second moment in ours. A main contribution of our paper is to show that information ambiguity aversion also exists when the uncertainty with the accuracy of the signal is measured by the variance, and it is

positively correlated with the degree of ambiguity aversion measured using the matched probability method.²

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the experimental design. Section 4 discusses the experimental results. Section 5 concludes.

2.2 Literature Review

This study complements and extends previous research in a number of ways.

First, this paper is related to experimental studies on how ambiguity attitudes impact individual decisions and price dynamics in experimental asset markets, e.g., Camerer and Kunreuther (?), Kocher and Trautmann (2013), Füllbrunn et al. (?), and Yang and Zhu (?). Previous studies on this topic usually frame ambiguous portfolios as "lotteries", e.g., Sarin and Martin (1993), Bleaney and Humphrey (2006), Halevy (2007), Bossaerts et al. (2010), Baillon and Bleichrodt (2015), etc. In their design, the "lottery choice" is used to represent "ambiguity" in the financial market. Differently from those studies, and following the theoretical work by Epstein and Schneider (2008), we study the impact of ambiguous signals having unknown variances instead of unknown means. By comparing subjects' attitudes toward ambiguity and their expectations regarding the variance of ambiguous signals, we confirm that ambiguity averse individuals are more likely to apply the worst-case scenario when forming expectations about the variance of ambiguous signals.

Second, our paper is related to the theoretical and empirical literature on how markets react to ambiguous information. Theoretical research has investigated how ambiguity aversion leads to asymmetric responses to information. Zhang (2006) finds that greater information uncertainty would lead to higher expected returns following good news and lower expected returns following bad news. Caskey (2008) shows that markets ambiguity-averse investors can result in persistent mispricing of the assets. Ambiguity-averse investors work to reduce ambiguity at the expense of information loss, which can explain underreaction and overreaction to accounting accruals. Li and Janssen (2018) find that the disposition effect, the reluctance to realized losses, and an eagerness to realize gains leads investors to underreact to private signal realizations. Our paper aims to examine signal extraction under ambiguous signals according to the theoretical work by Epstein and Schneider (2008). We find that ambiguity averse individuals will respond to ambiguous signals asymmetrically. They believe that bad news is more accurate

²Liang (2019) also studied agents' reaction to simple (risky) information, compound information and ambiguous information by eliciting the certainty equivalents of different bets. He finds that subjects under-react to ambiguous and compound information compared to simple information, and the under-reaction is greater for good news than bad news. In addition, he finds there is a lack of correlation between attitudes towards ambiguous priors versus ambiguous signals. Similar to Epstein and Halevy (2019), the accuracy of the signal is related to the first moment of the signal, but not the second moment as in our paper.

than the good news. To our knowledge, this paper is the first work to investigate this issue experimentally. Additionally, our paper contributes to the literature on beliefs updating about public signals and private signals, e.g. Heinemann et al. (2004), Boswijk (2007), Eil and Mao (2011), De Filippis et al. (2017), Duffy et al. (2018), Diks et al. (2019), Hommes et al. (2019), also on beliefs updating under compound uncertainty and ambiguity, e.g. Klibanoff et al. (2009), Corgnet et al. (2012), Ert and Trautmann (2014), Moreno and Rosokha (2016), Hanany and Klibanoff (2019). Our work is distinguished from these papers by allowing belief updating of the variance of signals rather than the mean of signals.

Third, our paper is related to the literature on ambiguity and the empirical distributional properties of financial market data. There is a lot of empirical and theoretical research on ambiguity and asset pricing, e.g., Chen and Epstein (2002), Cao et al. (2005), Gollier (2011), Illeditsch (2011), Jeong et al. (2015), Gallant et al. (2015), Bianchi et al. (2018), Brenner and Izhakian (2018). Much of this literature argues that ambiguity aversion leads to a higher equity premium in asset markets. In addition, some studies have shown that ambiguity has an impact on asset prices and its volatility. Epstein and Wang (1994) find that uncertainty can lead to considerable fluctuations in equilibrium prices. They show that some of the equilibrium prices are determined by the degree of ambiguity aversion of agents. Leippold et al. (2008) investigate asset pricing under both learning and ambiguity aversion and find that their model can successfully generate high equity premiums, low interest rates and excess volatility in returns. Our paper is also related to Gilboa and Schmeidler (1989), Hansen, Sargent, and Tallarini (1999) and Anderson, Hansen, and Sargent (2003), etc. However, there are very few experimental studies on the relationship between ambiguity and mispricing, price volatility and the return premium in asset markets. The main exception is Bossaerts et al. (2010), who study the effects of ambiguity and ambiguity aversion on equilibrium asset prices and portfolio choices in laboratory asset markets. They find that ambiguity-averse agents do not directly affect the price of ambiguous securities; rather the presence of such agents directly affects portfolio choices and therefore the distribution of wealth. In this paper, we use the experimental method to address two related questions: first, will ambiguity and ambiguity aversion lead to higher excess returns and/or negative skewness in these excess returns? Second, will ambiguity and ambiguity aversion lead to larger mispricing and price volatility in our experimental asset markets? We find supportive evidence that ambiguity and ambiguity aversion do lead to negative skewness, higher price volatility and asset mispricing.

Fourth, our paper is related to the literature on the measurement of ambiguity attitudes and risk attitudes. Since Knight (1921) and Ellsberg (1961) distinguished between uncertainty (unknown probability) and risk (known probability), there have been many studies on the measurement of risk and ambiguity aversion and the correlation between these two. Most of them find that there is a positive relation between ambiguity aversion and risk aversion. For example, Di Mauro and Maffioletti (2004) find that a “reflection effect” exists in both risky and ambiguous assignments. Du and Budescu (2005) find that in the gain domain, ambiguity aversion is more prevalent, while in the loss domain, ambiguity neutrality dom-

inates. Chakravarty and Roy (2009) find risk and ambiguity aversion has a positive relationship when it comes to the gain domain, but not in the loss domain. Bossaerts et al. (2010), Abdellaoui et al. (2011), Kocher and Trautmann (2013), Butler et al. (2014), and Dimmock et al. (2016; 2015) report a positive relationship between the risk and ambiguity attitudes. While our study finds correlation between ambiguity attitude and information ambiguity attitude, our result suggests that there is no significant correlation between risk aversion and ambiguity aversion.

2.3 Experimental Design

2.3.1 Signal Extraction, Ambiguity and Testable Hypotheses

Consider the theoretical framework of Epstein and Schneider (2008) Ex-ante, there is no ambiguity. Each agent has the same, unique normal prior regarding the random dividend, θ , payment on an asset. That is, $\theta \sim N(m, \sigma_\theta^2)$. Then, prior to trade in that asset, each agent gets a noisy private signal, s , about the likely value of that dividend, θ . Specifically,

$$s = \theta + \varepsilon,$$

where $\varepsilon \sim N(0, \sigma_s^2)$, $\sigma_s^2 \in [\underline{\sigma_s^2}, \overline{\sigma_s^2}]$.

The agents update their beliefs about θ using Baye's Rule to obtain a family of posteriors:

$$\theta \sim N\left(m + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_s^2}(s - m), \frac{\sigma_\theta^2 \sigma_s^2}{\sigma_\theta^2 + \sigma_s^2}\right),$$

where $\sigma_s^2 \in [\underline{\sigma_s^2}, \overline{\sigma_s^2}]$.

Following Epstein and Schneider's approach, in each period, agents consider buying/selling the asset by solving an expected utility maximization problem that uses the worst-case belief about θ chosen from the posteriors. After a signal has arrived, agents respond asymmetrically. For example, when evaluating an asset whose fundamental value is an increasing function of θ , s/he will use a posterior that has a lower mean. Therefore, if the news about θ is "good", specifically if $s > m$, then s/he will evaluate the signal as imprecise ($\sigma_s^2 = \overline{\sigma_s^2}$), while if the about θ is bad ($s < m$), s/he will view the signal as reliable ($\sigma_s^2 = \underline{\sigma_s^2}$). As a result, the agent discounts good news and overestimates the impact of bad news.

They also find that if individuals overvalue the variance of a signal of uncertain quality, then expected excess returns are higher when the quality of information is more uncertain. The signals of uncertain quality (ambiguous information) generate negative skewness in excess returns, while the signals of known quality (unambiguous information) generate positive skewness in excess returns.

Based on the theoretical predictions, we formulate the following testable hypotheses for the experiment.

Hypothesis 1 : Ambiguity-averse subjects are more likely to overestimate σ_s^2 when the signal is ambiguous.

Hypothesis 2 : When the signal is ambiguous, ambiguity-averse subjects overweight the variance of s when $s > m$, and underweight the variance of s when $s < m$.

Hypothesis 3 : The distribution of observed excess returns has negative skewness when the signal is ambiguous, and positive skewness when the signal is unambiguous.

Hypothesis 4 : Ambiguous signals will lead to larger mispricing and greater price volatility.

If Hypothesis 1 is rejected, and the variance expectation of ambiguity averse individuals is not larger when the signal is ambiguous, then there is no supporting evidence that individuals with ambiguity aversion tend to overestimate the variance under the ambiguous signal. If Hypothesis 2 is rejected, and ambiguity averse individuals do not assign higher weight to bad news and lower weight to good news, then there is no supporting evidence that ambiguity aversion individuals will react asymmetrically to the news. If Hypothesis 3 is rejected, and excess returns have positive skewness when the signal is ambiguous, then individuals require smaller excess returns under the ambiguous signal. If Hypothesis 4 is rejected, mispricing is not significantly different between the ambiguous signal and unambiguous signal. Hence, there is no supporting evidence that ambiguity will lead to price deviation and volatility.

2.3.2 Experimental Setup

Our experiment consists of two tasks and one survey. The first task is to measure subjects' attitude towards ambiguity, the second task is an asset market game, and the final, survey task involves elicitation of individual risk attitudes. We recruited 90 undergraduates from Nanyang Technological University as participants in this experiment. A typical session lasts 1 hour 40 minutes. The timeline of the experiment is summarized in Figure 2.1.

We categorize participants using the same method as Trautmann et al., (2015; 2011), Sutter et al. (2013), into the ambiguity-averse types and non-ambiguity averse types; the latter contain ambiguity-neutral and ambiguity-seeking types as well. To ascertain ambiguity attitudes, subjects are asked to make a set of 10 choices between two boxes, Box K and Box U. Each of the two boxes contains 100 balls. The color of the balls is either purple or orange. The numbers (and hence the fraction) of purple balls and orange balls are known in Box K, as the subjects can see the numbers of purple balls and orange balls (and hence the

Figure 2.1: Timeline of the Asset Market Experiment

fraction of purple and orange balls) on the computer screen. The numbers (and hence the fraction) of purple balls and orange balls are unknown in Box U. One ball will be drawn randomly from the box that the participant chooses, s/he will win 3 SGD if a purple ball is drawn. The information about the probability of winning is certain in Box K, while it is ambiguous in Box U. Each of the 10 choices between Box K and Box U appears in a single row on subject's decisions screens. From the top row to the last row, the fraction of purple balls in Box K decreases from 100% to 0% with a step decrease of 10%. The participant can choose between Box K or Box U in each row. If the participant switches her/his choice from Box K to Box U when the fractions of purple balls and orange balls are less than 50% for Box K, s/he is ambiguity averse. If the participant switches her/his choice from Box K to Box U when the fractions of purple balls and orange balls are 50% for Box K, s/he is ambiguity neutral. If the participant switches her/his choice from Box K to Box U when the fractions of purple balls and orange balls are more than 50% for Box K, s/he is ambiguity seeking.

In our experiment, there are two types of signals, a public signal and a private signal. The public signal is the information about the mean and variance of the dividend, θ . For simplicity, we assume that $\theta \sim N(3, 1)$, which means

$$m = 3, \sigma_\theta^2 = 1$$

There is a private signal s , which is the realized value of θ plus a normally distributed mean zero error term, ε . The private signal, s , is thus normally distributed with a mean realized value of θ and a variance of σ_s^2 . Six subjects are randomly selected to form one market. The participants' task is to select the weight, w , assigned to the private signal s ; the remaining weight, $1 - w$ is assigned to the public signal, the mean value for θ , which is known to be 3. Each subject's implied prediction for the dividend, $E_i(\theta_t)$, would be displayed once they have chosen w . Our design is similar to the Treatment W in Bao and Duffy (2020),

and different from their Treatment P that involves point prediction, and resembles a Learning-to-Forecast experiment (Bao et al., 2013; 2012, Hommes et al., 2005; 2007). We employ this design because the calculation of the posterior can be tricky for subjects, and by providing them the posterior based on their weight choice, we can help them to focus on the weight choice task. The dividend θ is the fundamental value of the asset (the one-period-lived asset is traded in a spot market). As for the value of the parameter, σ_s^2 , there will be four scenarios. The first three are associated with a constant and known σ_s^2 , the unambiguous case. In the last scenario, the subjects only know that $\sigma^2 \in [\underline{\sigma_s^2}, \overline{\sigma_s^2}]$, which is the ambiguous case. Each scenario consists of 5 periods.

Each subject's implied prediction of θ is

$$\text{Implied prediction of } \theta = (1 - w) \cdot 3 + w \cdot s$$

where w is the weight that the participants assign to the private signal.

In the first three scenarios or 15 periods, the value of σ_s^2 is known to subjects and takes on the following values:

$$\sigma_s^2 = \begin{cases} 1, & t \in [1, 5]. \\ 0.25, & t \in [6, 10]. \\ 4, & t \in [11, 15]. \end{cases}$$

If subjects use the signal extraction model, their prediction of θ should be

$$E(\theta) = \frac{\sigma_s^2}{\sigma_\theta^2 + \sigma_s^2} m + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_s^2} s \quad (2.1)$$

According to Equation (2.1), the weight assigned to the private signal should be 1/2 in Scenario 1, 4/5 in Scenario 2 and 1/5 in Scenario 3. The realized value of s is randomly generated and different in each period.

In Scenario 4, the final 5 periods, σ_s^2 is uniformly distributed between 0.25 and 4 and redrawn in each period. Namely,

$$\sigma_{s,t}^2 = V_t, \quad V_t \sim i.i.d.U(0.25, 4)$$

In Scenario 4, the subjects do not know that the variance is uniformly distributed but only the upper and lower bounds of σ_s^2 . They also do not know the realized value of the variance at the beginning of each period. In all scenarios with fixed σ_s^2 , the subjects will make their implied prediction for θ only by selecting the weight assigned to the private signal. In the final, fourth scenario with ambiguous σ_s^2 , in each period subjects will first submit their guess about the value of the variance for that period, σ_s^2 , and then they will submit a weight to attach to their private signal.

The second stage of the experiment is an asset market experiment. At the beginning of each period, subjects are given an endowment of 7 SGD, which is slightly more than double the mean value of the asset (which is 3). We use a very simple call market mechanism (Akiyama et al., 2017) to determine the single market price of the asset in each period. Subjects know the price determination mechanism of the market, but do not know the decisions made by others. After they submit their weight choice, w , and their implied prediction for θ , the market will be automatically cleared at a price equal to the median of all subjects' implied predictions for θ , the fundamental value of the asset. If the prediction of subject A is below the market clearing (median forecast) price, one unit of the asset will be sold by him/her to the other subjects whose prediction is higher than the market clearing price, therefore subject A is a seller and the profit is *market price* – *realized dividend* θ . Otherwise, subject A will be a buyer if his/her prediction is higher than the market price, the profit of the buyer is *realized dividend* θ – *market price*.

Subjects submit their implied prediction for θ in the 5 periods of each of the four scenarios. The signals and realizations of θ are randomly generated before the experiment, and are different in each period. After each period, the subjects receive feedback about their performance in the last period. They can see the realized market price, p_t , their own weight choice and implied market price prediction, and the actual, ex-post realization of θ_t . Subjects also submit their prediction of the variance of the ambiguous signal in the 5 periods in the final, scenario 4. The payoff for Task 2 is going to be determined in the following way: for the implied prediction of θ , the subjects are paid according to their trading profit from one randomly-chosen period among the 20 periods of the four scenarios. For the variance prediction task in scenario 4, subjects are paid according to the accuracy of their prediction of the variance in one randomly selected period among those last 5 periods.

Payoff for the implied prediction of θ :

$$\begin{aligned}\pi_{i,t}^{Buyer} &= 7 - p_t + \theta_t \\ \pi_{j,t}^{Seller} &= 7 + p_t - \theta_t\end{aligned}$$

Payoff for the prediction of variance:

$$\pi_{i,t}^{Variance} = 8 - \frac{10}{10 - |\sigma_{s,t}^2 - E_{i,t}(\sigma_s^2)|}$$

The payoff for the whole experiment is the sum of the show-up fee, which is 3 SGD, the earnings from tasks 1, 2 and the survey. The experiment takes 1.5 hours on average, the average total payment is around 19 SGD.³

³Refer to Appendix A for more information.

2.4 Experimental Results

2.4.1 Ambiguity Attitudes

According to Wakker (2010), the known probability of winning (that is, the known fraction of purple balls in the first stage of our experiment) of Box K is the matching probability when the participant is indifferent between Box K and Box U. In our experiment, the definition of matching probability follows Wakker (2010). If the subject switches from Box K when the winning probability is 20% to Box U, namely, for any winning probability below 20%, the subject prefers Box U. In that case, the subject's matching probability is 20%. As described in the experimental design, the winning probability is the fraction of purple balls in Box K. Therefore, the fraction of purple balls at the switching point is called the matching probability. The ambiguity neutral matching probability is 50%, such that a participant is ambiguity averse if his/her matching probability is below 50%, ambiguity neutral if his/her matching probability is equal to 50%, and ambiguity seeking if his/her matching probability is above 50%. We follow the same approach as Dimmock et al. (2016; 2015) to measure the ambiguity preferences of our participants:

$$AM_i = 0.5 - p_i^M$$

where AM_i is the measure of ambiguity for individual i and p_i^M is the matched probability. The value of this measure will be positive if the individual is ambiguity averse, 0 if the individual is ambiguity neutral, and negative if the individual is ambiguity seeking.⁴

There are 90 participants in our experiment. Using our ambiguity preference measure, we find that 66.67% (60 out of 90) of them are ambiguity averse, 22.22% (20 out of 90) are ambiguity neutral, and 11.11% (10 out of 90) are ambiguity seeking. On average, ambiguity averse individuals will switch to Box U when the winning probability is around 35.08%. Ambiguity seeking individuals will switch to the Box U when the winning probability is around 61%. Ambiguity neutral individuals will switch to the Box U when the winning probability is 50%. Table 2.1 summarizes the descriptive statistics of the ambiguity attitude. Panel A reports the matching probability and panel B is about the measure of ambiguity.

We use a simplified version of Holt and Laury (2002) to elicit participant's risk attitudes in the post-experiment questionnaire. Subjects were asked to choose between option A (2 SGD for sure) and option B (6 SGD with probability X and 0 with probability $1-X$) in each row and for 10 sequential rows. From the top row to the last row, the probability to win 6 SGD increases from 0 to 90%. Similar to the ambiguity measure, if a subject switches from option A to option B when the probability to receive 6 SGD is larger than 40%, then s/he is risk averse. If the subject switches from option A to option B when the probability to receive

⁴Refer to Dimmock et al. (2016) for more details.

Table 2.1: This table reports descriptive statistics about ambiguity attitudes among our subjects. Panel A reports on the matching probability and panel B on the measure of ambiguity attitudes, AM_i .

Panel A: Matching Probability						
	Obs	Mean	Median	Std	Min	Max
Ambiguity averse	60	35.08%	40%	0.0917	0%	40%
Ambiguity neutral	20	50%	50%	0	50%	50%
Ambiguity seeking	10	61%	60%	0.0316	60%	70%
Panel B: Measure of Ambiguity Attitudes, AM_i						
	Obs	Mean	Median	Std	Min	Max
Ambiguity averse	60	0.1491	0.1	0.0917	0.1	0.5
Ambiguity neutral	20	0	0	0	0	0
Ambiguity seeking	10	-0.11	-0.1	0.0316	-0.2	-0.1

6 SGD is 40%, then s/he is risk neutral. If the subject switches from option A to option B when the probability to receive 6 SGD is smaller 40%, then s/he is risk seeking. We do not find any evidence of a correlation between the ambiguity aversion and risk aversion. ⁵

In the following subsections, we will use either subjects' individual ambiguity measure, AM_i , or dummy variables categorizing subjects as ambiguity averse, or neutral or loving, test the hypothesis we proposed in the previous section concerning the behavior of ambiguity averse subjects in our experiment.

2.4.2 Expected Variance of Ambiguous Signals

Following Epstein and Schneider (2008), we use subjects' guess (or expectation) about the variance of the private signal in Scenario 4 as a measure for their perceived nosiness of that signal. As Panel A of Table 2.2, reveals, the mean variance expectation is 1.6073 for ambiguity averse individuals, 1.422 for the ambiguity neutral individuals, and 1.4205 for the ambiguity seeking individuals. Panel A also reports other descriptive statistics of variance expectations under ambiguous signals conditional on the type of subjects' ambiguity attitudes. There is a significant difference in expected variance between the ambiguity averse and non-ambiguity averse individuals according to the rank sum test ($z = 1.849$ and $p = 0.0645$). The expected variance by the ambiguity averse individuals is significantly higher than that by the ambiguity neutral individuals ($z = 1.784$ and $p = 0.0744$), however, the expected variance by the ambiguity averse individuals is not significantly higher than that by the ambiguity seeking individuals ($z = 0.934$ and $p = 0.3503$).

To further investigate whether ambiguity aversion is positively related with over-estimation of the variance of ambiguous signals, we calculate the difference ($\sigma_{diff,i}^2$) between the expectation of the variance and the realized value of the variance of

⁵Refer to Table B1 in Appendix B for more information.

the ambiguous signal, that is the $\sigma_{diff,i}^2 = E_{i,t}(\sigma_s^2) - \sigma_{s,i,t}^2$. Panel B of Table 2.2 reports the descriptive statistics of this indicator. This difference for ambiguity averse individuals is significantly higher than for non ambiguity averse individuals ($z = 1.849$ and $p = 0.0645$).

Table 2.2: Panel A reports for the given number of subjects classified as ambiguity averse, ambiguity neutral and ambiguity seeking, their mean expectation for the variance, as well as the median, standard deviation, minimum, and maximum expectation of the variance. Panels B report these same statistics for the difference between the variance expectation and the realized value of variance of ambiguous signals.

Panel A						
	Obs	Mean	Median	Std	Min	Max
Ambiguity averse	60	1.6073	1.2	1.0843	0.25	4
Ambiguity neutral	20	1.422	1	1.0932	0.25	4
Ambiguity seeking	10	1.4205	1.2	0.9449	0.25	4
Panel B						
	Obs	Mean	Median	Std.	Min	Max
Ambiguity averse	60	0.4673	0.2332	1.0432	-1.4414	3.2567
Ambiguity neutral	20	0.282	0.0005	1.0084	-1.4414	2.9943
Ambiguity seeking	10	0.2805	0.0332	0.9433	-1.4414	2.3086

To address our first hypothesis regarding whether ambiguity aversion leads to overestimation of the variance of ambiguous signals, we report on various specifications of the following pooled linear regression model with random effect using all data from our experiment:

$$Dev(\sigma_{i,t}^2) = c + a_1 AM_i + a_2 RK_i + \varepsilon_{i,t} \quad (2.2)$$

Here, $Dev(\sigma_{i,t}^2) = E_{i,t}(\sigma_s^2) - \sigma_{s,i,t}^2$ is the difference between the expectation of the variance and the realized value of the variance of the ambiguous signal of individual i at period t . AM_i is the measure of individual i 's ambiguity attitude RK_i denotes individual i 's risk attitude.

The result of the estimation of Equation (2.2) is reported in Table 2.3. For Models 1 and 4, AM_i is the continuous measure of ambiguity attitudes. For Models 2, 3, 5, and 6, we use dummy measure of ambiguity attitudes, with $AM_i = 0$ being the default ambiguity averse type, 1 is ambiguity neutral, and 2 is ambiguity seeking. In Models 3 and 6, $AM_i = 0$ is ambiguity averse, 1 is non-ambiguity averse. The dummy variable $RK_i = 0$ means risk averse, while 1 means non-risk averse. The default specification is always ambiguity aversion and risk aversion. Models 1, 2 and 3 exclude the risk attitudes, Models 4, 5 and 6 test all variables in Equation (2.2) (AM_i is the continuous variable in Model 4), and Model 7 excludes the ambiguity attitudes.

Table 2.3 reveals that the correlation between the prediction of variance and the measure of ambiguity is positive and the coefficient is significant at the 5% level

(Models 1 and 4). The coefficient indicates that when the level of the ambiguity aversion of an individual increases by 0.1, the expectation of variance of the ambiguous signal is 0.0997 higher than the realization of variance. The mean measure of ambiguity is 0.1491 for ambiguity averse individuals, 0 for the ambiguity neutral individuals, and -0.11 for ambiguity seeking individuals. Hence, on average, ambiguity averse individuals have a larger expectation of variance for ambiguous signals by 0.015 as compared with ambiguity neutral individuals, and by 0.0258 as compared with ambiguity seeking individuals. Risk attitudes do not significantly decrease the variance expectation (Model 7). When compared with non ambiguity averse individuals, the ambiguity averse individuals tend to increase their expectation of the variance of the ambiguous signal significantly by 0.186 (Model 3).

Table 2.3: This table reports the result of the estimation of Equation (2.2). The dependent variable is $\sigma_{diff,i,t}^2 = E_{i,t}(\sigma_s^2) - \sigma_{s,i,t}^2$ is the difference between the expectation of the variance and the realized value of the variance of the ambiguous signal of individual i at period t . As for the independent variables, Model 1, Model 2 and Model 3 excludes the risk attitude, Model 4, 5 and 6 test all the variables in the Equation (2.2) (AM_i is the continuous variable in Model 4), and Model 7 excludes the ambiguity attitude. Standard errors are clustered at both the subject and period levels.

Dep var: $\sigma_{diff,t}^2$	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Measure of ambiguity	0.997** (2.16)			0.990** (2.13)			
Default: Ambiguity averse							
Ambiguity neutral		-0.185 (-1.34)			-0.184 (-1.34)		
Ambiguity seeking		-0.187 (-1.30)			-0.192 (-1.31)		
Non-ambiguity averse			-0.186* (-1.72)			-0.187* (-1.74)	
Default: Risk averse							
Non-risk averse				0.0438 (0.40)	0.0615 (0.56)	0.0612 (0.57)	0.0572 (0.55)
Cons	0.321** (2.07)	0.467** (2.50)	0.467** (2.50)	0.312* (1.91)	0.454** (2.34)	0.454** (2.33)	0.393** (2.23)
N	450	450	450	450	450	450	450
adj.R ²	0.013	0.007	0.007	0.014	0.008	0.008	0.001
t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01							

To summarize, we do not reject Hypothesis 1 since we find that there is a significant and positive relationship between ambiguity aversion and subjects' expectations for the variance in the case of ambiguous signals. The more ambiguity averse subjects tend to predict a greater variance of the ambiguous signals.

Result 1 : We do not reject Hypothesis 1. We find that more ambiguity averse individuals are more likely to overestimate the variance of ambiguous signals.

2.4.3 Asymmetric Response to the Ambiguous Signals

According to Epstein and Schneider (2008), after receiving an ambiguous signal, more ambiguity-averse subjects are more likely to overestimate the variance of the private signal s when the signal is good news (in our experimental setting, when $s > 3$), and underestimate the variance of s when the signal is bad news (in our experimental setting, when $s < 3$).

In other words, they will regard the good news as imprecise, expect the variance of the ambiguous signal to be higher and assign a lower weight to the good news. On the contrary, they will regard the bad news as more precise, expect a lower variance of the ambiguous signal and assign a higher weight to the bad news. Subjects will update their priors about the fundamental value of the asset based on Bayes rule and obtain their posterior beliefs. Therefore, the theoretical prediction for the weight they assign to the private signal, $\hat{w}^{ss}$, can be written as:

$$\hat{w}^{ss} = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_s^2}$$

Recall that in our experiment, σ_θ^2 is perfectly known by subjects to equal 1, while σ_s^2 is the variance of the private signal, s . The variance for the private signal, s , in the first three scenarios, when the private signal is unambiguous, is 1, 0.25 and 4, respectively. Theoretically, the subject should select 0.5 as the weight assigned to the private signal in Scenario 1, 0.8 in Scenario 2, and 0.2 in Scenario 3. The mean and median of the weight assigned to the private signal are 0.5230, 0.5023 in Scenario 1, 0.7897, 0.8289 in Scenario 2, and 0.2246, 0.1810 in Scenario 3. Table 2.4 reports on descriptive statistics for weights assigned to the private signals in these first three scenarios. We can infer that people follow the signal extraction model when dealing with unambiguous signals. The actual weight assigned to the private signal in Scenario 1 is marginally significantly larger than the theoretical prediction using a rank sum test ($z = 1.652$ and $p = 0.0986$). We do not observe a significant difference between the actual weight assigned to the private signal and the theoretical prediction in Scenario 2 ($z = -0.826$ and $p = 0.4089$) and in Scenario 3 ($z = -1.101$, and $p = 0.2709$) according to the rank sum test. One possible explanation for this difference is that there is a learning process for the participants to learn about the signal extraction model. We observe the same result for ambiguity averse individuals, ambiguity neutral and seeking individuals. The actual weight assigned to the private signal is significantly larger than the theoretical prediction in Scenario 1 for ambiguity averse individuals, but not significantly larger in Scenarios 2 and 3. The result of rank sum test for ambiguity averse individuals is $z = 1.683$, $p = 0.0923$ for Scenario 1, $z = -0.673$, $p = 0.5007$ for Scenario 2 and $z = -0.337$, $p = 0.7364$ for Scenario 3. The actual weight assigned to the private signal is significantly lower than the theoretical prediction in Scenario 3 for ambiguity neutral individuals, but not significantly different for these types in Scenario 1 and 2. The result of rank sum test for ambiguity neutral individuals is $z = 3.437$, $p = 0.0006$ for Scenario 1, $z = 0.578$, $p = 0.5631$ for Scenario 2 and $z = -1.735$, $p = 0.0828$ for Scenario 3. There is no significant difference between the actual weight assigned to the

unambiguous private signal and the theoretical prediction for ambiguity seeking participants. The result of the rank sum test for ambiguity seeking individuals is $z = 0$, $p = 1.0000$ for Scenario 1, $z = -0.808$, $p = 0.4139$ for Scenario 2 and $z = 0$, $p = 1.0000$ for Scenario 3. The results above show that individuals do learn to make predictions as if they follow the signal extraction model when the signal is unambiguous.

Table 2.4: This table reports the descriptive statistics of the weight assigned to the unambiguous private signals for Scenario 1, 2 and 3.

		Mean	Median	Std	Min	Max	Weight (Default)
All subjects	Scenario 1	0.5230	0.5023	0.2521	0	1	0.5
	Scenario 2	0.7897	0.8289	0.2111	0	1	0.8
	Scenario 3	0.2246	0.1810	0.2273	0	1	0.2
ambiguity averse	Scenario 1	0.5354	0.5037	0.2420	0	1	0.5
	Scenario 2	0.7929	0.8403	0.2059	0	1	0.8
	Scenario 3	0.2396	0.1985	0.2316	0	1	0.2
ambiguity neutral	Scenario 1	0.4777	0.4994	0.2779	0	1	0.5
	Scenario 2	0.7839	0.8203	0.2300	0	1	0.8
	Scenario 3	0.1965	0.1352	0.2421	0	0.9927	0.2
ambiguity seeking	Scenario 1	0.5386	0.5622	0.2517	0	1	0.5
	Scenario 2	0.7827	0.7937	0.2062	0	1	0.8
	Scenario 3	0.1910	0.1835	0.1542	0	0.5618	0.2

To further investigate how the individuals react to ambiguous signals in financial markets, we will focus on Scenario 4, where the variance of the private signal s , is ambiguous and varies between 0.25 and 4. Recall that there are 5 periods in Scenario 4: the news is good in 3 periods (the private signal $s > 3$), and bad in the other two periods (the private signal $s < 3$). In this scenario, the participants are asked to make their implied prediction of the fundamental value by selecting the weight assigned to the private signal and make their variance expectation of the ambiguous signal as well. Therefore, we use the variance expectation and the weight assigned to the private signal as separate dependent variables to find out whether ambiguity averse individuals overestimate bad news and underestimate good news in the setting with ambiguous signals.

First, we use the variance expectation as an independent variable to check how people evaluate the ambiguous signals. If the subjects respond to the ambiguous signals asymmetrically, they will give a lower variance expectation to bad news, and a higher variance expectation to good news. Panel A in Table 2.5 reports descriptive statistics on subjects' variance expectations for ambiguous signals, differentiated according to whether the private signal is good news or bad news. The variance expectation for bad news tends to be lower than that for good news, overall and across ambiguity types. The expected variance of bad news is significantly lower than the expected variance of the good news of the ambiguity averse individuals according to the rank sum test ($z = -5.011$ and $p = 0.0000$). The result holds for ambiguity neutral individuals according to the same test ($z = -2.834$ and $p = 0.0046$), but does not hold for the ambiguity seeking individuals ($z = 0.099$ and $p = 0.9208$). Overall, The expected variance of bad news is significantly lower than the expected variance of good news based on the rank sum test ($z = -5.369$ and $p = 0.0000$). We observe a lower variance

expectation for bad news signals and a higher variance expectation for good news signals.

Second, we check the weight assigned to the private signal. If subjects respond to the ambiguous signals asymmetrically, they will give higher weight to bad news, and lower weight to good news. We report the descriptive statistics of the weight assigned to the private signal in Panel B of Table 2.5. We find that the weight of the private signal for the bad news tends to be higher than that for good news regardless of the ambiguity attitude. On average, the weight of the private signal is 0.5010 for bad news and 0.4783 for good news. According to the rank sum test, we find that there is no significant difference between the weights assigned to bad news and good news for ambiguity averse individuals ($z = 0.742$ and $p = 0.4578$), ambiguity neutral individuals ($z = 0.7$ and $p = 0.4838$) or ambiguity seeking individuals ($z = 0.139$ and $p = 0.8897$). Overall, we do not find significant difference between the weight of bad news and the weight of good news based on the rank sum test ($z = 0.957$ and $p = 0.3387$). That is, the weight of bad news is not significantly higher than the weight of good news. According to the signal extraction model, the variance expectation of the ambiguous signal and the weight assigned to the ambiguous signals should be equivalent to measure the asymmetric response to the ambiguous signals. In other words, if individuals expect the variance to be lower, they will put a high weight to the ambiguous signal, vice versa.

Table 2.5: This table reports on descriptive statistics of the variance expectation of the ambiguous signals (good news versus bad news) in Panel A, and on descriptive statistics of the weights assigned to the ambiguous signal (good news versus bad news) in Panel B.

Panel A: Variance Expectation of the Ambiguous Signal						
		Mean	Median	Std	Min	Max
Ambiguity averse	Good news	1.8674	1.6625	1.1409	0.25	4
	Bad news	1.2173	1	0.8607	0.25	4
Ambiguity neutral	Good news	1.6948	1.3	1.2084	0.25	4
	Bad news	1.0128	1	0.7337	0.25	3.5
Ambiguity seeking	Good news	1.4329	1.1	1.0298	0.25	4
	Bad news	1.4020	1.225	0.8267	0.25	3.5
Total	Good news	1.7807	1.5	1.1493	0.25	4
	Bad news	1.1924	1	0.8335	0.25	4
Panel B: Weight Assigned to the Ambiguous Signal						
		Mean	Median	Std.Dev	Min	Max
Ambiguity averse	Good news	0.4758	0.4962	0.2484	0	1
	Bad news	0.4940	0.4991	0.2451	0	1
Ambiguity neutral	Good news	0.5066	0.4977	0.2665	0.0823	1
	Bad news	0.5539	0.4984	0.2703	0.1602	1
Ambiguity seeking	Good news	0.4368	0.3932	0.2823	0	1
	Bad news	0.4374	0.4021	0.2550	0.0930	0.8836
Total	Good news	0.4783	0.4956	0.2561	0	1
	Bad news	0.5010	0.4983	0.2527	0	1

As stated above, we find that the variance expectation of the bad news is significantly lower than that of the good news, and the weight assigned to bad news is not significantly higher than that assigned to the good news. To further check the findings from our descriptive analysis, we again estimate the OLS regression using panel data method with random effect to test the determinants of both the variance expectation of the ambiguous signal as well as the weight assigned to private, ambiguous signals:

$$\begin{aligned} E_{i,t}(\sigma_s^2) &= a_0 + a_1 \text{BadNews}_{i,t} + \varepsilon_{i,t} \\ w_{i,t} &= a_0 + a_1 \text{BadNews}_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (2.3)$$

Here, $E_{i,t}(\sigma_s^2)$ is the variance expectation of individual i in period t , and $w_{i,t}$ is the weight that individual i assigned to his/her private signal in period t . BadNews_t is a dummy variable for bad news ($\text{BadNews}_t = 1$ if $s < 3$, $\text{BadNews}_t = 0$ if $s > 3$). The dependent variable in Panel A of Table 2.6 is the variance expectation. In Panel B of that table, the dependent variable is the weight. Model 1 uses the entire subject pool, Model 2 uses the data on subjects classified as ambiguity averse, Model 3 uses the data on subjects who are ambiguity neutral, and Model 4 uses the data on subjects who are ambiguity seeking.

The results reported in Panel A in Table 2.6 show that compared with good news signals (the baseline) when individuals receive bad news signals, they tend to significantly lower their expectations for the variance of those signals. The overall decrease for the entire sample is 0.588, which is significantly different from 0 at the 1% significant level. Ambiguity averse individuals lower their variance expectation of bad news even more, by 0.650 (Model 2). This suggests that individuals regard bad news as more precise than good news when the signal is ambiguous. In other words, ambiguity averse individuals react more to bad news than to good news. Importantly, we also find that ambiguity seeking individuals do not lower their variance expectation of bad news (Model 4). Panel B in Table 7 reports on regression results where the dependent variable is the weight that subjects assigned to the private signal, s . The regression results reveal that there is no significant difference between the weight assigned to good news and bad news under ambiguous signals for the whole sample, or for any of the subsamples based on ambiguity attitudes.

Overall, we find that there is mixed support for Hypothesis 2. On the one hand, we observe a consistent response to ambiguous signals. Ambiguity averse individuals give a lower variance expectation to the bad news, which indicates that ambiguity averse individuals regard the bad news as being more precise and should put a higher weight to bad news compared with good news. Moreover, if we investigate the weight that individuals assigned to the ambiguous signals, we find that ambiguity averse individuals tend to put a higher weight on the bad news than on good news for ambiguous signals, but the differences are not statistically significant. At the beginning of Section 2.4.3, we find that when the variance of the signal is a certain number from Scenario 1 to 3, individuals apply the signal extraction model when choosing the weight that is assigned to the private sig-

Table 2.6: This table reports the results of panel data estimation of Equation (2.3). The dependent variable is the variance expectation in Panel A, and the weight assigned to the private signal in Panel B. The first column reports results using the whole sample, the second through fourth columns report the results on each sub-sample of ambiguity averse, ambiguity neutral and ambiguity seeking subjects.

Dependent variable: $E_{i,t}(\sigma_s^2)$	Panel A			
	Whole sample	Ambiguity-averse	Ambiguity-neutral	Ambiguity-seeking
Bad news	-0.588*** (-6.72)	-0.650*** (-6.02)	-0.632*** (-3.93)	-0.0309 (-0.12)
Cons	1.781*** (25.10)	1.867*** (22.04)	1.695*** (10.06)	1.433*** (8.66)
Dependent variable: $w_{i,t}$	Panel B			
	Whole sample	Ambiguity-averse	Ambiguity-neutral	Ambiguity-seeking
Bad news	0.0226 (0.9)	0.0182 (0.65)	0.0473 (0.73)	0.000594 (0.01)
Cons	0.484*** (27.59)	0.483*** (24.44)	0.507*** (12.77)	0.437*** (6.13)
N	450	300	100	50
<i>t</i> statistics in parentheses * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$				

nal. Hence, they have learned that the variance tells them the accuracy of the signal. While in Scenario 4, subjects are asked to make their variance expectation of the ambiguous signals and choose the weight assigned to the ambiguous signals. Subjects focus on the variance expectation more than the weight. They believe that the variance of the ambiguous signal will be lower for the bad news and higher for good news.

Result 2 : We find mixed support for Hypothesis 2. On the one hand, ambiguity averse individuals do regard the bad news as more precise compared with good news, as evidenced by their expectation for the variance of bad news signals. On the other hand, we do not find that ambiguity averse individuals assign a significantly higher weight to bad news.

2.4.4 Distribution of Excess Returns

The excess return on the asset, R_t , is defined as $R_t = p_t - \theta_t$ in our experiment, where p_t is the market price in period t and θ_t is the realized value of θ in period t . This is a simplification of Epstein and Schneider (2008). First, we check the normality of excess returns in each of our four scenarios. We observe that excess returns under ambiguous signals are significantly different from a normal distribution ($p = 0.000$). The same is true of excess returns in Scenarios 1 and 3 as well ($p = 0.00$). However, excess returns in Scenario 2 are not significantly different from a normal distribution ($p = 0.1970$).

Figure 2.2 shows the distributions of excess returns in each of our four scenarios.

We observe that excess returns are more intensely found to lie above 0 under ambiguous signals, while more intensely distributed below 0 in Scenarios 1, 2 and 3 (unambiguous signals).

Figure 2.2: This figure depicts the distribution of the excess return under ambiguous signals and unambiguous signals. Scenario 1 (left top), Scenario 2 (right top) and Scenario 3 (left bottom) includes the unambiguous signals, Scenario 4 (right bottom) consists of the ambiguous signals. The red line is the kernel density of the distribution. The x-axis is the value of the excess returns, and the y-axis is the number of observations.

We calculate the skewness of excess returns for the ambiguous averse individuals under ambiguous signals and unambiguous signals. The skewness is found to be negative under ambiguous signals (-0.1485), and positive (0.5028) in Scenario 1, (0.0095) in Scenario 2. To summarize, there is a negative skewness of excess return under ambiguous signals and positive skewness under unambiguous signals (except Scenario 3) for all individuals. See Table: 2.7 for further details.

Table 2.7: This table reports the skewness, mean, median, standard deviation, minimum and maximum of excess returns under each of our 4 scenarios. The variance of the private signal in Scenario 1 is 1, in Scenario 2 is 0.25 and in Scenario 3 is 4, between 0.25 and 4, unknown in Scenario 4.

	Skewness	Mean	Median	std	Min	Max
Scenario 1	0.5028	-0.1978	-0.7932	1.1579	-1.5655	2.2446
Scenario 2	0.0095	-0.2339	-0.3579	0.3251	-1.0716	0.3801
Scenario 3	-0.2901	-0.5595	-0.2202	1.4678	-3.0323	1.5735
Scenario 4	-0.1485	0.5531	0.4390	1.3794	-2.0188	3.2056
Overall	0.0199	-0.1095	-0.1526	1.2409	-3.0323	3.2056

To better understand the skewness of excess returns under ambiguous signals, we look for differences in excess returns when signals are ambiguous (Scenario 4, Period 16 to 20 in our experiment) and when signals are unambiguous (Scenarios 1 to 3, Periods 1 to 15). We find that subjects require a higher return when signals are ambiguous. We observe that excess returns under ambiguous signals are significantly larger than under unambiguous signals according to a rank sum test ($z = 12.711$ and $p = 0.0000$). To confirm that individuals require an excess return premium when the signal is ambiguous, we report estimates from the following panel regression model with random effect of excess returns in period t , R_t , in Table 2.8:

$$\begin{aligned}
 R_t &= a_0 + a_1 Unambiguous_t + \varepsilon_t \\
 R_t &= b_0 + \sum_{K=1}^3 b_K ScenarioK_t + \varepsilon_t
 \end{aligned} \tag{2.4}$$

All of the independent variables in this regression analysis are dummy variables. The dummy variable $Unambiguous_t = 0$ when the signal is ambiguous, and 1 otherwise. The dummy variable $ScenarioK_t$ is 1 for each Scenario $k=1,2,3$, and 0 for the baseline ambiguous signal Scenario 4. The model with the independent variable is $Unambiguous_t$ is reported on in Model 1, and the model with the 3 scenario dummies is reported on in Model 2.

The regression results show that for the whole sample, individuals request significantly higher excess returns, by 0.884, under ambiguous signals than under unambiguous signals. Compared with the three scenarios where the signal is unambiguous with different variances, excess returns in the scenario of ambiguous signals are significantly higher. For example, excess returns tend to be higher by 0.751 in ambiguous scenario a compared with the unambiguous scenario with a variance of 1 at 1% significant level according to Model 2. To summarize, we do not reject Hypothesis 3. We observe negative skewness in excess returns under

Table 2.8: This table reports results from estimation of Equation (2.4). The dependent variable is excess returns in period t , R_t . The independent variable is a dummy for unambiguous signals in Model 1, and dummies for Scenarios 1-3 in Model 2.

	Model 1	Model 2
Default: Ambiguous signals		
Non-Ambiguous signals	-0.884*** (-13.75)	
Default: Scenario 4 (ambiguous signals)		
Scenario 1 (unambiguous signals, $\sigma_s^2 = 1$)		-0.751*** (-9.60)
Scenario 2 (unambiguous signals, $\sigma_s^2 = 0.25$)		-0.787*** (-10.06)
Scenario 3 (unambiguous signals, $\sigma_s^2 = 4$)		-1.113*** (-14.23)
Cons	0.553*** (9.94)	0.553*** (10.00)
N	1800	1800
t statistics in parentheses *p<0.1 ** p<0.05 *** p<0.01		

the ambiguous signal and positive skewness in excess returns under unambiguous signals of all subjects. Indeed, we find that individuals require a higher excess return under ambiguous signals relative to any of our three scenarios involving unambiguous signals.

Result 3 : We do not reject Hypothesis 3. We find that there is negative skewness in the distribution of excess returns under ambiguous signals and positive skewness in the distribution of excess returns under unambiguous signals. Further, individuals require a higher excess return when the signal is ambiguous, relative to cases where the signal is unambiguous.

2.4.5 Mispricing and Price Volatility

According to Stöckl et al. (2010), mispricing in experimental asset markets can be measured by the relative deviation (RD) or by the relative absolute deviation (RAD). These two indicators measure the relative and relative absolute deviation of asset prices from the fundamental value. The relative deviation (RD) and relative absolute deviation (RAD) of the asset price for market k in period t defined by:

$$RD_{k,t} = \frac{p_{k,t} - p_t^{FV}}{p_t^{FV}}$$

$$RAD_{k,t} = \frac{|p_{k,t} - p_t^{FV}|}{p_t^{FV}}$$

Here, $p_{k,t}$ is the market price for market k in period t , while p_t^{FV} is the fundamental value of the asset in period t .

We find that individuals are more likely to overestimate the fundamental value when the signal is ambiguous. The median RD is negative for non-ambiguous signals, and positive for ambiguous signals. Generally, the median RD in the scenarios involving non-ambiguous signals is 0.0890, while it is 0.4482 in the scenario of ambiguous signals. Also, the price deviation is larger when the signal is ambiguous. The median RAD is 0.3765 for the scenario of non-ambiguous signals and 0.5783 for the scenario of ambiguous signals (Refer to Table B2 in Appendix B). The RD of the ambiguous signals is significantly larger than that of the unambiguous signals ($z = 11.384$ and $p = 0.0000$), and the different results in terms of RAD are also significant ($z = 7.022$ and $p = 0.0000$). Figure 2.3 depicts the cumulative distribution function of the RD (top panel) and RAD (bottom panel) in each scenario. It shows that the median RD is between 0.5 and 1 for ambiguous signals, and between -0.5 and 0 for all unambiguous signals. The RAD under ambiguous signals is larger than that of Scenarios 2 and 3. To confirm the findings from the descriptive statistics and the CDFs, we again check Hypothesis 4 using a panel data with random effect regression analysis. The equation tested is given by:

$$\begin{aligned} RD_t &= a_0 + a_1 Unambiguous_t + \varepsilon_t \\ RD_t &= b_0 + \sum_{K=1}^3 b_K ScenarioK_t + \varepsilon_t \\ RAD_t &= a_0 + a_1 Unambiguous_t + \varepsilon_t \\ RAD_t &= b_0 + \sum_{K=1}^3 b_K ScenarioK_t + \varepsilon_t \end{aligned} \tag{2.5}$$

Where all of the independent variables are dummy variables of the same type defined previously in the discussion of Table 2.8. The dependent variable is RD in Panels A, and RAD in Panels B. The independent dummy variable(s) in Model 1 are $Unambiguous_t$, while in Model 2 they are the dummy variables $ScenarioK_t$ for the three unambiguous signal scenarios.

The results are reported in Table 2.9. The results of Model 1 indicate that RD under ambiguous signals tends to be significantly higher than RD under unambiguous signals by 0.356 (Panel A). Similarly, RAD tends to be higher by 0.219 (Panel B). The result of Model 1 shows that compared with the three scenarios with unambiguous signals, RD (Panel A) and RAD (Panel B) is significantly larger in the scenario with ambiguous signals. For example, RD and RAD given ambiguous signals are larger by 0.478 and 0.491 as compared with the unambiguous signal scenario 2 with a variance of 0.25.

Figure 2.3: Figure 2.3 depicts the cumulative distribution function of the RD (top panel) and RAD (bottom panel) in each scenario. The x-axis is the value of RD (top panel) and RAD (bottom panel), and the y-axis is the probability. The purple line is the RD/RAD for Scenario 4 (ambiguous signals), the blue line is the RD/RAD for Scenario 1, the orange line is the RD/RAD for Scenario 2, and the yellow line is the RD/RAD for Scenario 3.

Table 2.9: This table reports the result of estimation of Equation (2.5). The dependent variable is RD in Panels A, and RAD in Panels B. The independent dummy variable(s) in Model 1 are $Unambiguous_t$, while in Model 2 they are the dummy variables $ScenarioK_t$ for the three unambiguous signal scenarios.

	Panel A: RD		Panel B: RAD	
	Model 1	Model 2	Model 1	Model 2
Default: Ambiguous signals				
Non-Ambiguous signals	-0.356*** (-9.95)		-0.219*** (-7.25)	
Default: Scenario 4 (ambiguous signals)				
Scenario 1 (unambiguous signals, $\sigma_s^2 = 1$)		-0.150*** (-3.49)		0.0488 (1.40)
Scenario 2 (unambiguous signals, $\sigma_s^2 = 0.25$)		-0.478*** (-11.11)		-0.491*** (-14.10)
Scenario 3 (unambiguous signals, $\sigma_s^2 = 4$)		-0.440*** (-10.23)		-0.216*** (-6.20)
Cons	0.448*** (14.46)	0.448*** (14.73)	0.578*** (22.08)	0.578*** (23.50)
N	1800	1800	1800	1800
t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01				

In line with Epstein and Schneider (2008), our measure of price volatility is the variance of the price, $var(p)$. We find that on average, the price volatility under ambiguous signals is larger. The median price volatility is 0.8125 given unambiguous signals and 1.5087 given ambiguous signals (Refer to Table B3 in Appendix B for more information). The price volatility in ambiguous signals is significantly larger than that in the unambiguous signals ($z = 3.053$ and $p = 0.0023$) according to a rank sum test. Especially, the rank sum test shows that the price volatility is significantly larger in Scenario 4 than in Scenario 1 ($z = 7.78$, $p = 0.0000$), and Scenario 3 ($z = 11.284$, $p = 0.0000$). These findings are confirmed using the following panel linear regression models with random effect:

$$\begin{aligned} var(p_t) &= a_0 + a_1 Unambiguous_t + \varepsilon_t \\ var(p_t) &= b_0 + \sum_{K=1}^3 b_K ScenarioK_t + \varepsilon_t \end{aligned} \quad (2.6)$$

where all the independent variables are dummy variables, as previously defined and the dependent variable, $var(p_t)$ is the price volatility in period t . The independent variable(s) in Model 1 is $Unambiguous_t$, while in Model 2 it is the scenario-specific, $ScenarioK_t$ dummy variables for the unambiguous signal cases. The results are reported in Table 2.10. The price volatility of the ambiguous signal is not significantly larger compared with the unambiguous signals according to Model 1. The result of Model 2 shows that price volatility tends to be higher under ambiguous signals by 0.565 than in Scenario 1, by 1.209 than in Scenario 3.

Table 2.10: This table reports the result of estimation of Equation (2.6). The dependent variable is price volatility. The independent variable(s) in Model 1 is $Unambiguous_t$, while in Model 2 it is the scenario-specific, $ScenarioK_t$ dummy variables for the unambiguous signal cases.

Dep var: $var(p_t)$	Model 1	Model 2
Default: Ambiguous signals		
Non-ambiguous signals	0.0351 (0.55)	
Default: Scenario 4 (ambiguous signals)		
Scenario 1 (unambiguous signals, $\sigma_s^2 = 1$)		-0.565*** (-7.48)
Scenario 2 (unambiguous signals, $\sigma_s^2 = 0.25$)		1.879*** (29.24)
Scenario 3 (unambiguous signals, $\sigma_s^2 = 4$)		-1.209*** (-19.10)
Cons	1.440*** (25.83)	1.440*** (25.76)
N	360	360
t statistics in parentheses * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$		

Hence, based on the findings above, we do not reject the Hypothesis 4. The larger price deviation is observed given the ambiguous signals. Also, the price volatility

is higher in the ambiguous signals. Ambiguous signals will lead to higher price deviation and volatility in the experimental financial market.

Result 4 : We do not reject Hypothesis 4. We find that the price deviation and price volatility under ambiguous signals is significantly larger than under unambiguous signals.

2.5 Conclusion

This paper tests insights from a theoretical model by Epstein and Schneider (2008) using a laboratory experiment. In general, our results are in line with Epstein and Schneider (2008) theoretical assumptions and predictions. We find that more ambiguity averse individuals are indeed more likely to overestimate the variance of ambiguous signals, they tend to believe that bad news signals are more accurate than good news signals, when there is ambiguity about signal precision. Further, ambiguous signals lead to larger mispricing and price volatility in asset markets. The only discrepancy we find with the theory is that while individuals tend to consider ambiguous signals on bad (good) news as more (less) accurate, they do not assign a significantly different weight to those signals in forming their price expectations.

Our paper contributes to the literature on information processing in financial markets. Given our finding that ambiguous signals are a source of asset mispricing and excess volatility, reducing the ambiguity of information in asset markets may be viewed as a stabilizing policy.

In future research, it would be useful to consider alternative measures of ambiguity attitudes. Indeed, Trautmann et al. (2011) and Kocher, Lahno and Trautmann (2018) find that different measures of ambiguity attitudes result in further individual heterogeneity in ambiguity attitudes. Baillon et al. (2018) elicit ambiguity aversion for natural events with unknown subjective probabilities, which provides a more precise and general measurement of ambiguity aversion. While our paper mainly applies the measurement of ambiguity attitudes (risk choices and ambiguous choices) following the Trautmann et al. (2011), procedure, further checks on whether heterogeneity in ambiguity attitudes matter for financial market decisions would be useful. Further, our current work only considers signals with interval ambiguity; it would be of interest to explore other cases where the signals are associated with other types of ambiguities, e.g., disjoint ambiguity or two-point ambiguity as in Chew et al. (2017) to see if subjects process signals with different types of ambiguity in different ways. We leave these extensions to future research.

2.6 Appendix A

Experimental Instructions Welcome to this experiment on economic decision-making. Please read these instructions carefully as understanding it well is crucial for your payoff from the experiment. The experiment consists of two tasks and one survey. Your payoff will depend on your decision in all parts of the experiment.

Instructions for Task 1

In Task 1, you can choose either **Box K** or **Box U** in each row. Each of the two boxes contains 100 balls. The color of the balls is either **purple** or **orange**. Your payoff depends on your choice of the box. You will receive 3 SGD if a **purple ball is drawn**.

The number (and hence the fraction) of purple balls and orange balls is **known** in Box K. The numbers of purple balls and orange balls (and hence the fraction of purple and orange balls) are going to be shown on the computer screen. Thus, the probability for a purple ball to be drawn, namely, for you to win the payment of 3 SGD is **known** for Box K if you choose Box K. If you choose Box K, please click "Box K".

The number (and hence the fraction) of purple balls and orange balls is **unknown** in the Box. The number (and hence the fraction) of purple balls and orange balls is unknown in the Box U. Thus, the probability for you to win the payment of 3 SGD is **unknown** if you choose Box U: it can be any probability between 0% and 100%. If you choose Box U, please click "Box U".

When making your choices, you may only switch once between the two boxes, i.e., from Box K to Box U or from Box U to Box K. You cannot switch back and forth. For example, if you choose Box K in Rows 1-2, and Box U in row 3, you will not be allowed to choose Box K again in the remaining Rows 4 and below. *(This example is for illustration purposes only, and is not a suggestion for what you should do in the experiment).*

After you have made all choices, your payoff for Task 1 will be determined as follows. First, we will randomly choose one Row (choice) from all choices that you made. Then, one ball will be drawn randomly from the box K or U that you indicated for that Row (choice). If a purple ball is drawn, you receive 3 SGD; if an orange ball is drawn you receive 0.

The Payment in the Experiment

The payment of this experiment will be the sum of four parts:

The show-up fee, which is S\$3.

The payoff (in SGD) in Task 1.

The payoff (in SGD) in Task 2.

The payoff (in SGD) in a survey.

Instructions for Task 2

Background knowledge about Normal Distribution

In this experiment, you are going to predict the realized value of α , a randomly distributed variable following the normal distribution.

If you are not familiar with the normal distribution, here is some basic information about it. The shape of the normal distribution is a bell curve. For a normal distribution $N(\mu, \sigma^2)$, where μ is the mean and σ^2 is the variance of the distribution, the probability that the realization of the random variable is close to the mean μ is larger than the probability that it is far away from the mean. The square root of the variance, σ , is called the standard deviation of the distribution. For a normal distribution, values of the random variable that are less than one standard deviation away from the mean of the distribution account for 68% of all realizations (or mathematically, $\Pr(\mu - \sigma \leq X \leq \mu + \sigma) \approx 68\%$); while values that are two standard deviations away from the mean account for 95% of all realizations (or mathematically, $\Pr(\mu - 2\sigma \leq X \leq \mu + 2\sigma) \approx 95\%$); finally, values that are three standard deviations away from the mean account for 99.7% of all realizations (or mathematically, $\Pr(\mu - 3\sigma \leq X \leq \mu + 3\sigma) \approx 99.7\%$).

Task 2

In Task 2, you are endowed with 7 SGD in each period. Your task in each period is to predict the intrinsic value (or the true value) of the asset for that period. Here, intrinsic value means the amount of money that you can receive if you hold the asset until the end of the period. The intrinsic value of the asset is denoted by α . The realization of the intrinsic value, α , is drawn at the beginning of each period, but you don't see the realized value immediately. Instead, you predict the value of α in each period by choosing the **weights** that you assign to a public and a private signal about the intrinsic value, α .

- The Public signal**, which you and everyone else is informed about, concerns the **distribution** from which the intrinsic value of the asset, α , is drawn and its **unconditional mean and variance**.

- The **public signal** is: a is randomly generated each period and follows a normal distribution: $a \sim N(3,1)$. **The mean of a is 3 and its variance is 1. This public signal will be constant for all periods.** The public signal tells you that the probability that the realization of a_t lies between $[3 - 1, 3 + 1]$, or $[2, 4]$ is 68%; the probability that the realization of a_t lies between $[3 - 2 \times 1, 3 + 2 \times 1]$, or $[1, 5]$ is 95%; and the probability that the realization of a_t lies between $[3 - 3 \times 1, 3 + 3 \times 1]$, or $[0, 6]$ is 99.7%.

b) **The Private signal**, is a random variable known only to you, and tells you information about the realization of a in this particular period.

- The **private signal** s about the **true value** of the intrinsic value a , in period t , s_t equals a plus a noise term e_t , which follows the same distribution in all periods in the same block, but takes different realizations in each period.

$$s_t = a_t + e_t, \text{ where } e_t \sim N(0, \sigma_s^2)$$

Where a_t is the unknown intrinsic value of the asset you are trying to forecast. The noise term e has zero mean, variance σ_s^2 .

- So the **private signal** is the true value of a_t plus a small normally distributed error term having a mean of zero and a variance of σ_s^2 . The realization of the error term e_t is a random draw from the same distribution, $N(0, \sigma_s^2)$ for all participants, but your draw is independent of the draw of others. **The realization of both a_t and e_t in each period does not depend on the previous period realizations. Thus, the realization of a_t is a different random draw in each period t and therefore the private signal, s_t is a different random draw in every period t .**

s_t contains information about true value of a . σ_s^2 is a measure of the noisiness of the signal. The signal is more accurate, or less noisy if σ_s^2 is smaller.

Assume, for example, that the signal s_t is 4.3, in other words, the information about the realized value of a_t is: The probability that the realization of a_t lies between $4.3 - \sigma_s$ and $4.3 + \sigma_s$ is 68%, the probability that the realization of a_t lies between $4.3 - 2\sigma_s$ and $4.3 + 2\sigma_s$ is 95%, and the probability that the realization of a_t lies between $4.3 - 3\sigma_s$ and $4.3 + 3\sigma_s$ is 99.7%. For example, the variance of the error term, σ_s^2 , is known to be 0.25 for that period. You should understand that this means that the standard deviation of the error term, $\sigma_s = 0.5$, and following the same logic as described earlier, the probability that the realization of a_t lies between $[4.3 - 0.5, 4.3 + 0.5]$, or $[3.8, 4.8]$ is 68%; the probability that the realization of a_t lies between $[4.3 - 2 \times 0.5, 4.3 + 2 \times 0.5]$, or $[3.3, 5.3]$ is 95%; and the probability that the realization of a_t lies between $[4.3 - 3 \times 0.5, 4.3 + 3 \times 0.5]$, or $[2.8, 5.8]$ is 99.7%.

Instructions:

Your task for 5 consequent periods and for each of the four scenarios (different values of σ_s) is to **select the weight, w , that you want to assign to the private signal, where $0 \leq w \leq 1$. Your choice of the weight for the private signal also determines the weight, $1-w$, that you attach the public signal, which is simply that the mean value for a is 3. Thus your implied prediction for a in period t , a_t is given by**

$$\text{Your Implied Prediction} = w \times \text{the private signal} + (1 - w) \times 3$$

Your **implied prediction** will be closer to the private signal if you assign a higher weight to it, and closer to the public signal, that is, the mean of 3, if you assign a lower weight to the private signal. For example, if the private signal is 2.8 and the weight you choose to assign to it is 0.6, then your implied prediction for a is $0.6 \times 2.8 + (1 - 0.6) \times 3 = 2.88$.

Six of you will be randomly assigned to one market. This assignment remains unchanged through the all periods/scenarios of Task 2. After all participants have submitted their weight choices, the implied predictions of a , will be computed.

The market price of the asset will be the **median** of all implied predictions of a . The median is the number such that half of all predictions lie below it and half lie above it. You can also think of the median of all individuals' expectation as the market value of the asset. The transaction mechanism is: If your implied prediction of a is **above the market price**, which implies that your expected valuation of the asset is higher than the median of all expected values of the asset in the market, then you are a **buyer** and will buy the unit of the asset at the market price. If your implied prediction of a is **below the market price**, which implies that your expected valuation of the asset is lower than the median of all expected values of the asset in the market, then you are a **seller** and will sell the unit of the asset at the market price.

There are **four scenarios** about the variance σ_s^2 of the noise term e_t of the **private signal s** . They are as below:

- (1) $\sigma_s^2 = 1$, which means the noise term e has zero mean, variance 1 and the standard deviation of 1;
- (2) $\sigma_s^2 = 0.25$, which means the noise term e has zero mean, variance 0.25 and the standard deviation of 0.5;
- (3) $\sigma_s^2 = 4$, which means the noise term e has zero mean, variance 4 and the standard deviation of 2;
- (4) $0.25 \leq \sigma_s^2 \leq 4$. In this scenario, We do not know the exact value of the variance σ_s^2 . We only know that the variance σ_s^2 is between 0.25 and 4. That is, the lowest possible value of the variance is 0.25, the highest possible value of the variance is 4. The realization of variance of the private signal is randomly drawn at the beginning of each period.

In the first three scenarios, you need to make your best selection for the weight to assign to the private signal and the implied prediction of a .

In the last scenario, you need to make two decisions:

- (1) Enter your expectation for the value of the variance σ_s^2 (a number between 0.25 and 4):

(2) Make your selection of the weight to give to the private signal s and the implied prediction of a

The Payoff in Task 2

Your total payoff in Task 2 is going to be determined in the following way: for the weight selection task, you are going to be paid according to your performance in a randomly selected period from the 20 periods of four scenarios. For the variance prediction task, you are going to be paid according to your performance in a randomly selected period in the last scenario of 5 periods. The unit of payment is again Singapore dollars.

Recall that at the start of each period you are endowed with 7 SGD. Your **payoff for the weight selection task (profit) in SGD is going to be determined in the following way:**

Trading Profit of a buyer in one period = 7 – market price + realized value of a

Trading Profit of a seller in one period = 7 + market price – realized value of a

So, if you are a buyer, you buy the asset from your endowment of 7 SGD and get the actual realized value of a in return. If you are a seller, you sell the asset at the market price and in doing so you give up the realized value of the asset, a . As you can see, the profit for a buyer/seller is going to be higher if the realized value of the intrinsic value is higher/smaller than the market price.

The payoff for the prediction of variance task is going to be determined in the following way:

Payoff for the prediction of variance

$$= 8 - \frac{10}{10 - |\text{Your prediction of variance} - \text{The realized value of variance}|}$$

The payoff for the prediction of variance is going to be higher/lower if the prediction error is larger/smaller.

The picture below is the screenshot of Task 2. You have to slide the slider bar to select the weight, w , between 0 and 1 that you would like to assign to the private signal. The remaining weight goes to the public signal, the mean of 3. The prediction of a will be given according to the weight you selected. You can play with different weights to explore different predictions for a . When you are satisfied with your prediction for a , please click the “OK” button to submit.

Period

1 out of 20

Public Signal: a is randomly generated and follows a normal distribution $a \sim N(3, 1)$. The mean of a is 3, and variance is 1.

Private Signal: x is about the true value of a . $x = a + e$, $e \sim N(0, \sigma_e^2)$. In this Scenario, the variance σ_e^2 of noise term e is 1.

Please select the weight that you want to assign to the private signal by slide the slider bar below.

The weight of private signal is going to be 0 if the slider bar stays at the left end of the interval, and the implied price prediction is equal to the public signal, 3.

The weight of the private signal is going to be 1 if the slider bar stays at the right end of the interval, and the price prediction is the private signal.

When you slide the slider bar, you can read the associated weight assigned to the private signal associated to each point in the interval.

You can see the implied prediction for each weight for the private signal. When you have made the decision about the weight and implied prediction that you want to choose, you can click OK to submit your decision.

In this period, your private signal, s , is 2.4795
Weight of private signal, w , is 0.4455
Implied prediction of a is 2.7881

OK

To check the validity of our first hypothesis, we computed the difference ($\tilde{\sigma}_{diff,i}^2$) between the expectation of variance and the mean of the variance interval, that is the $\tilde{\sigma}_{diff,i}^2 = E_{i,t}(\sigma_s^2) - 2.125$. The top panel of Figure A1 shows histograms of the variance expectations in the ambiguous signal case, overall and disaggregated by ambiguity measure. The bottom panel shows the cumulative frequency distributions of these same variance expectations overall, and disaggregated by ambiguity measure.

Figure A1: The probability density of variance prediction (top panel), the cumulative probability of variance prediction (bottom panel). The x-axis is variance prediction, y-axis is the number of observations in the top panel and cumulative probability in the bottom panel. The black vertical line is the mean of the variance interval (2.125).

2.7 Appendix B

Table B1 reports the numbers of individuals who are ambiguity averse and risk averse/neutral

/seeking, ambiguity seeking and risk aversion/neutral/seeking, and ambiguity neutral and risk aversion/neutral/seeking. This table reveals that there is no interaction between ambiguity attitudes and risk attitudes as we have measured them. It can be inferred from the cross tabulation that 52.2% of subjects are both ambiguity averse and risk averse. The test statistics do not report significant interrelation between the frequency of ambiguity attitude and the risk attitude (*Pearson* $\chi^2 = 1.6762$ and $p = 0.795$. *p of Fisher statistic* = 0.853). Hence, the two variables (ambiguity attitude and risk attitude) can be viewed as being independent.

Table B1: This table reports the frequency distribution of ambiguity attitudes and risk attitudes. The rows report the numbers of subjects who are ambiguity averse, ambiguity neutral and ambiguity seeking. The columns report the numbers of subjects who are risk averse, risk neutral and risk seeking.

	Risk averse	Risk neutral	Risk seeking	Total
Ambiguity averse	47	11	2	60
Ambiguity neutral	16	4	0	20
Ambiguity seeking	7	3	0	10
Total	70	18	2	90

Table B2: This table reports the descriptive statistics of the Relative Deviation and Relative Absolute Deviation for each scenario in Panel A and Panel B.

Panel A: Relative Deviation					
	Mean	Median	Std	Min	Max
Scenario 1	0.2979	-0.2242	0.9474	-0.3571	3.0284
Scenario 2	-0.0298	-0.0638	0.0979	-0.1629	0.2246
Scenario 3	0.0078	-0.0750	0.4835	-0.5025	0.9536
Unambiguous signal (total)	0.0890	-0.0947	0.6491	-0.5440	3.0475
Scenario 4	0.4482	0.1450	0.7256	-0.3614	1.7811
Overall	0.1810	-0.0489	0.6753	-0.5025	3.0284
Panel B: Relative Absolute Deviation					
	Mean	Median	Std	Min	Max
Scenario 1	0.6272	0.2928	0.7696	0.0682	3.0284
Scenario 2	0.0877	0.0914	0.0525	0.0062	0.2246
Scenario 3	0.3625	0.3154	0.3197	0.0003	0.9536
Unambiguous signal (total)	0.3765	0.2143	0.5361	0.0001	3.0475
Scenario 4	0.5783	0.2663	0.6266	0.0010	1.7811
Overall	0.4139	0.2133	0.5634	0.0003	3.0284

Table B3: This table reports the descriptive statistics of price volatility for each scenario in Panel A, and with regard to individual's ambiguity attitude in Panel B.

		Mean	Median	Std	Min	Max
Unambiguous signals	Scenario 1	0.8754	0.8125	0.2481	0.5907	1.4354
	Scenario 2	3.3191	3.3969	0.1201	2.4830	4.1549
	Scenario 3	0.2317	0.2131	0.3987	0.0252	0.4080
	Total	1.4754	0.8125	1.3613	0.0252	4.1549
Ambiguous signals	Scenario 4	1.4403	1.5087	0.5283	0.3652	2.4141
Whole sample		1.4666	0.9755	1.2074	0.0252	4.1549

Chapter 3

Prediction and Predictability of Asset Prices: An Experiment

3.1 Introduction

The use of charts and graphical displays has a long history in markets (Lo et al., 2011; 2000). Barberis et al. (1998) propose a model that individuals make predictions based on the seeming predictability of past price dynamics. They tend to overreact to the continuing trends in earnings and underreact to earnings surprises on average. They claim that investors use the number of reversals in the sequence as the indicator of a change of earnings regime in the future. Bloomfield and Hales (2002) provide primary experimental support for the model of Barberis et al. (1998). They conducted a two-stage experiment. The participants were shown 16 different eight-period sequences in stage 1 and 30-period rolling windows of a sequence in stage 2. The participants were asked to make a price prediction for stocks. They found that, in line with the past studies, e.g., Kahneman and Tversky (1973), Griffin and Tversky (1992), investors do not regard the random walk sequences as random even after they are told so. In addition, they find that individuals tend to make a reversed prediction for sequences with more reversals and make a trend-following prediction for sequences with fewer reversals.

Motivated by their seminal work, we run a follow-up study to further examine the mechanism of their results. Our experiment consists of two main stages. Stage 1 requires the participants to make price predictions for 30 days after the last price shown on the graph based on the 365-days price of a stock series. The payoff in Stage 1 depends on the accuracy of the forecast. The smaller the prediction error, the higher the payoff. In Stage 2, the participants were shown 16 plots that were created as "random walks" (same as Bloomfield and Hales, 2002). Initially, the participants were given one unit of the bet, whose value is either 0 or 100 points depending on the next movement (on how the series of the graph move next). That is, the value of the asset will be 100 points if it moves upward, and 0 point if it moves downward. The participants were asked to name the price at which they were willing to sell this asset back to us. The range of prices should

be between 0 and 100. To calculate the earnings, a random number between 0 and 100 (each number is equally likely) is generated. If the randomly generated number is less than or equal to the price the participants have set for the asset, then, the subject will keep the bet and the payoff would be either 0 or 100 points depending on the next move of the series represented on the plot. If the randomly generated number is greater than the price set by the participants for the asset, then the participants would receive the points equal to the randomly generated number. We discuss more details about our experiment design in the Section 3.

Our findings of Stage 1 are summarized as follows: first, the number of reversals seems to be a good indicator of the difficulty of forecasting a time series. The chance for a subject to make a correct prediction of price movement is lower when the number of reversals is higher. Secondly, individuals tend to make their forecast far from the actual price and the last observed price when the number of reversals is higher. From Stage 2, we observe that individuals are more likely to overreact to the random walk sequences when there are fewer reversals, underreact to the sequence when there are more reversals. Additionally, individuals tend to make their price predictions closer to 50 for sequences with higher reversals.

Our paper contributes to the literature in several ways. First, our study can serve as an extension of Bloomfield and Hales (2002). They conduct an experiment on how subjects use past trend reversals to estimate the probability of future reversals and provided insights on such ‘regime-shifting’ beliefs. They conclude that their subjects tend to use past trend reversals as a reference even though they are told that the trends’ ups and downs were random. Subjects also tend to predict reversion after seeing many reversals and to predict trending after seeing few reversals. Our findings are consistent with Bloomfield and Hales (2002) that participants are more likely to overreact to the random walk sequences when there are fewer reversals and underreact to the sequence when there are more reversals. The main difference between our paper and Bloomfield and Hales (2002) is twofold: first, we use the real stock price series instead of pure random walk sequences in our experiment, which allows the participants to make decisions based on true stock price dynamics. Secondly, in addition to replicating their original results, we also tested the relationship between the deviation of the price forecast from the true stock price and the number of reversals in each stock series. Our paper supplements their work by finding that the possibility for a subject to correctly predict the price movement is lower when the number of reversals is higher in stock series. Moreover, price deviates from the true stock price for stock series with more reversals.

In addition, we extend the research question to forecast real stock prices. Frieder (2008) explored how individuals extrapolate past news to provide an indication of future trends. Her study showed that after viewing positive news, investors tend to have substantial buying activities. Moreover, Huber et al. (2010) carry out an experiment to determine the behavior of investors in making decisions under risk. Subjects are to guess the outcomes of a series of coin toss either by themselves or depend on the ‘experts’. Hot hand belief is observed when subjects choose to rely on experts who were successful in the past. Gambler’s fallacy is found consistent in subjects who determine the coin themselves, as the

frequency of betting head increases after streaks of tails. Rötheli (2011) examined how subjects extrapolate patterns in time series to provide expectations of the stock price and exchange rate. Loh and Warachka (2012) conclude that investor expectations are influenced by trends in prior quarterly earnings surprises. Their evidence supports the gambler's fallacy in Rabin (2002) where investors appear to underreact to trends in earnings surprises. Our paper is also related with the literature on heterogeneous expectations and regime-swift in learning to forecast experiment asset markets, e.g., Anufriev et al. (2016), Bao and Zong (2019), Bao et al. (2012), Hommes (2013b; 2017) and Zhu et al. (2020). Our paper investigates how internal factor (in our paper, the reversals of stock series) rather than external factors (quality of news) affects the individuals' expectation.

Third, we investigate possible behavioral factors that help to explain subjects' prediction behavior and errors. Christelis et al. (2010), Benjamin et al. (2013), Dutton and Lynn (2013) find that people with high IQ (or fluid intelligence, measured by Raven Test) are more likely to participate in the stock market than those with low IQ scores. Moreover, Grinblatt et al. (2012) further find that high-IQ investors outperform low-IQ investors in trading. These high-IQ individuals tend to buy winning stocks and sell losing stocks. Different from their work, our paper suggests that fluid intelligence does not affect an individual's forecast performance.

Akiyama et al. (2014) find that participants with a higher CRT score are more sensitive to the uncertainty of the other investors' behavior and make a larger price forecast deviation than those with lower CRT score. Breaban and Noursair (2015) and Cueva and Rustichini (2015) find a negative correlation between the average cognitive skill of subjects and the degree of mispricing observed in the market. Corgnet et al. (2014) and Cueva and Rustichini (2015) find that higher cognitive skills leads to higher earnings. Bosch-Rosa et al. (2018) study the relation between average cognitive ability (usually measured by CRT) of investors and mispricing in an experimental market. They find that the market with lower sophistication individuals has insignificant mispricing than that with high-sophistication individuals. Our paper finds that cognitive ability is negatively related to the forecast ability when the stock series is a random walk. However, this result is not consistent.

Hefti et al. (2016) examine the relationship between the achievement of market success and two different skills: cognitive skills and the theory of the mind (which is measured by eye test). They find that both a high level of cognitive skills and mentalizing skills are crucial to be successful in asset-market experiments. Corgnet et al. (2018) demonstrate that high IQ, cognitive skills, and theory of mind explain trading performance in market experiments with private information. Differently, our paper finds that mentalizing skills do not affect an individual's forecasting performance when the stock series is a random walk.

Eckel and Füllbrunn (2015) find that males are more likely to make a larger deviation from the fundamental price than females. Cueva and Rustichini (2015) find that mispricing in mixed-gender markets is larger than that in a single-gender market (either all-male or all-female). Hanaki et al. (2017) find that increasing

the male participants in a market leads to the increase of the degree of mispricing. Differently, our paper finds that males are more likely to decrease the price deviation for random-walk stock series, but this result is not always significant. Additionally, our paper is related with the study about loss aversion and risk aversion, e.g., Gjerstad and Hall (2005), Eckel and Grossman (2015). Our paper does not observe any significant and consistent relationship between the prediction performance of participants and loss aversion (and risk aversion).

Lastly, we explain whether the prediction behavior can be explained by other properties that broadly related to the predictability of the data, e.g., Hommes and Zhu (2011). Our result suggests that the price volatility of stock series exhibits similarity to the reversals of the stock series, that is, the higher the volatility of the stock series, the less accurate the prediction is. While the autocorrelation coefficient of the stock series cannot explain the prediction behavior well when the stock series is a random walk. According to Anufriev et al. (2019; 2016), the higher the autocorrelation, the lower the prediction error and the more accurate the prediction, however, our result indicates that the autocorrelation coefficient is higher, the prediction error is higher for random-walk series.

The remainder of this paper is organized as follows. Section 2 discusses the literature. Section 3 describes the model. Section 4 summarizes the experimental design. Section 5 and Section 6 present the analysis of the experimental data. Section 7 concludes.

3.2 The Regime-Shifting Model

The regime-shifting model proposed by Barberis et al. (1998) finds that individuals tend to overreact to long-term earnings surprise, but underreact to current earnings performance. Assume that the earning at time t is N_t and follow a random walk, which is defined as below:

$$N_t = N_{t-1} + y_t \quad (3.1)$$

where y_t is the shock of earnings at time t . There are two possibilities of y , either $+y$ or $-y$. They assume that the earnings are paid as a dividend. The value y_t is determined by two models as discussed below. The investors believe that the earnings move, which is y_t , between two regimes. One regime is that the earnings are mean-reverting, and the other regime is that the earnings follow the trend. The earnings matrices of the two regimes are reported in Table 3.1.

π_i is the probability that the transition of shocks of earnings in each regime. $\pi_i = \pi_L$ is for mean-reverting regime, $\pi_i = \pi_H$ is for trend regime. The model assumes that $\pi_L < \pi_H$, for example, π_L could be smaller than 0.5 and π_H is larger than 0.5. In other words, a positive shock is more likely to be reversed under a mean-reverting regime and to be followed under a trend regime. The transition matrix is

Table 3.1: This table report the earning matrices of the two regimes. π_i is the probability that transition of shocks of earnings in each regime.

	$y_{t+1} = y$	$y_{t+1} = -y$
$y_t = y$	π_i	$1 - \pi_i$
$y_t = -y$	$1 - \pi_i$	π_i

the probability that the transition from one regime to another is reported in Table 3.2.

Table 3.2: This table report the transition matrices of the two regimes. $regime_i = regime_1$ for mean-reverting regime, $regime_i = regime_2$ for trend regime.

	$regime_{t+1} = 1$	$regime_{t+1} = 2$
$regime_t = 1$	$1 - \lambda_1$	λ_1
$regime_t = 2$	λ_2	$1 - \lambda_2$

λ_1 and λ_2 are the probabilities of transition from one regime to another and are assumed to be particularly small, which means that the probability of transit from one regime to another is extremely low. Additionally, $\lambda_1 < \lambda_2$ indicates that investors think the mean-reverting regime to be more likely than the trend regime. The investor makes prediction of earnings to value the stock and determines which regime he/she is in by observing the earnings each period. In period $t + 1$, he/she gets q_{t+1} that is the probability that y_{t+1} is from mean-reverting regime by Bayesian updating.

$$q_{t+1} = Pr(s_{t+1} = 1 \mid y_{t+1}, y_t, q_t) \quad (3.2)$$

Here, we only propose two explicit examples to explain the updating rule. The first one explains the mean-reverting regime where the shock in period $t + 1$ has a different sign with that in period t . q_{t+1} is given below:

$$q_{t+1} = \frac{((1 - \lambda_1)q_t + \lambda_2(1 - q_t))(1 - \pi_L)}{((1 - \lambda_1)q_t + \lambda_2(1 - q_t))(1 - \pi_L) + (\lambda_1 q_t + (1 - \lambda_2)(1 - q_t))(1 - \pi_H)} \quad (3.3)$$

π_L and $-pi_H$ $q_{t+1} > q_t$ implies that investors put more weight on the belief of the mean-reverting regime if he/she observes an opposite sign of shock in period $t + 1$. While, if the shocks to the earnings in period $t + 1$ has the same sign as that in period t , the investor is more likely to believe he/she is in a mean-reverting and make a reversed prediction about the stock earnings for next period. The second example describes this situation as below:

$$q_{t+1} = \frac{((1 - \lambda_1)q_t + \lambda_2(1 - q_t))\pi_L}{((1 - \lambda_1)q_t + \lambda_2(1 - q_t))\pi_L + (\lambda_1 q_t + (1 - \lambda_2)(1 - q_t))\pi_H} \quad (3.4)$$

In that case, $q_{t+1} < q_t$, which means the investor assigns a higher weight to trend regime when the signs of the shocks in period t and period $t + 1$, he/she tend to believe that the earnings are in the trend regime. He/she is more likely to follow the trend of earnings to make a prediction.

Generally, Bloomfield and Hales (2002) checked whether people would believe the earnings of the stock stay in a mean-reverting regime when there are more reversals in the series. They argue that the model assumes that the realized return follows a random walk in both regimes. However, investors do not believe that. The only difference between the two regimes is the transition probability. In the mean-reverting regime, the shocks of earnings tend to be reversed in the next period. Investors believe that in this regime, the change of earnings is more likely to move in the opposite direction rather than in the positive direction. While the trend regime indicates that the changes are likely to be followed by the change of the same signs.

Further, the model presents that the price of the stock is the present value of the future cash flow (dividend paid every period), so the implication for the price is the expected value :

$$P_t = E_t \left\{ \frac{N_{t+1}}{1 + \delta} + \frac{N_{t+2}}{(1 + \delta)^2} \dots \right\} \quad (3.5)$$

If individuals do follow the random walk process, they would expect $E_t(N_{t+i}) = N_t$, $P_t = \frac{N_t}{\delta}$, where δ is the discount rate. If individuals underreact to the earnings news, then the stock price may not sufficiently reflect the shocks.

3.3 Experiment Design

Our experiment consists of three stages. Stage 1 is the part that participants make price prediction of the stock series, Stage 2 is the replication of Bloomfield and Hales (2002), and Stage 3 contains the Raven test, the Social Intelligence Test, the Cognitive Reflection Test (CRT), Loss aversion and Risk aversion. Stage 1 and Stage 2 are the main stages of our experiment. We recruited 81 undergraduates from Nanyang Technological University in various disciplines and schools. We have incentivized all stages in our experiment except the demographic questionnaire to ensure that the subjects would make reliable and true decisions concerning all questions. The experiment lasted for 1.5 hours on average, the average payment of the experiment is around 20 SGD for each individual. We will discuss Stage 1 and Stage 2 for more details in the following subsection. The timeline of our experiment is shown in Figure 3.1.

3.3.1 Stage 1

In Stage 1, the participants are presented with 20 graphs that show 12 months of end-of-day prices of randomly selected stocks from the S&P 500 starting from a

Figure 3.1: This figure depicts the timeline of our experiment.

randomly selected day between January 1st 2008 and June 30th 2018. For each graph, the individual was asked to forecast what will be the end-of-day price for this stock 30 days after the last price shown on the graph. The end-of-day prices have been rescaled, as a result, all starting prices were equal to 100 for each graph. So, a priori, there are 1,916,250 possible charts. So people would not know which one is which. We did not tell the participants about the name of the stock or the starting date, which was randomly selected.

The participants are informed that the stock series is randomly selected for each graph, and the starting day is also randomly chosen. Since our whole experiment is the individual decision-making experiment, so the stock series for each individual may be different in each period. The payoff for Stage 1 depends on the accuracy of the prediction. Let p_i^e be the price prediction by individual i , p_i^{obs} be the last price shown in the graph and observed by individual i . The reward for Stage 1 is given in Eq. (3.6):

$$\max\{200 - 1000 \times |\frac{p_i^e - p_i^{obs}}{p_i^{obs}}|, 0\} \quad (3.6)$$

If the individual's forecast p_i^e is exactly at the price observed p_i^{obs} , then he/she receives 200 points. For each percentage point difference between p_i^e and p_i^{obs} , 10 points will be subtracted. If the price forecast differs from the observed price by more than 20 %, the individual would receive 0 points. The exchange rate in our experiment is 20 *points* = 1 *SGD*. One out of 20 stocks that individuals forecast will be chosen randomly for payment in Stage 1.

3.3.2 Stage 2

We calibrate and simplify the experimental design of Bloomfield and Hales (2002). The participants are told that a model of a random process is constructed that works much like flipping a fair coin. Based on this model, there are two possible outcomes. An upward movement indicates a "heads" outcome, and a downward movement indicates a "tails" outcome. The subjects are exposed to the term "random walk", we explain it to them in the following way: "Since outcomes of coin flips are unpredictable, they result in a sequence known as a "random walk". That is, statistical models are unable to predict future outcomes from past ones, and on average, there is no upward or downward trend. Random walk sequences almost always contain intervals of recognizable patterns. However, since these patterns can change greatly at any time, statistical models are still unable to predict future outcomes.

In Stage 2, the participants were shown 16 plots that were created as "random walks". Initially, the participants were given one unit of the asset (in our instruction, we use "bet" to make it less confusing to the participants), whose value was either 0 or 100 points depending on the next movement (on how the series of the graph move next). If the value of the asset will be 100 points if it moves upward, and 0 point if it moves downward. In line with Bloomfield and Hales (2002), we also followed Becker et al. (1964) to measure the individual's belief about the probability of the upward change of the graph. The asset generates 100 points if it moves upward, and 0 points if it moves downward.

The subjects were asked to name the price (in points) at which they were willing to sell this asset back to us. The range of prices should be between 0 and 100. The earnings for this stage are calculated as follows (it is slightly different from Bloomfield and Hales (2002), because the Bloomfield and Hales (2002)'s payment method is complex for the subject to understand). One of the 16 plots at random was selected, eight of them are mirror images (consistent with Bloomfield and Hales, 2002). Then we generated a random number between 0 and 100 (each number is equally likely). If the randomly generated number is less than or equal to the price the participants have set for the asset, then the subject will keep the bet and the payoff would be either 0 or 100 points depending on the next move of the series represented on the plot. If the randomly generated number is greater than the price set by the participants for the asset, then the participants would receive the points equal to the randomly generated number. Here are two numerical examples of how the simplified payment mechanism works: first, if the price set for the asset is 60 points and the randomly generated number is 50, the subject keeps the bet and the payoff would be either 0 or 100 points. Second, if the price set for the bet to be 40 points and the randomly generated number is 50, the subject receives 50 points. In other words, if the participant sets a lower price, which implies the participant is pessimistic. The participant gets positive profit from the lower value of the asset (0) and negative profit from the higher value of the asset (100). If the participant sets a higher price, which implies the participant is optimistic. He/she gets the profit by the price set.

3.4 Experimental Results for Stage 1

81 undergraduates participated in the experiment in NTU, and they made price forecasts for 20 periods in Stage 1 of the experiment. In each period, the subjects are asked to make the prediction of the price of a randomly selected stock for 30 days after the last price is shown (price observed) in each period.

3.4.1 Prediction on the Direction of Price Movement

To investigate whether the participants are able to predict the direction of the price movement correctly, we calculate the price change both for the expected price and the actual price from the price observed and check whether these changes are in the same direction for each period. The price change is given by:

$$\text{Actual Price Change} : \Delta p_{j,f} = p_{j,f} - p_{j,end} \quad (3.7)$$

$$\text{Expected Price Change} : E(\Delta p_{j,end}) = p_j^e - p_{j,end} \quad (3.8)$$

Where $j = 1, 2, \dots, 20$, represents the stock series. p_j^e is the expected price for the current series, $p_{j,f}$ is the actual price at the current series, which the participants are required to make a prediction about, $p_{j,end}$ is the last price observed by the subjects at the current series. The price observed and the actual price in each period are independent of series to series. There are 20 observations of the price change for each participant in Stage 1.

We calculate the frequency when the sign of $\Delta p_{j,f}$ equals to the sign of $E(\Delta p_{j,f})$ (the absolute value is nonzero) for series j to measure the correct prediction of stock series, which is given below:

$$\text{sign } \Delta p_{j,f} = \text{sign } E(\Delta p_{j,f})$$

In other words, when $\text{sign } \Delta p_{j,f} = \text{sign } E(\Delta p_{j,f})$, the actual price increase/decrease, the expected price should increase/decrease as well. If $\text{sign } \Delta p_{j,f} \neq \text{sign } E(\Delta p_{j,f})$, the actual price decreases/increases, expected price should increase/decrease. When the value of $\Delta p_{j,f}$ is 0, the value of $E(\Delta p_{j,f})$ should also be 0.

We find that the median of the times that the participants make a correct prediction of the price movement of the stock series is 10, while the mean is 9.87. Figure 3.2 shows the cumulative distribution function (CDF) of the number of series that the participants correctly predict the price movement of the stock series. The minimum is four series, and the maximum is 14 series.

Approximately 61.73% of the participants make the correct prediction of the price

Figure 3.2: This figure shows the cumulative distribution function (CDF) of the number of series that the participants make correct price prediction of the stock price in the yellow line, the positive price change in the blue line, and the negative price change in the orange line. The x-axis is the number of series that the participants make the correct price movement, and the y-axis is the cumulative probability.

movement of the stock series for more than 10 series (half of the prediction series), which is barely any better than pure guessing. The specific number of observations is reported in Table 3.3 below. No participant correctly predicts the price movement of the stock series for all 20 series. 37 participants (out of 81) make a correct prediction of the price movement of the stock series for no more than ten series (less than half of 20 series). The rank-sum test confirms the statistical finding that generally, individuals make a correct prediction of price movement for less than 10 stock series ($z=-0.909$, $p=0.3635$).

We further check the number of correct predictions of a positive price change and negative price change that is reported in Table 3.3. We observe that no participants correctly predict the positive price change or negative price change for more than 10 series. Most participants make the correct positive/negative price change prediction for 4, 5 or 6 series. We also do not find any significant difference between the number of correct predictions of the positive price change and negative change ($z= -1.133$, $p=0.2572$).

Overall, we do not find evidence that the subjects can predict the direction of the price movement (overreact to the stock series) better than pure guessing (in which case their success rate should be 50% on expectation).

Result 1: *We do not find evidence that the subjects can predict the direction of the price movement (overreact to the stock series) better than pure guessing.*

Table 3.3: This table reports the detailed number of observations that the subjects predict the direction of price movement correctly in the top panel, the number of observations that subject makes positive/negative price change prediction correctly in the middle/bottom panel.

Number of Correct Prediction of Price Movement	Correct Prediction of Price movement		
	Freq.	Percent	Cum.
4	1	1.23	1.23
6	2	2.47	3.7
7	5	6.17	9.88
8	11	13.58	23.46
9	17	20.99	44.44
10	14	17.28	61.73
11	12	14.81	76.54
12	10	12.35	88.89
13	8	9.88	98.77
14	1	1.23	100
Correct Prediction of Positive Price Change			
	Freq.	Percent	Cum.
0	1	1.23	1.23
1	3	3.7	4.94
2	4	4.94	9.88
3	10	12.35	22.22
4	18	22.22	44.44
5	13	16.05	60.49
6	20	24.69	85.19
7	8	9.88	95.06
8	4	4.94	100
Correct Prediction of Negative Price Change			
2	4	4.94	4.94
3	10	12.35	17.28
4	17	20.99	38.27
5	15	18.52	56.79
6	16	19.75	76.54
7	14	17.28	93.83
8	4	4.94	98.77
9	1	1.23	100
Total	81	100	

3.4.2 Reversals and Correct Prediction to Stock Series

In the previous session, we have confirmed the heterogeneity of the price prediction on the price movement among subjects. In this session, we take a further look at the factors that contribute to such a difference. We first check whether the number of reversals of the stock price series accounts for the correct prediction

or incorrect prediction of the price movement. A reversal is a change in the price direction of an asset. A reversal can occur on the upside or downside. We count the number of reversals of the dynamics of stock prices shown to the subject. We observe that 55% series in which the stocks prices exhibit 116 to 129 reversals, while the 45% exhibits 130-138 reversals from Figure 3.3. The maximum is 138, and the minimum is 116.

Figure 3.3: This figure shows the cumulative distribution function (CDF) of the number of reversals of stock price series. The x-axis is the number of reversals in each stock price series, and the y-axis is the cumulative probability.

Motivated by Barberis et al. (1998) and Bloomfield and Hales (2002), to further check the relation between the number of reversals and the prediction of the direction of price movement, we do the pooled logit regression. The equation tested is given by:

$$y_{i,j} = \text{logit}(c + b_1 \#Reversals_j + b_2 Z_i + \epsilon_j) \quad (3.9)$$

Where $y_{i,j}$ is a binary outcome variable. $y_{i,j} = 1$ means the correct prediction to the price movement of individual i at series j , $y_{i,j} = 0$ means the incorrect prediction to the price movement. $\#Reversals_j$ is the number of reversals in the dynamic of the stock price in each series. Z_i contains the social intelligence test, Raven's matrices test, cognitive reflection test (CRT), loss aversion and risk aversion elicitation, as well as age and gender. The descriptive statistics of Social intelligence test, Raven test, CRT, loss aversion and risk aversion are summarized in Table B1 of Appendix B. We use the continuous measurement of these test. Social intelligence test, Raven test, CRT are measured by the number of correct answers. Loss aversion is measured by the number of lotteries that a participant rejects (the choice involving loss). Risk aversion is measured by the number of certain payoff choices for a participant. The higher the measure is, the more loss/risk averse. The correlation of those tests are reported in Table B2. The independent variable is (are) $\#Reversals_j$ in Panel A, $\#Reversals_j$ and Z_i in Panel B. $\#Reversals_j$ is the number of reversals of the stock series in the whole years in Model 1, that in the last 3 months in Model 2 and in the last 6 months in Model 3. The result is reported in Table 3.4. For every one unit change in the number of reversals, the log odds of correct prediction of the price movement (versus incorrect prediction) decrease by 0.0035 (not significantly) as reported in Model

1, either Panel A or Panel B. In other words, with the increase of reversals, the correct prediction of the movement of a price decrease. Additionally, our results suggest an opposite impact of the number of reversals in the last 3-month stock series and the whole year/last 6-month stock series on the accuracy of prediction of price movement. More reversals observed in the last 3-month stock series tend to increase the accuracy of prediction of price movement by 0.0288 significantly as shown in Table 3.4, while individuals are more likely to make fewer correct prediction of price movement when more reversals are observed in the last 6 months stock series as reported in Model 3 of Table 3.4¹.

We do not observe any consistent and significant impact of other profiles, e.g., social intelligence test, raven test, CRT, etc., on the correct prediction of price movement, as shown in Panel B. Additionally, we check the interaction between reversals and skills (Social intelligence test, Raven test, CRT, etc.), but we do not observe the significant impact of those variables on the correct prediction as reported in Model 1 of Table B3, Table B4 and Table B5 in Appendix B.

Additionally, we check whether the trend of the stock series affects individuals' prediction of price movement. We run the regression of Eq. (3.10).

$$y_{i,j} = \text{logit}(c + b_1\#Reversals_j + b_2Trend_j + b_3\#Reversals_j * Trend_j + b_4Z_i + \epsilon_j) \quad (3.10)$$

where $y_{i,j}$, $\#Reversals_j$ and Z_i are defined in Eq. (3.9). $Trend_j = 0$ is that the stock series j follows the trend, $Trend_j = 1$ means no trend observed in the stock series. The independent variable is (are) $\#Reversals_j$, $Trend_j$ in Panel A, $\#Reversals_j$, $Trend_j$ and Z_i in Panel B. $\#Reversals_j$ is the number of reversals of the stock series in the whole years in Model 1, that in the last 3 months in Model 2 and in the last 6 months in Model 3. $Trend_j = 1$ is no trend observed of the stock series in the whole years in Model 1, that in the last 3 months in Model 2 and in the last 6 months in Model 3. The result is reported in Table 3.5.

We find that individuals are less likely to make a correct prediction of the price movement when the stock series has no trend than that has a trend. Comparing with the stock series (one year) with the trend, the log odds of correct prediction of the price movement (versus incorrect prediction) decrease by 6.187 significantly for stock series with no trend as reported in Model 1 of Panel A and 6.218 of Panel B. The results remain the same when the stock series is in the last 6 months as reported in Model 3. However, we do not observe any significant difference of correct prediction of price movement for stock series with trend or without trend in the last 3 months as reported in Model 2. Moreover, we find that if the stock series, no matter one year (the coefficient is 0.0507) or last 6

¹The interpretation of the logit model is: the coefficient for reversal in last 3 months= 0.0288 which is interpreted as the expected change of the number of correct prediction of price movement in log odds for a one-unit increase in the number of reversals. The odds ratio can be calculated by exponentiating this value to get 1.0292, which means we expect to see about 2.92% increase in the odds of the number of correct predictions of price movement for a one-unit increase in the number of reversals.

Table 3.4: This table reports the result of pooled logit regression: $y_{i,j} = \text{logit}(c + b_1\#Reversals_j + b_2Z_i + \varepsilon_j)$, where $y_{i,j}$ is a binary outcome variable. $y_{i,j} = 1$ is the correct prediction to the price movement of individual i at series j , $y_{i,j} = 0$ is the incorrect prediction to the price movement. $\#Reversals_j$ is the number of reversals in the dynamic of the stock price in each series. Z_i contains the social intelligence test, Raven's matrices test, cognitive reflection test (CRT), loss aversion and risk aversion elicitation, as well as age and gender. The independent variable is (are) $\#Reversals_j$ in Panel A, $\#Reversals_j$ and Z_i in Panel B. $\#Reversals_j$ is number of reversals of the stock series in the whole years in Model 1, that in the last 3 months in Model 2 and in the last 6 months in Model 3.

Panel A			
	Model 1	Model 2	Model 3
Dep: Correct prediction of price movement			
#Reversals in 1 Year	-0.00349 (-0.44)		
#Reversals in last 3 months		0.0288** (2.54)	
#Reversals in last 6 months			-0.0145 (-1.58)
Cons	0.426 (0.42)	-1.342*** (-2.58)	1.316 (1.54)
<i>pseudoR</i> ²	0.002	0.003	0.001
Panel B			
	Model 1	Model 2	Model 3
Dep: Correct prediction of price movement			
#Reversals in 1 Year	-0.00350 (-0.44)		
#Reversals in last 3 months		0.0288** (2.55)	
#Reversals in last 6 months			-0.0146 (-1.58)
Social intelligence test	-0.00887 (-0.66)	-0.00890 (-0.66)	-0.00888 (-0.66)
Raven test	0.0144 (0.52)	0.0144 (0.52)	0.0144 (0.52)
CRT	-0.0252 (-0.67)	-0.0253 (-0.66)	-0.0252 (-0.67)
Loss aversion	-0.0809 (-1.08)	-0.0812 (-1.08)	-0.0810 (-1.08)
Risk aversion	-0.0318 (-0.53)	-0.0319 (-0.53)	-0.0318 (-0.53)
Age	-0.0243 (-0.87)	-0.0244 (-0.87)	-0.0243 (-0.87)
Male	0.0165 (0.14)	0.0165 (0.14)	0.0165 (0.14)
Cons	1.572 (1.20)	-0.195 (-0.20)	2.466** (2.08)
<i>pseudoR</i> ²	0.002	0.005	0.003
N	1620	1620	1620
t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01			

months (the coefficient is 0.0665), has no trend, more reversals will increase the correct prediction of price movement. The interaction term of no trend and reversals is positive. Therefore, the trend of the stock series indeed positively affect individuals' prediction of the price movement of the stock series.

Table 3.5: This table reports the result of pooled logit regression: $y_{i,j} = \text{logit}(c + b_1\#Reversals_j + b_2Trend_j + b_3\#Reversals_j * Trend_j + b_4Z_i + \epsilon_j)$, where $y_{i,j}$, $\#Reversals_j$ and Z_i are defined in Eq. (3.9). $Trend_j = 0$ is that the stock series j follows trend, $y_{i,j} = 1$ means no trend observed in the stock series. The independent variable is (are) $\#Reversals_j$ in Panel A, $\#Reversals_j$ and Z_i in Panel B. $\#Reversals_j$ is number of reversals of the stock series in the whole years in Model 1, that in the last 3 months in Model 2 and in the last 6 months in Model 3. $Trend_j = 1$ is no trend observed of the stock series in the whole years in Model 1, that in the last 3 months in Model 2 and in the last 6 months in Model 3.

	Panel A			Panel B		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Dep: Correct prediction of price movement						
No Trend in the whole series	-6.187*** (-2.77)			-6.218*** (-2.77)		
#Reversals in 1 Year	-0.0307** (-2.21)			-0.0308** (-2.21)		
No Trend*#Reversals in 1 Year	0.0507*** (2.95)			0.0509*** (2.95)		
No Trend in the last 3 months series		-0.672 (-0.64)			-0.589 (-0.56)	
#Reversals in last 3 months		0.0212 (1.30)			0.0222 (1.36)	
No Trend*#Reversals in last 3 months		0.0145 (0.64)			0.0127 (0.56)	
No Trend in the last 6 months series			-5.818*** (-3.18)			-5.831*** (-3.19)
#Reversals in last 6 months			-0.0592*** (-3.75)			-0.0594*** (-3.76)
No Trend*#Reversals in last 6 months			0.0663*** (3.29)			0.0665*** (3.30)
Social intelligence test				-0.00892 (-0.65)	-0.00885 (-0.65)	-0.00895 (-0.66)
Raven test				0.0172 (0.62)	0.0143 (0.52)	0.0145 (0.53)
CRT				-0.0285 (-0.75)	-0.0251 (-0.66)	-0.0254 (-0.67)
Loss aversion				-0.0762 (-1.01)	-0.0812 (-1.08)	-0.0816 (-1.08)
Risk aversion				-0.0320 (-0.53)	-0.0305 (-0.51)	-0.0321 (-0.53)
Age				-0.0261 (-0.93)	-0.0239 (-0.85)	-0.0245 (-0.88)
Male				0.0160 (0.14)	0.0184 (0.16)	0.0166 (0.15)
Cons	3.738** (2.06)	-0.994 (-1.32)	5.157*** (3.66)	4.912** (2.44)	0.0915 (0.08)	6.325*** (3.88)
N	1620	1620	1620	1620	1620	1620
pseudoR ²	0.010	0.003	0.007	0.012	0.008	0.005

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

The above findings can be summarized as Result 2, Result 3 and Result 4:

Result 2: *The number of reversals in the whole year or last half-year stock series seems to be a good indicator of the difficulty of forecasting a time series. The chance for a subject to make a correct prediction of price movement is lower*

when the number of reversals in the whole year/last 6 months stock series is higher, but this result is not significant. We find that subjects tend to make more correct predictions of price movement when the number of reversals is higher in the last 3-months stock series.

Result 3: *The trend of the stock series also helps the subjects to make a more accurate prediction of the stock series (significant in the long term, but not significant in the short term). Comparing with the trend series with more reversals, individuals are more likely to make a correct prediction of price movement for the non-trend stock series with more reversals.*

Result 4: *We do not find evidence that subjects' correct prediction of the price movement of stock series is influenced by other behavioral factors like loss aversion, risk preference, social intelligence, or cognitive ability.*

3.4.3 Reversals and the Magnitude of Prediction Error

In the preceding section, we find that the higher the number of reversals leads to the lower correct prediction of the price movement. In this section, we check whether individuals will follow the last observed price to make the price prediction when the number of reversals is higher. We do the regression for Eq. (3.11) and Table 3.6 and Table 3.7 reports the results of the regression.

$$\begin{aligned} |E(\Delta p_{j,end})| &= c + b_3 \#Reversals_j + b_4 Z_i + \varepsilon_t \\ \text{Absolute prediction error} &= c + b_3 \#Reversals_j + b_4 Z_i + \varepsilon_t \end{aligned} \quad (3.11)$$

Where $|E(\Delta p_{j,end})| = |p_j^e - p_{j,end}|$ is the absolute value of the difference between the price prediction and last observed price of series j , *Absolute prediction error* $= |p_j^e - p_{j,f}|$ is the absolute value of the difference between the price prediction and the actual price of series j . $\#Reversals_j$ is the number of reversals in the dynamic of the stock price in each series. Z_i is the different profiles of individual i , which is the exact one as in Eq. (3.9). The dependent variable is $|E(\Delta p_{j,end})| = |p_j^e - p_{j,end}|$ in Table 3.6 and *Absolute prediction error* $= |p_j^e - p_{j,f}|$ in Table 3.7. The independent variable is (are) $\#Reversals_j$ in Panel A, and $\#Reversals_j, Z_i$ in Panel B. $\#Reversals_j$ is the number of reversals of the whole year stock series in Model 1, of the last 3 months in Model 2 and of the last 6 months in Model 3.

We find that the deviation of price prediction from the price observed is positively related to the number of reversals in the stock price series, as reported in both Panels of Table 3.6. With one more unit increment of reversals in the stock price series within one year, the deviation of price prediction from the last observation increases by 0.143, according to Model 1 in Table 3.6. We obtain a similar result for the deviation of price prediction from the actual price in Table 3.7. With one more unit increment of reversals in the stock price series, the deviation of price prediction from the actual price rises by 0.146, according to Model 1 in Table 3.7. Also, we observe similar results for the deviation of price prediction from the last observation and actual price for reversals in stock price series in the last 3 months. While, with the one more unit increment of reversals in stock price series in the last 6 months, the deviation of price prediction from the last observation increases by 0.190 according to Model 3 in Table 3.6, the deviation of price prediction from the actual price decreases by 0.146 according to Model 3 in Table 3.7.

As for the other profiles of participants, we observe that males tend to make predictions closer to the last observed price by 2.787 and actual price by 2.652 than females. More loss-averse individuals tend to make closer predictions to price observed by 1.262. We further check the interaction between the number of reversals and skills that are reported in Model 2 and Model 3 of Table B3, Table B4 and Table B5 in Appendix B, and we do not observe a consistent and significant interaction between reversals and skills on prediction errors.

Table 3.6: This table reports the results of the regression of first equation of Equation (3.11). $|E(\Delta p_{j,end})| = c + b_3 \#Reversals_j + b_4 Z_i + \varepsilon_t$. $|E(\Delta p_{j,end})| = |p_j^e - p_{j,end}|$ is the absolute value of the difference between the price prediction and last observed price at series j . The independent variable is (are) $\#Reversals_j$ in Panel A, and $\#Reversals_j, Z_i$ in Panel B. $\#Reversals_j$ is the number of reversals of the whole year stock series in Model 1, of the last 3 months in Model 2 and of the last 6 months in Model 3.

Panel A			
	Model 1	Model 2	Model 3
Dep: $ E(\Delta p_{j,end}) $			
$\#Reversals$ in 1 Year	0.143*** (3.01)		
$\#Reversals$ in last 3 months		0.287*** (2.78)	
$\#Reversals$ in last 6 months			0.190** (2.46)
Cons	-12.59** (-2.13)	-7.288 (-1.61)	-11.67* (-1.67)
$adj.R^2$	0.004	0.008	0.005
Panel B			
	Model 1	Model 2	Model 3
Dep: $ E(\Delta p_{j,end}) $			
$\#Reversals$ in 1 Year	0.143*** (3.03)		
$\#Reversals$ in last 3 months		0.287*** (2.80)	
$\#Reversals$ in last 6 months			0.190** (2.48)
Social intelligence test	0.00910 (0.14)	0.00910 (0.14)	0.00910 (0.14)
Raven test	-0.107 (-0.73)	-0.107 (-0.73)	-0.107 (-0.73)
CRT	0.438 (1.57)	0.438 (1.57)	0.438 (1.57)
Loss aversion	-1.262* (-1.92)	-1.262* (-1.93)	-1.262* (-1.92)
Risk aversion	-0.282 (-1.24)	-0.282 (-1.25)	-0.282 (-1.25)
Age	-0.137 (-1.24)	-0.137 (-1.25)	-0.137 (-1.24)
Male	-2.787*** (-2.94)	-2.787*** (-2.95)	-2.787*** (-2.94)
Cons	-3.264 (-0.61)	2.040 (0.48)	-2.347 (-0.35)
$adj.R^2$	0.018	0.022	0.019
N	1620	1620	1620
t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01			

Table 3.7: This table reports the results of the regression of second equation of Equation (3.11). $Absolute\ prediction\ error = c + b_3\#Reversals_j + b_4Z_i + \varepsilon_t$. $Absolute\ prediction\ error = |p_j^e - p_{j,f}|$ is the absolute value of the difference between the price prediction and the actual price of series j . The independent variable is (are) $\#Reversals_j$ in Panel A, and $\#Reversals_j, Z_i$ in Panel B. $\#Reversals_j$ is the number of reversals of the whole year stock series in Model 1, of the last 3 months in Model 2 and of the last 6 months in Model 3.

Panel A			
	Model 1	Model 2	Model 3
Dep: <i>Absolute prediction error</i>			
#Reversals in 1 Year	0.146*** (2.80)		
#Reversals in last 3 months		0.00855 (0.08)	
#Reversals in last 6 months			-0.146* (-1.70)
Cons	-8.238 (-1.27)	10.15** (2.08)	23.99*** (3.05)
<i>adj.R</i> ²	0.002	-0.001	0.002
Panel B			
	Model 1	Model 2	Model 3
Dep: <i>Absolute prediction error</i>			
#Reversals in 1 Year	0.146*** (2.81)		
#Reversals in last 3 months		0.00855 (0.08)	
#Reversals in last 6 months			-0.146* (-1.70)
Social intelligence test	0.0257 (0.27)	0.0257 (0.27)	0.0257 (0.27)
Raven test	-0.180 (-0.88)	-0.180 (-0.88)	-0.180 (-0.88)
CRT	0.488 (1.44)	0.488 (1.43)	0.488 (1.43)
Loss aversion	-1.166 (-1.53)	-1.166 (-1.53)	-1.166 (-1.53)
Risk aversion	-0.0937 (-0.25)	-0.0937 (-0.25)	-0.0937 (-0.25)
Age	-0.0498 (-0.29)	-0.0498 (-0.29)	-0.0498 (-0.29)
Male	-2.652** (-2.39)	-2.652** (-2.38)	-2.652** (-2.38)
Cons	-1.853 (-0.25)	16.53*** (2.67)	30.37*** (3.48)
<i>adj.R</i> ²	0.008	0.005	0.007
N	1620	1620	1620
t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01			

Further, we check whether the number of reversals leads to the underreaction and overreaction to the stock prices. We tested the equation below:

$$\begin{aligned} \text{Prediction error} &= c + b_5 \#Reversals_j + b_6 Z_i + \varepsilon_t \\ E(\Delta p_{j,end}) &= c + b_5 \#Reversals_j + b_6 Z_i + \varepsilon_t \end{aligned} \quad (3.12)$$

where $\#Reversals_j$ and Z_i are the same variables in Eq. (3.9). $\text{Prediction error} = p_j^e - p_{j,f}$ denotes the price forecast deviates from the actual price, and $E(\Delta p_{j,end}) = p_j^e - p_{j,end}$ denotes the price forecast deviates from the last observed price. $\#Reversals_j$ is the number of reversals of the whole year stock series in Model 1, of the last 3 months in Model 2 and of the last 6 months in Model 3. The dependent variable is $\text{Prediction error} = p_j^e - p_{j,f}$ in Table 3.8. The independent variable is (are) $\#Reversals_j$ in Panel A, and $\#Reversals_j, Z_i$ in Panel B. We do not observe the impact of the reversals in the whole year stock series on prediction behavior, while we do observe that more reversals in the last 3/6 months could lead to overreaction from the actual price. We also find that individuals with high social intelligence scores and raven scores or more loss averse tend to underreact to the actual price, while with high CRT scores tend to overreact to the actual price. The result that the dependent variable is $E(\Delta p_{j,end})$ is reported in Table B6 in Appendix B. The results suggest that subjects with higher social intelligence score/raven test scores tend to underreact to the last observed stock prices by 0.279/0.456 in the stock series. While higher CRT scores make participants overreact to the stock prices by 0.795. Participant tends to underreact to the last observed price when he/she is more loss averse. We do not observe the number of reversals affects the reaction to the last observed price. We further check the interaction between the number of reversals and skills that are reported in Model 4 and Model 5 of Table B3, Table B4 and Table B5 in Appendix B, and we do not observe the significant interaction between reversals and skills on prediction errors, except that individuals with high CRT score tend to overreact to the actual price and last observed price when the stock series has more reversals.

Result 5: *Individuals tend to make larger predicted price changes from last observed price when the number of reversals is higher. We find that more reversals in the stock price series of the whole year/last 6 months lead to higher/lower price changes from the actual price.*

Result 6: *Males make more precise prediction of the price than female. More loss averse individuals tend to make a closer prediction to the last observed price. We do not find that individuals' risk preference and other profiles affect their accuracy of prediction.*

Result 7: *More reversals of the last 3/last 6 months lead to overreaction to the actual price. Subjects with higher social intelligence score/raven test scores tend to underreact to the stock prices. While higher CRT scores make participants overreact to the stock prices. Participant tends to underreact to the stock price when he/she is more loss averse. Individuals with high CRT score tend to overreact to the actual price and last observed price when the stock series has more reversals.*

Table 3.8: This table reports the regression results of Eq. (3.12), where $\#Reversals_j$ and Z_i are the same variables in Eq. (3.9). The dependent variable is $Prediction\ error = p_j^e - p_{j,f}$. The independent variable is (are) $\#Reversals_j$ in Panel A, and $\#Reversals_j, Z_i$ in Panel B. $\#Reversals_j$ is the number of reversals of the whole year stock series in Model 1, of the last 3 months in Model 2 and of the last 6 months in Model 3.

Panel A			
	Model 1	Model 2	Model 3
Dep: <i>Prediction error</i>			
#Reversals in 1 Year	0.0296 (0.49)		
#Reversals in last 3 months		0.713*** (5.89)	
#Reversals in last 6 months			0.706*** (7.54)
Cons	-5.484 (-0.72)	-34.32*** (-6.31)	-66.72*** (-7.75)
<i>adj.R</i> ²	0.001	0.025	0.036
Panel B			
	Model 1	Model 2	Model 3
Dep: <i>Prediction error</i>			
#Reversals in 1 Year	0.0296 (0.49)		
#Reversals in last 3 months		0.713*** (5.93)	
#Reversals in last 6 months			0.706*** (7.57)
Social intelligence test	-0.279** (-2.37)	-0.279** (-2.39)	-0.279** (-2.41)
Raven test	-0.456* (-1.83)	-0.456* (-1.85)	-0.456* (-1.86)
CRT	0.795** (2.01)	0.795** (2.04)	0.795** (2.05)
Loss aversion	-1.589* (-1.85)	-1.589* (-1.87)	-1.589* (-1.88)
Risk aversion	0.198 (0.41)	0.198 (0.42)	0.198 (0.42)
Age	0.104 (0.46)	0.104 (0.47)	0.104 (0.48)
Male	-1.496 (-1.17)	-1.496 (-1.19)	-1.496 (-1.19)
Cons	6.343 (0.69)	-22.50*** (-2.91)	-54.89*** (-5.40)
<i>adj.R</i> ²	0.003	0.028	0.039
N	1620	1620	1620
t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01			

3.4.4 Other Measures of Predictability and Prediction of Price

In this section, we further check whether the volatility and autocorrelation of stock series would affect the prediction of the stock price in both the direction and prediction error. The measurement of volatility (vol_j) used in this section is the variance of stock series (σ_j), and amplitude of stock series, that is, $Amplitude_j = p_{max} - p_{min}$. The measurement of the autocorrelation of the stock price series is the autocorrelation coefficient, ρ . Since the stock series is not stationary, we applied AR (20) to get the mean. Additionally, we use the one-period lagged subject i 's return of stock series j , $Return_{i,j-1}$, as the proxy to measure the predictability of the stock series. We run the pooled regression of Eq. (3.13).

$$\begin{aligned} y_{i,j} &= c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + \varepsilon_t \\ \text{Absolute prediction error} &= c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + \varepsilon_t \\ |E(\Delta p_{j,end})| &= c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + \varepsilon_t \end{aligned} \quad (3.13)$$

Where $y_{i,j}$, *Absolute prediction error*, $|E(\Delta p_{j,end})|$ and Z_i is same as in Eq. (3.9) and Eq. (3.11). The main independent variable is $Amplitude_j$ and σ_j in Table 3.9, ρ and $Return_{i,j-1}$ in Table 3.10. The dependent variable is (are) $y_{i,j}$ in Model 1 and Model 4, *Absolute prediction error* in Model 2 and Model 5, $|E(\Delta p_{j,end})|$ in Model 3 and Model 6. Panel B includes all independent variables in Eq. (3.13), while Panel A excludes Z_i . Table 3.9 reports the results of the regression.

Our results suggest that with the increase of one unit of the amplitude of the stock series, the log odds of correct prediction of the price movement (versus incorrect prediction) decrease by 0.0133 significantly, as reported in Model 1 of Table 3.9. In other words, with the increase of amplitude, the correct prediction of the movement of a price decreases. Also, with the increase of one unit of the amplitude of the stock series, the prediction of price deviates from the actual price by 0.147 and the observed price increases by 0.0422 significantly. The result is robust when other profiles are added. Thus, with the increase of the gap between the maximum price and minimum price of the stock series, individuals tend to make less accurate of the prediction of the price movement, higher deviation of the price prediction from the actual price and observed price.

The result is consistent if we use the variance of the stock series as the main independent variable and is reported in Model 4 to Model 6 of Table 3.9. Increasing the variance of the stock series leads to the fewer correct prediction of the price movement of the stock series, also larger price deviation from the actual price. Our findings indicate that the volatility of the stock series is also an indicator of the price forecast.

Additionally, the regression results of autocorrelation indicate that the log odds of correct prediction of the price movement (versus incorrect prediction) decrease by 2.76 significantly, as reported in Model 1 of Table 3.10. In other words, with

Table 3.9: This table reports the regression results of Eq. (3.13). The main independent variable is the amplitude of the stock series in Model 1 to Model 3, the variance of stock series in Model 4 to Model 6. The dependent variable is (are) $y_{i,j}$ in Model 1 and Model 4, *Absolute prediction error* in Model 2 and Model 5, $|E(\Delta p_{j,end})|$ in Model 3 and Model 6. Panel B includes all independent variables in Eq. (3.13), while Panel A excludes Z_i .

Panel A						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Amplitude of series	-0.0133*** (-4.39)	0.147*** (7.27)	0.0422** (2.43)			
Variance of series				-0.00228*** (-5.72)	0.0183*** (6.46)	0.00133 (0.68)
Cons	0.514*** (3.87)	4.584*** (5.08)	4.162*** (4.92)	0.287*** (3.88)	8.021*** (13.75)	5.686*** (10.78)
$pseudo/adj.R^2$	0.009	0.020	0.002	0.015	0.018	0.000
Panel B						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Amplitude of series	-0.0134*** (-4.40)	0.147*** (7.29)	0.0422** (2.45)			
Variance of series				-0.00229*** (-5.73)	0.0183*** (6.47)	0.00133 (0.69)
Social intelligence test	-0.00897 (-0.66)	0.0257 (0.28)	0.00910 (0.14)	-0.00905 (-0.66)	0.0257 (0.28)	0.00910 (0.14)
Raven test	0.0145 (0.53)	-0.180 (-0.89)	-0.107 (-0.73)	0.0147 (0.53)	-0.180 (-0.89)	-0.107 (-0.73)
CRT	-0.0255 (-0.67)	0.488 (1.45)	0.438 (1.57)	-0.0257 (-0.67)	0.488 (1.44)	0.438 (1.57)
Loss aversion	-0.0818 (-1.08)	-1.166 (-1.54)	-1.262* (-1.92)	-0.0825 (-1.09)	-1.166 (-1.54)	-1.262* (-1.92)
Risk aversion	-0.0322 (-0.53)	-0.0937 (-0.26)	-0.282 (-1.26)	-0.0324 (-0.53)	-0.0937 (-0.26)	-0.282 (-1.25)
Age	-0.0246 (-0.88)	-0.0498 (-0.29)	-0.137 (-1.24)	-0.0248 (-0.88)	-0.0498 (-0.29)	-0.137 (-1.24)
Male	0.0167 (0.15)	-2.652** (-2.40)	-2.787*** (-2.93)	0.0168 (0.15)	-2.652** (-2.40)	-2.787*** (-2.93)
Cons	1.674** (2.00)	10.97** (2.06)	13.49*** (3.96)	1.457* (1.75)	14.41*** (2.74)	15.01*** (4.53)
$pseudo/adj.R^2$	0.010	0.025	0.016	0.017	0.024	0.014
N	1620	1620	1620	1620	1620	1620
t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01						

the increase of autocorrelation of the stock series, the correct prediction of the movement of a price decreases. Also, with the increase of one unit of the autocorrelation of the stock series, the prediction of price deviates from the actual price increases by 29.43 significantly. We do not observe that autocorrelation of stock series significantly increases the price deviation from the observed price. The results of Model 1 to Model 3 in Table 3.10 indicate that with higher autocorrelation of the stock series, individuals tend to make a less accurate prediction of the price movement and higher deviation from the actual price. While theoretically, if a stock series has a high autocorrelation, then that means that its previous values can make a good feature for predicting future values. Therefore, individuals are supposed to make a more accurate prediction of the price movement and less deviation from the actual price when the stock series is highly autocorrelated. However, in our experiment, when the stock series is a random walk, individuals fail to follow the logic of autocorrelation. We do not observe any significant impact of the one period lagged return on the correct prediction of the price movement nor the prediction deviation as reported in Model 4 to Model 6 in Table 3.10.

Table 3.10: This table reports the regression results of Eq. (3.13). The main independent variable is the autocorrelation coefficient in Model 1 to Model 3 and the lagged return of subject i in stock series j in Model 4 to Model 6. The dependent variable is (are) $y_{i,j}$ in Model 1 and Model 4, *Absolute prediction error* in Model 2 and Model 5, $|E(\Delta p_{j,end})|$ in Model 3 and Model 6. Panel B includes all independent variables in Eq. (3.13), while Panel A excludes Z_i .

Panel A						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ρ	-2.763*** (-6.20)	29.43*** (7.38)	2.556 (0.79)			
One period lagged return				-0.0000987 (-0.12)	-0.000488 (-0.07)	-0.00560 (-1.00)
Cons	2.039*** (6.03)	-11.43*** (-3.84)	3.960 (1.57)	-0.00975 (-0.08)	10.54*** (13.80)	6.455*** (11.76)
$pseudo/adj.R^2$	0.017	0.039	0.000	0.000	0.001	0.000
Panel B						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ρ	-2.770*** (-6.21)	29.43*** (7.41)	2.556 (0.79)			
One period lagged return				-0.0000664 (-0.08)	0.00112 (0.16)	-0.00372 (-0.64)
Social intelligence test	-0.00909 (-0.66)	0.0257 (0.28)	0.00910 (0.14)	-0.00939 (-0.68)	0.0631 (0.67)	0.0243 (0.39)
Raven test	0.0147 (0.54)	-0.180 (-0.91)	-0.107 (-0.73)	0.00710 (0.25)	-0.117 (-0.57)	-0.0698 (-0.50)
CRT	-0.0258 (-0.68)	0.488 (1.46)	0.438 (1.57)	-0.0373 (-0.96)	0.368 (1.10)	0.331 (1.24)
Loss aversion	-0.0829 (-1.09)	-1.166 (-1.55)	-1.262* (-1.92)	-0.0932 (-1.21)	-0.924 (-1.25)	-1.042* (-1.67)
Risk aversion	-0.0326 (-0.54)	-0.0937 (-0.26)	-0.282 (-1.25)	-0.0452 (-0.74)	-0.0862 (-0.23)	-0.328 (-1.51)
Age	-0.0249 (-0.88)	-0.0498 (-0.30)	-0.137 (-1.24)	-0.0286 (-1.00)	-0.0620 (-0.36)	-0.171 (-1.60)
Male	0.0169 (0.15)	-2.652** (-2.41)	-2.787*** (-2.93)	0.0572 (0.49)	-2.285** (-2.07)	-2.364** (-2.54)
Cons	3.218*** (3.55)	-5.049 (-0.82)	13.29*** (3.06)	1.467* (1.72)	14.80*** (2.85)	15.13*** (5.44)
$pseudo/adj.R^2$	0.019	0.044	0.014	0.002	0.003	0.012
N	1620	1620	1620	1539	1539	1539
t statistics in parentheses *p<0.1 ** p<0.05 *** p<0.01						

Furthermore, we check the interaction between the volatility, autocorrelation of stock series, one period lagged return and skills, we do not observe the consistent and significant influence of those interaction terms on the correct prediction of price movement or prediction error as reported in Table B7, Table B8, Table B9 and Table B10 in Appendix B.

Result 8: *Individuals tend to make a less accurate prediction of the price movement, and make their forecast far from the actual price and the last observed price when the volatility of the stock series is high or when the autocorrelation of the stock series is high.*

3.5 Experimental Results for Stage 2

In Section 3.4, we find that with more reversals in the stock series, individuals tend to make fewer correct predictions of price movement. Also, their prediction of the stock price is far from the observed price and actual price when there are

more reversals in the stock series. To further check whether it is because the information exposed to the subjects is not explicit enough (the participants are informed that the stock series is randomly selected), we examine the result of Stage 2 that is constructed under a pure random walk.

Bloomfield and Hales (2002) proposed that the measure used for reaction to the past trend of the price ($REACT_{BH}$) is as below:

$$REACT_{BH} = p_{asset} - 50 \quad (3.14)$$

where p_{asset} is the price set by the participant to sell the asset back to us. Then we compare this difference with the most recent change of the random walk series. The prediction of movement is overreaction if $REACT_{BH} > 0$, in other words, offer price is larger than 50, when the most recent change is upward or $REACT_{BH} < 0$, the offer price is smaller than 50 when the most recent change is downward. The prediction of movement is underreaction if $REACT_{BH} < 0$ when the most recent change is upward or $REACT_{BH} > 0$ when the most recent change is downward.

Follow Bloomfield and Hales (2002) and make the comparison easier, we define the measure of reaction to the trend of price ($REACT$) as given:

$$REACT = \begin{cases} p_{asset} - 50 & \text{if orientation is natural} \\ 50 - p_{asset} & \text{if orientation is mirror} \end{cases} \quad (3.15)$$

The prediction of movement is overreaction if $REACT > 0$, in other words, offer price is larger/smaller than 50, when the most recent change is upward/downward. The prediction of movement is underreaction if $REACT < 0$, that is, offer price is smaller/larger than 50, when the most recent change is upward/downward.

In line with Bloomfield and Hales (2002), we categorize the random walk sequences as low reversal sequence if the number of reversals is 0 and 1, moderate reversal sequence if the number of reversals is 3 and 4 and high reversal sequence if the number of reversals is 6 and 7. According to the rank-sum test, we find that the underreaction is significantly in high reversal sequence ($z=7.852$, $p=0.0000$ comparing high reversal sequence with low reversal sequence, $z=6.401$, $p=0.0000$ comparing high reversal sequence with moderate reversal sequence), overreaction in low reversal sequence ($z=7.852$, $p=0.0000$ comparing low reversal sequence with high reversal sequence, $z=1.105$, $p=0.2692$ comparing low reversal sequence with moderate reversal sequence).

Table 3.11 below summarizes the results of mean reaction and statistical test. Our findings are consistent with Bloomfield and Hales (2002). We find that on average, individuals tend to overreact to the sequence by 4.9259/4.4259 with lower reversals and moderate reversals significantly, and underreact to the sequence by 1.0216 with higher reversals (not significantly). We observe a reversal story for natural orientation sequences and mirror orientation sequences. When the se-

quence is natural oriented, that is, the most recent change is upward, individuals tend to overreact to the sequences with lower reversals and underreact to the sequences with higher reversals. While the result is reversed when the most recent change is downward. The result is summarized in Table B11 in Appendix B.

Table 3.11: This table reports the mean reaction and the statistical result (rank sum test) of the deviation from 0 for each sequence shape at each reversal level. The first number in last column is the z-statistics of rank sum test, and the number in parentheses is the p-value.

Sequence shape	Reversal category	Reversals	Reaction	Mean Reaction for category	Statistical result of difference from 0
low	0	15.0247
low	1	-7.2099
low	1	1.2716
low	1	10.61728	4.9259	5.464 (0.0000)
moderate	3	7.4753
moderate	4	1.3765	4.4259	3.481 (0.0005)
high	6	-3.3889
high	7	1.3457	-1.0216	-1.417 (0.1566)

We further do the pooled logit regression to check the relation between the reaction to sequences and reversals. The equation tested is given below:

$$\begin{aligned}
overreaction_{i,t} = & \logit(a + b_1\#Reversals_{i,t} + b_2Category\ of\ sequence_{i,t} + b_3Mirror_{i,t} \\
& + b_4\#Reversals_{i,t} * Mirror_{i,t} / Category\ of\ sequence_{i,t} * Mirror_{i,t} + b_5Z_i + \epsilon)
\end{aligned}
\tag{3.16}$$

where the $overreaction_{i,t}$ a dummy variable that indicates whether individual i overreacts to the random walk sequence at period t . $overreaction_{i,t} = 1$ is the overreaction to random walk sequence and $overreaction_{i,t} = 0$ is underreaction to the random walk sequence. $\#Reversals_{i,t}$ is the number of reversals of the random walk sequence for individual i at period t . $Mirror_{i,t} = 1$ is mirror orientation. $Mirror_{i,t} = 0$ is natural orientation. $Category\ of\ sequence_{i,t}$ is also a dummy variable, $Category\ of\ sequence_{i,t} = 0$ is low reversals sequence, 1 is moderate reversals sequence and 2 is high reversals sequence. Z_i is the same variable adopted in Eq. (3.9). Model 1 and Model 2 examine how the number of reversals affects overreaction to a random walk sequence. For every one unit change in the number of reversals, the log odds of overreaction to the sequences (versus underreaction) decrease by 0.333 significantly as reported in Model 1. In other words, with the increase of reversals, the overreaction to random walk sequences decreases. Model 3 and Model 4 test the relation between the number of reversals, which is represented by $Category\ of\ sequence_{i,t}$ (in dummy), and overreaction to random walk sequence. The log odds of overreaction to the sequences (versus underreaction) decrease by 0.276 (not significantly) comparing low reversal sequences with moderate sequences and 0.768 significantly comparing low reversal sequences with high sequences. Hence, individuals tend to overreact to a random walk sequence when the reversals are lower. We also observe that when the sequence is the mirror image, individuals are less likely to overreact to the most recent changes. That is, when the most recent change is downward, individuals

tend to underreact to it. While the interaction between reversals and orientation of the sequences indicates that participants are more likely to overreact to the most recent downward change when the sequence has more reversals. The result is reported in Table [3.12](#).

Table 3.12: This table reports the logit regression result of Eq. (3.16). where the $overreaction_{i,t}$ a dummy variable that indicates whether individual i overreacts to the random walk sequence at period t . $overreaction_{i,t} = 1$ is the overreaction to random walk sequence and $overreaction_{i,t} = 0$ is underreaction to the random walk sequence. $Mirror_{i,t} = 1$ is mirror orientation. $Mirror_{i,t} = 0$ is natural orientation. $\#Reversals_{i,t}$ is the number of reversals of the random walk sequence for individual i at period t . $Category\ of\ sequence_{i,t}$ is also a dummy variable, $Category\ of\ sequence_{i,t} = 0$ is low reversals sequence, 1 is moderate reversals sequence and 2 is high reversals sequence. Z_i contains the survey information regarding the social intelligence test, raven test, CRT, etc.

	Model 1	Model 2	Model 3	Model 4
Dep: overreaction				
Reversals	-0.333*** (-9.51)	-0.335*** (-9.53)		
Mirror	-1.435*** (-7.90)	-1.441*** (-7.91)	-1.013*** (-6.23)	-1.018*** (-6.24)
Reversals*Mirror	0.451*** (9.34)	0.453*** (9.36)		
Default: Low reversals sequence				
Moderate reversals sequence			-0.276 (-1.42)	-0.277 (-1.42)
High reversals sequence			-2.124*** (-8.55)	-2.132*** (-8.58)
Moderate reversals sequence*Mirror			0.766*** (2.78)	0.769*** (2.78)
High reversals sequence*Mirror			2.886*** (9.12)	2.898*** (9.14)
Social intelligence test		0.0131 (0.82)		0.0131 (0.83)
Raven test		-0.0220 (-0.68)		-0.0222 (-0.68)
CRT		-0.00111 (-0.02)		-0.00115 (-0.03)
Loss aversion		-0.133 (-1.50)		-0.134 (-1.51)
Risk aversion		0.0700 (0.97)		0.0705 (0.98)
Age		-0.0427 (-1.32)		-0.0430 (-1.33)
Male		0.0599 (0.44)		0.0603 (0.45)
Cons	0.773*** (6.02)	1.827* (1.89)	0.375*** (3.31)	1.435 (1.48)
N	1296	1296	1296	1296
pseudoR ²	0.059	0.062	0.065	0.068
t statistics in parentheses * p<0.1 **p<0.05 *** p<0.01				

Further, we check the deviation of the price offered by individuals from the expected price, which is 50, concerning different categories of sequences. The equation tested is given below:

$$\begin{aligned}
REACT = a + b_1 \#Reversals_{i,t} + b_2 \text{Category of sequence}_{i,t} \\
+ b_3 Z_i + \varepsilon
\end{aligned} \tag{3.17}$$

where $REACT$ is the measure of reaction to reversals as stated in Eq. (3.15). $\#Reversals_{i,t}$, $\text{Category of sequence}_{i,t}$ and Z_i are the same variables in Eq. (3.16). The dependent variable is $REACT$, the deviation of the price offered by individuals from 50. The main independent variable is (are) $\#reversals_{i,t}$ in Model 1 and Model 3, $\text{Category of sequence}_{i,t}$ in Model 2 and Model 4. Model 3 and Model 4 includes all variables. Panel A reports the results of the subsample of the sequence of natural orientation, while Panel B reports the results of the subsample of the sequence of mirror orientation. The regression result is reported in Table 3.13.

We find that more reversals lead to deviation below 50 regardless of the orientation of the sequences. The deviation decreases by 4.618, according to Model 1. The results remain constant when we are using the dummy variable about the category of sequences that is divided by the number of reversals in sequence as the primary independent variable. The result of Model 2 in Panel A tells that the deviation from 50 declines by 5.926/26.65 when these sequences are natural orientation with moderate/high reversal. Additionally, the magnitude of this deviation is larger for natural orientation than that for mirror orientation (the result is reported in Model 2 o Panel B). Besides, we also find that males tend to make a higher positive deviation from the mean expectation than females.

Further, we check the behavioral consistency between Stage 1 and Stage 2. The correlation coefficient between the number of correct predictions of price movement in Stage 1 and the number of overreaction to random sequences in Stage 2 is 0.0107, the number of underreaction to random sequences in Stage 2 is -0.0107, $\#overreaction - \#underreaction$ to random sequences in Stage 2 is 0.0053. All those coefficients are not significant at 5% level. The regression results are reported in Table B12 in Appendix B. We failed to find any significant relationship between the number of overreaction/underreaction to the random sequences in Stage 2 and the overreaction/underreaction to the realized price or the last observed price in Stage 1. The regression results are summarized in Table B12 and Table B13 in Appendix B. Hence, we do not find any consistent and significant relationship between the performance in Stage 2 and Stage 1.

Result 9: *Individuals tend to overreact to the random walk sequences when there are fewer reversals, underreact to the sequence when there are more reversals, which confirms the findings of Bloomfield and Hales (2002). Individuals tend to underreact to the most recent upward change with more reversals, but they are more likely to overreact to the most recent downward change for the sequences with more reversals. In other words, more reversals of the sequences lead individuals to make a prediction below 50. The magnitude of this deviation is larger for natural orientation than that for mirror orientation.*

Result 10: *We failed to observe significant evidence to support the significant*

Table 3.13: This table reports the regression result of Eq. (3.17). *REACT* is the measure of reaction to reversals as stated in Eq. (3.15). *#Reversals_{i,t}*, *Category of sequence_{i,t}* and *Z_i* are the same variables in Eq. (3.16). The main independent variable is (are) *#reversals_{i,t}* in Model 1 and Model 3, *Category of sequence_{i,t}* in Model 2 and Model 4. Model 3 and Model 4 includes all variables. Panel A reports the results of the subsample of the sequence of natural orientation, while Panel B reports the results of the subsample of the sequence of mirror orientation.

	Panel A				Panel B			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
#Reversals	-4.618*** (-11.14)		-4.618*** (-11.28)		2.292*** (4.94)		2.292*** (4.99)	
Default: Low reversal sequence								
Moderate reversals sequence		-5.926** (-2.41)		-5.926** (-2.40)		4.926* (1.90)		4.926* (1.89)
High reversals sequence		-26.65*** (-10.90)		-26.65*** (-11.04)		14.75*** (5.57)		14.75*** (5.63)
Social intelligence test			0.512* (1.94)	0.512* (1.92)			-0.106 (-0.37)	-0.106 (-0.37)
Raven test			0.407 (0.85)	0.407 (0.85)			0.201 (0.33)	0.201 (0.33)
CRT			-0.306 (-0.41)	-0.306 (-0.41)			0.777 (0.93)	0.777 (0.94)
Loss aversion			0.270 (0.18)	0.270 (0.18)			-2.715* (-1.67)	-2.715* (-1.67)
Risk aversion			1.991 (1.37)	1.991 (1.36)			-0.391 (-0.27)	-0.391 (-0.27)
Age			-0.924 (-1.64)	-0.924* (-1.65)			-0.175 (-0.29)	-0.175 (-0.29)
Male			5.346** (2.50)	5.346** (2.49)			-5.203** (-2.17)	-5.203** (-2.18)
Cons	17.91*** (11.59)	12.77*** (9.27)	9.741 (0.59)	4.607 (0.28)	-4.589** (-2.55)	-2.920* (-1.84)	10.45 (0.58)	12.12 (0.68)
N	648	648	648	648	648	648	648	648
adj. R ²	0.164	0.156	0.171	0.163	0.037	0.043	0.042	0.048
t statistics in parentheses * p<0.1 **p<0.05 *** p<0.01								

correlation of performance between Stage 1 and Stage 2. More reversals lead to a lower deviation from 50, and males are more likely to deviate from 50 than females.

3.6 Conclusion

We have studied the predictability of the past price dynamics and individual's price prediction in a laboratory experiment, which is an extension of Bloomfield and Hales (2002). The first stage of the experiment provides evidence that individuals seem to make more correct predictions of the real stock price when the stock price series contains more reversals. Our results of Stage 1 suggest that the number of reversals in the short term horizon could be a good indicator of predictability of the stock series. The larger the number of reversals of the stock series, the more predictable the series is. That is also consistent with the theoretical findings by Barberis et al. (1998). People are more likely not to follow the trend when there are more reversals in the stock series. Individuals may realize that the price trend is not persistent if there are more reversals in the stock series.

Besides, we also find that the volatility of the stock series, for instance, variance and amplitude, contains the information of the predictability of the stock series. It is difficult for individuals to predict accurately when the volatility of the stock series is higher. The results of Stage 2 in our experiment are consistent with Bloomfield and Hales (2002), which is that individuals underreact to sequences with more reversals (not significant) and overreact to sequences with fewer reversals. Besides, we find that individuals tend to set a lower price (below 50) to the sequence with more reversals regardless of whether the most recent change is upward or downward. We also find that individuals overreact (underreact) to random sequences in Stage 2 would be more likely to have over (under) price prediction to the last observed price in Stage 1. However, this is not significant.

The more reversals in the stock price series would require high cognitive loading since it is more complicated to find the pattern. However, we do not observe the significant and persistent impact of social intelligence, cognitive skills on prediction behavior.

Lastly, our findings may provide a new perspective on the efficiency of individual decision making based on price charts in financial markets.

3.7 Appendix A

Instruction for Part 1

Welcome to Part 1 of our experiment. In this part of the experiment, you will be shown 20 graphs showing 12 months of end-of-day prices of randomly selected stocks from the SP 500 starting from a randomly selected day between January 1st 2008 and June 30th 2018. You will not be told about the name of the stock or the starting date which was randomly selected. **Please note that end-of-day prices have been rescaled so that all starting prices will be equal to 100.**

For each graph, you will be asked to forecast what will be the end-of-day price for this stock **30 days after the last price shown on the graph.**

You will be rewarded based on the accuracy of your forecasts as follows.

$$\max[200 - 10 \mid (your\ forecast - realized\ price) / (realized\ price) 100 \mid, 0]$$

If your forecast is exactly at the realized price, then you will receive 200 points. For each percentage point difference between your forecast and the realized price, 10 points will be subtracted.

If your forecast differs from the realized price by more than 20%, you will receive 0 point.

You will do a similar forecasting task for all the 20 randomly chosen stocks. **You will be paid for the points you have obtained in one of the 20 predictions.**

You will not be informed about the accuracy of your forecast until this part of the experiment ends.

Instruction for Part 2

We have constructed a model of a random process that works much like flipping a fair coin. Using this model, we have created sequences of outcomes. An upward movement indicates a “heads” outcome, and a downward movement indicates a “tails” outcome.

Since outcomes of coin flips are unpredictable, they result in a sequence known as a “random walk.” That is, statistical models are unable to predict future outcomes from past ones and, on average, there is no upward or downward trend. Random walk sequences almost always contain intervals of recognizable patterns. However, since these patterns can change greatly at any time, statistical models are still unable to predict future outcomes.

You will be shown 16 plots we have created as described. You are given one unit of bet that will generate either 0 or 100 points depending on the next movement (on how the series move next). Your bet generates 100 points if it moves upward, and 0 point if it moves downward.

You are asked to name the price (in points) at which you are willing to sell this bet back to us. The price you can set is between 0 and 100 points.

We will calculate your earnings for this part as follows.

We will select one of the 16 plots at random and then generate a random number between 0 and 100 (each number is equally likely). If the randomly generated number is less than or equal to the price you have set for the bet, then, you will keep the bet and your payoff will be either 0 or 100 points depending on the next move of the series represented on the plot. If the randomly generated number is greater than the price you have set for the bet, then, you will receive the points equal to the randomly generated number.

Example 1. If you set the price for the bet to be 50 points and the randomly generated number is 40, you keep the bet and your payoff will be either 0 or 100 points.

Example 2. If you set the price for the bet to be 50 points and the randomly generated number is 60, you receive 60 points.

You will be paid for the points you have obtained in one of the 16 plots. You will not be informed about the accuracy of your forecast until this part of the experiment ends.

Figure A1: This figure depicts the dynamic of stock series 1 to stock series 4 of Stage 1 in the experiment.

Figure A2: This figure depicts the dynamic of stock series 5 to stock series 8 of Stage 1 in the experiment.

Figure A3: This figure depicts the dynamic of stock series 9 to stock series 12 of Stage 1 in the experiment.

Figure A4: This figure depicts the dynamic of stock series 13 to stock series 16 of Stage 1 in the experiment.

Figure A5: This figure depicts the dynamic of stock series 17 to stock series 20 of Stage 1 in the experiment.

3.8 Appendix B

Table B1: This table reports the descriptive statistics of the results of the social intelligence test, raven test, crt, loss aversion and risk aversion. The data is categorized into three levels in the second to fourth columns: low if the score is below 33 percentile of the whole sample, medium is the score is between 33 percentile and 67 percentile of the whole sample and high is the score is above the 67 percentile of the whole sample. The last column reports the statistics of the whole sample.

Social Intelligence Test				
	Low	Medium	High	Whole sample
Obs.	27	29	25	81
Mean	19.9259	24.5172	28.76	24.2963
Median	20	25	28	25
Std	2.0367	1.0896	1.7861	3.9257
Min	15	23	27	15
Max	22	26	34	34
Raven Test				
	Low	Medium	High	Whole sample
Obs.	23	22	36	81
Mean	8.8696	11.2727	13.5556	11.6049
Median	9	11	13	12
Std	1.1795	0.4558	0.8433	2.1545
Min	6	11	13	6
Max	10	12	16	16
CRT				
	Low	Medium	High	Whole sample
Obs.	24	35	22	81
Mean	3.1667	5.6286	7	5.2716
Median	3.5	6	7	6
Std	1.0072	0.4902	0	1.6125
Min	1	5	7	1
Max	4	6	7	7
Loss aversion				
	Low	Medium	High	Whole sample
Obs.	25	40	16	81
Mean	3	4	5.0625	3.9012
Median	3	4	5	4
Std	0	0	0.25	0.7349
Min	3	4	5	3
Max	3	4	6	6
Risk aversion				
	Low	Medium	High	Whole sample
Obs.	14	44	23	81
Mean	3	4	5.4783	4.2469
Median	3	4	5	4
Std	0	0	0.5931	0.9156
Min	3	4	7	3
Max	3	4	7	7

Table B2: This table reports the correlation coefficients among the profiles of subjects. Individuals are more likely to have a higher score in Raven test if they have a higher score in CRT. Loss aversion and risk aversion is positively related, that is more loss averse people are more risk averse.

	Social intelligence test	Raven test	CRT	Loss aversion	Risk aversion
Social intelligence test	1.0000				
Raven test	-0.2476 (0.2586)	1.0000			
CRT	-0.1392 (1.0000)	0.3875* (0.0035)	1.0000		
Loss aversion	-0.1067 (1.0000)	-0.1276 (1.0000)	0.044 (1.0000)	1.0000	
Risk aversion	0.0003 (1.0000)	0.0818 (1.0000)	-0.1476 (1.0000)	0.3153* (0.0414)	1.0000

Table B3: This table reports the regression results of $y_{i,j} = \text{logit}(c + b_1\#Reversals_j + b_2Z_i + b_3\#Reversals * Z_i + \varepsilon_j)$ in Model 1, *Absolute prediction error* $= c + b_3\#Reversals_j + b_4Z_i + b_5\#Reversals * Z_i + \varepsilon_i$ in Model 2, $|E(\Delta p_{j,end})| = c + b_3\#Reversals_j + b_4Z_i + b_5\#Reversals * Z_i + \varepsilon_i$ in Model 3, *Prediction error* $= c + b_5\#Reversals_j + b_6Z_i + b_7\#Reversals * Z_i + \varepsilon_i$ in Model 4 and $E(\Delta p_{j,end}) = c + b_5\#Reversals_j + b_6Z_i + b_7\#Reversals * Z_i + \varepsilon_i$ in Model 6, where $y_{i,j}$, Z_i are defined in Eq. (3.9), $|E(\Delta p_{j,end})|$ and *Absolute prediction error* are defined in Eq. (3.11), *Prediction error* and $E(\Delta p_{j,end})$ are defined in Eq. (3.12). *#Reversals* is the number of reversals of the stock series in 1 year.

	Model 1	Model 2	Model 3	Model 4	Model 5
Dep:	$y_{i,j}$	<i>Absolute prediction error</i>	$ E(\Delta p_{j,end}) $	<i>Prediction error</i>	$E(\Delta p_{j,end})$
#Reversals in 1 year	0.209 (1.59)	0.522 (0.93)	0.678 (1.53)	0.0231 (0.03)	-0.0650 (-0.12)
Social intelligence test	0.239 (0.86)	0.119 (0.09)	0.351 (0.32)	1.393 (0.83)	1.393 (1.02)
Raven test	0.199 (0.35)	2.532 (0.84)	3.428 (1.32)	5.395 (1.50)	5.395* (1.80)
CRT	-0.0653 (-0.08)	-5.648 (-1.06)	-7.043 (-1.44)	-10.67* (-1.72)	-10.67** (-1.99)
Loss aversion	-2.030 (-1.29)	17.57 (1.46)	15.77 (1.40)	19.90 (1.46)	19.90* (1.66)
Risk aversion	1.294 (1.04)	-3.487 (-0.69)	-4.138 (-0.97)	-4.680 (-0.66)	-4.680 (-0.88)
Age	1.040* (1.79)	-1.275 (-0.53)	-0.344 (-0.17)	-5.487* (-1.66)	-5.487** (-2.19)
Male	-2.547 (-1.08)	24.13 (1.36)	21.62 (1.31)	13.27 (0.66)	13.27 (0.74)
#Reversals*Social intelligence test	-0.00192 (-0.89)	-0.000722 (-0.07)	-0.00265 (-0.30)	-0.0130 (-0.98)	-0.0130 (-1.20)
#Reversals*Raven test	-0.00143 (-0.33)	-0.0210 (-0.87)	-0.0274 (-1.32)	-0.0454 (-1.59)	-0.0454* (-1.90)
#Reversals*CRT	0.000310 (0.05)	0.0476 (1.11)	0.0580 (1.47)	0.0889* (1.80)	0.0889** (2.07)
#Reversals*Loss aversion	0.0151 (1.25)	-0.145 (-1.50)	-0.132 (-1.45)	-0.167 (-1.53)	-0.167* (-1.72)
#Reversals*Risk aversion	-0.0103 (-1.07)	0.0263 (0.66)	0.0299 (0.88)	0.0378 (0.69)	0.0378 (0.91)
#Reversals*Age	-0.00825* (-1.83)	0.00950 (0.50)	0.00161 (0.10)	0.0433* (1.67)	0.0433** (2.19)
#Reversals*Male	0.0199 (1.08)	-0.208 (-1.46)	-0.189 (-1.42)	-0.114 (-0.71)	-0.114 (-0.80)
Cons	-25.89 (-1.52)	-50.46 (-0.71)	-72.30 (-1.30)	7.188 (0.07)	20.28 (0.30)
N	1620	1620	1620	1620	1620
<i>pseudo/adj.R</i> ²	0.006	0.006	0.018	0.001	0.010

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Table B4: This table reports the regression results of $y_{i,j} = \text{logit}(c + b_1\#Reversals_j + b_2Z_i + b_3\#Reversals * Z_i + \varepsilon_j)$ in Model 1, $\text{Absolute prediction error} = c + b_3\#Reversals_j + b_4Z_i + b_5\#Reversals * Z_i + \varepsilon_{jt}$ in Model 2, $|E(\Delta p_{j,end})| = c + b_3\#Reversals_j + b_4Z_i + b_5\#Reversals * Z_i + \varepsilon_t$ in Model 3, $\text{Prediction error} = c + b_5\#Reversals_j + b_6Z_i + b_7\#Reversals * Z_i + \varepsilon_t$ in Model 4 and $E(\Delta p_{j,end}) = c + b_5\#Reversals_j + b_6Z_i + b_7\#Reversals * Z_i + \varepsilon_t$ in Model 6, where $y_{i,j}$, Z_i are defined in Eq. (3.9), $|E(\Delta p_{j,end})|$ and $\text{Absolute prediction error}$ are defined in Eq. (3.11), Prediction error and $E(\Delta p_{j,end})$ are defined in Eq. (3.12). $\#Reversals$ is the number of reversals of the stock series in the last 3 months.

	Model 1	Model 2	Model 3	Model 4	Model 5
	$y_{i,j}$	$\text{Absolute prediction error}$	$ E(\Delta p_{j,end}) $	Prediction error	$E(\Delta p_{j,end})$
#Reversals in last 3 month	0.311 (1.63)	0.651 (0.62)	1.257 (1.43)	1.026 (0.78)	0.266 (0.26)
Social intelligence test	0.139 (0.97)	0.320 (0.36)	0.457 (0.58)	0.719 (0.66)	0.719 (0.79)
Raven test	-0.185 (-0.64)	2.106 (0.98)	1.684 (0.87)	4.037 (1.63)	4.037* (1.90)
CRT	0.382 (0.96)	-5.970 (-1.48)	-4.930 (-1.31)	-7.242 (-1.65)	-7.242* (-1.83)
Loss aversion	-0.550 (-0.70)	12.42 (1.34)	11.47 (1.31)	13.89 (1.39)	13.89 (1.51)
Risk aversion	0.0392 (0.06)	-2.709 (-0.77)	-4.302 (-1.32)	-1.157 (-0.25)	-1.157 (-0.32)
Age	0.518* (1.74)	-1.136 (-0.66)	-0.225 (-0.14)	-3.803* (-1.74)	-3.803** (-2.13)
Male	-1.139 (-0.94)	17.64 (1.30)	15.85 (1.24)	16.00 (1.09)	16.00 (1.18)
#Reversals*Social intelligence test	-0.00323 (-1.04)	-0.00642 (-0.33)	-0.00978 (-0.55)	-0.0218 (-0.92)	-0.0218 (-1.06)
#Reversals*Raven test	0.00436 (0.70)	-0.0499 (-1.05)	-0.0391 (-0.89)	-0.0981* (-1.81)	-0.0981** (-2.04)
#Reversals*CRT	-0.00890 (-1.03)	0.141 (1.55)	0.117 (1.36)	0.175* (1.78)	0.175* (1.94)
#Reversals*Loss aversion	0.0102 (0.60)	-0.297 (-1.41)	-0.278 (-1.38)	-0.338 (-1.51)	-0.338 (-1.61)
#Reversals*Risk aversion	-0.00156 (-0.11)	0.0571 (0.75)	0.0878 (1.20)	0.0296 (0.30)	0.0296 (0.37)
#Reversals*Age	-0.0118* (-1.83)	0.0237 (0.63)	0.00193 (0.05)	0.0853* (1.80)	0.0853** (2.12)
#Reversals*Male	0.0253 (0.96)	-0.443 (-1.44)	-0.407 (-1.39)	-0.382 (-1.16)	-0.382 (-1.23)
Cons	-13.13 (-1.50)	-12.90 (-0.27)	-42.39 (-1.10)	-36.84 (-0.60)	-0.301 (-0.01)
N	1620	1620	1620	1620	1620
$pseudo/adj.R^2$	0.007	0.007	0.027	0.030	0.016

t statistics in parentheses * p<0.1 **p<0.05 *** p<0.01

Table B5: This table reports the regression results of $y_{i,j} = \text{logit}(c + b_1\#Reversals_j + b_2Z_i + b_3\#Reversals * Z_i + \varepsilon_j)$ in Model 1, $\text{Absolute prediction error} = c + b_3\#Reversals_j + b_4Z_i + b_5\#Reversals * Z_i + \varepsilon_i$ in Model 2, $|E(\Delta p_{j,end})| = c + b_3\#Reversals_j + b_4Z_i + b_5\#Reversals * Z_i + \varepsilon_i$ in Model 3, $\text{Prediction error} = c + b_5\#Reversals_j + b_6Z_i + b_7\#Reversals * Z_i + \varepsilon_i$ in Model 4 and $E(\Delta p_{j,end}) = c + b_5\#Reversals_j + b_6Z_i + b_7\#Reversals * Z_i + \varepsilon_i$ in Model 6, where $y_{i,j}$, Z_i are defined in Eq. (3.9), $|E(\Delta p_{j,end})|$ and $\text{Absolute prediction error}$ are defined in Eq. (3.11), Prediction error and $E(\Delta p_{j,end})$ are defined in Eq. (3.12). $\#Reversals$ is the number of reversals of the stock series in the last 6 months.

	Model 1	Model 2	Model 3	Model 4	Model 5
	$y_{i,j}$	$\text{Absolute prediction error}$	$ E(\Delta p_{j,end}) $	Prediction error	$E(\Delta p_{j,end})$
#Reversals in last 6 month	0.229 (1.49)	0.569 (0.64)	0.962 (1.48)	0.941 (0.89)	0.237 (0.31)
Social intelligence test	0.202 (0.87)	0.578 (0.39)	0.870 (0.78)	1.221 (0.70)	1.221 (0.91)
Raven test	0.0213 (0.05)	1.902 (0.53)	2.087 (0.71)	5.894 (1.47)	5.894* (1.80)
CRT	0.546 (0.83)	-6.168 (-0.94)	-5.894 (-1.00)	-9.867 (-1.39)	-9.867 (-1.58)
Loss aversion	-0.853 (-0.65)	15.45 (1.03)	13.99 (1.01)	16.77 (1.06)	16.77 (1.16)
Risk aversion	0.310 (0.30)	-2.246 (-0.39)	-3.033 (-0.72)	-4.141 (-0.60)	-4.141 (-0.83)
Age	0.767 (1.59)	-0.222 (-0.08)	-0.235 (-0.11)	-4.167 (-1.25)	-4.167* (-1.71)
Male	-2.184 (-1.10)	17.83 (0.82)	19.57 (0.98)	9.972 (0.43)	9.972 (0.47)
#Reversals*Social intelligence test	-0.00229 (-0.91)	-0.00599 (-0.38)	-0.00934 (-0.76)	-0.0163 (-0.87)	-0.0163 (-1.10)
#Reversals*Raven test	-0.0000740 (-0.01)	-0.0226 (-0.58)	-0.0238 (-0.73)	-0.0689 (-1.59)	-0.0689* (-1.90)
#Reversals*CRT	-0.00620 (-0.87)	0.0722 (1.01)	0.0687 (1.05)	0.116 (1.50)	0.116* (1.68)
#Reversals*Loss aversion	0.00837 (0.59)	-0.180 (-1.10)	-0.165 (-1.08)	-0.199 (-1.15)	-0.199 (-1.25)
#Reversals*Risk aversion	-0.00371 (-0.33)	0.0234 (0.38)	0.0299 (0.64)	0.0471 (0.64)	0.0471 (0.86)
#Reversals*Age	-0.00859* (-1.65)	0.00187 (0.06)	0.00107 (0.05)	0.0464 (1.30)	0.0464* (1.72)
#Reversals*Male	0.0239 (1.11)	-0.222 (-0.93)	-0.243 (-1.10)	-0.124 (-0.49)	-0.124 (-0.53)
Cons	-19.98 (-1.41)	-35.47 (-0.43)	-73.46 (-1.25)	-76.52 (-0.77)	-9.996 (-0.14)
N	1620	1620	1620	1620	1620
$pseudo/adj.R^2$	0.005	0.006	0.019	0.038	0.010

t statistics in parentheses *p<0.1 ** p<0.05 *** p<0.01

Table B6: This table reports the regression results of Eq. (3.12), where Z_i is the same variable in Eq. (3.9). $\#Reversals_j$ is the number of reversals of the whole year stock series in Model 1, of the last 3 months in Model 2 and of the last 6 months in Model 3 and all are included in Model 4. The dependent variable is $E(\Delta p_{j,end}) = p_j^e - p_{j,end}$. The independent variable is (are) $\#Reversals_j$ in Panel A, and $\#Reversals_j, Z_i$ in Panel B.

Panel A			
	Model 1	Model 2	Model 3
Dep: $E(\Delta p_{j,end})$			
$\#Reversals$ in 1 Year	-0.0585 (-1.12)		
$\#Reversals$ in last 3 months		-0.0470 (-0.42)	
$\#Reversals$ in last 6 months			0.00272 (0.03)
Cons	7.607 (1.17)	2.215 (0.45)	-0.189 (-0.03)
$adj.R^2$	0.000	0.000	0.001
Panel B			
	Model 1	Model 2	Model 3
Dep: $E(\Delta p_{j,end})$			
$\#Reversals$ in 1 Year	-0.0585 (-1.13)		
$\#Reversals$ in last 3 months		-0.0470 (-0.43)	
$\#Reversals$ in last 6 months			0.00272 (0.03)
Social intelligence test	-0.279*** (-3.60)	-0.279*** (-3.60)	-0.279*** (-3.60)
Raven test	-0.456*** (-2.70)	-0.456*** (-2.69)	-0.456*** (-2.69)
CRT	0.795*** (2.63)	0.795*** (2.63)	0.795*** (2.63)
Loss aversion	-1.589** (-2.29)	-1.589** (-2.29)	-1.589** (-2.29)
Risk aversion	0.198 (0.71)	0.198 (0.71)	0.198 (0.71)
Age	0.104 (0.76)	0.104 (0.76)	0.104 (0.76)
Male	-1.496 (-1.47)	-1.496 (-1.47)	-1.496 (-1.47)
Cons	19.43*** (3.10)	14.04*** (2.81)	11.64 (1.55)
$adj.R^2$	0.010	0.009	0.009
N	1620	1620	1620
t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01			

Table B7: This table reports the regression results of $y_{i,j} = c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 vol_j * Z_i + \varepsilon_t$ in Model 1, *Absolute prediction error* $= c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 vol_j * Z_i + \varepsilon_t$ in Model 2, $|E(\Delta p_{j,end})| = c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 vol_j * Z_i + \varepsilon_t$ in Model 3, *Prediction error* $= c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 vol_j * Z_i + \varepsilon_t$ in Model 4, $E(\Delta p_{j,end}) = c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 vol_j * Z_i + \varepsilon_t$ in Model 5, where the notation of all variables are in Eq. (3.13). The main independent variable is amplitude of the stock series.

	Model 1	Model 2	Model 3	Model 4	Model 5
	$y_{i,j}$	<i>Absolute prediction error</i>	$ E(\Delta p_{j,end}) $	<i>Prediction error</i>	$E(\Delta p_{j,end})$
Amplitude	-0.00406 (-0.08)	0.129 (0.53)	-0.0704 (-0.41)	0.00155 (0.00)	-0.0328 (-0.16)
Social intelligence test	-0.0226 (-0.62)	-0.131 (-0.80)	-0.172 (-1.19)	-0.201 (-0.99)	-0.201 (-1.17)
Raven test	0.0189 (0.26)	-0.690* (-1.72)	-0.538 (-1.48)	-0.360 (-0.78)	-0.360 (-0.89)
CRT	-0.0984 (-0.95)	1.452* (1.93)	1.058 (1.49)	0.515 (0.61)	0.515 (0.68)
Loss aversion	0.183 (0.90)	-3.039* (-1.75)	-2.571 (-1.55)	-2.336 (-1.24)	-2.336 (-1.35)
Risk aversion	0.0897 (0.55)	0.577 (0.92)	0.576 (1.01)	0.119 (0.15)	0.119 (0.18)
Age	-0.0331 (-0.45)	0.337 (1.07)	-0.00638 (-0.02)	0.240 (0.60)	0.240 (0.71)
Male	-0.566* (-1.85)	-2.547 (-1.00)	-2.371 (-0.98)	-5.039* (-1.81)	-5.039** (-1.97)
Amplitude*Social intelligence test	0.000338 (0.41)	0.00387 (0.88)	0.00447 (1.32)	-0.00192 (-0.35)	-0.00192 (-0.46)
Amplitude*Raven test	-0.000104 (-0.06)	0.0126 (1.29)	0.0106 (1.38)	-0.00236 (-0.20)	-0.00236 (-0.26)
Amplitude*CRT	0.00180 (0.76)	-0.0238 (-1.44)	-0.0153 (-1.07)	0.00690 (0.36)	0.00690 (0.44)
Amplitude*Loss aversion	-0.00657 (-1.42)	0.0463 (1.25)	0.0323 (0.97)	0.0185 (0.45)	0.0185 (0.52)
Amplitude*Risk aversion	-0.00303 (-0.81)	-0.0166 (-0.97)	-0.0212 (-1.64)	0.00195 (0.09)	0.00195 (0.12)
Amplitude*Age	0.000210 (0.12)	-0.00955 (-1.19)	-0.00322 (-0.52)	-0.00337 (-0.31)	-0.00337 (-0.44)
Amplitude*Male	0.0144** (2.06)	-0.00259 (-0.05)	-0.0103 (-0.21)	0.0875 (1.41)	0.0875* (1.68)
Cons	1.303 (0.59)	11.69 (1.29)	18.05** (2.40)	10.10 (0.87)	13.21 (1.48)
N	1620	1620	1620	1620	1620
<i>pseudo/adj.R</i> ²	0.015	0.023	0.013	0.001	0.008

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Table B8: This table reports the regression results of $y_{i,j} = c + b_7vol_j/\rho_j/Return_{i,j-1} + b_8Z_i + b_9vol_j * Z_i + \varepsilon_t$ in Model 1, *Absolute prediction error* $= c + b_7vol_j/\rho_j/Return_{i,j-1} + b_8Z_i + b_9vol_j * Z_i + \varepsilon_t$ in Model 2, $|E(\Delta p_{j,end})| = c + b_7vol_j/\rho_j/Return_{i,j-1} + b_8Z_i + b_9vol_j * Z_i + \varepsilon_t$ in Model 3, *Prediction error* $= c + b_7vol_j/\rho_j/Return_{i,j-1} + b_8Z_i + b_9vol_j * Z_i + \varepsilon_t$ in Model 4, $E(\Delta p_{j,end}) = c + b_7vol_j/\rho_j/Return_{i,j-1} + b_8Z_i + b_9vol_j * Z_i + \varepsilon_t$ in Model 5, where the notation of all variables are in Eq. (3.13). The main independent variable is variance of the stock series.

	Model 1	Model 2	Model 3	Model 4	Model 5
	$y_{i,j}$	<i>Absolute prediction error</i>	$ E(\Delta p_{j,end}) $	<i>Prediction error</i>	$E(\Delta p_{j,end})$
Var	-0.00132 (-0.20)	0.0196 (0.48)	-0.0178 (-0.82)	-0.0100 (-0.19)	-0.00504 (-0.19)
Social intelligence test	-0.0166 (-0.82)	-0.0429 (-0.39)	-0.0829 (-0.93)	-0.229* (-1.67)	-0.229** (-2.17)
Raven test	0.0115 (0.28)	-0.422 (-1.60)	-0.324 (-1.44)	-0.418 (-1.36)	-0.418* (-1.67)
CRT	-0.0432 (-0.75)	0.999** (2.07)	0.861* (1.95)	0.716 (1.32)	0.716 (1.52)
Loss aversion	0.0195 (0.17)	-2.075* (-1.86)	-1.961* (-1.89)	-2.200* (-1.81)	-2.200** (-2.03)
Risk aversion	0.0155 (0.17)	0.250 (0.58)	0.115 (0.34)	0.286 (0.52)	0.286 (0.71)
Age	-0.0248 (-0.60)	0.147 (0.70)	-0.0812 (-0.48)	0.154 (0.57)	0.154 (0.77)
Male	-0.273 (-1.60)	-2.977* (-1.83)	-3.297** (-2.18)	-3.176* (-1.78)	-3.176** (-2.00)
Var*Social intelligence test	0.0000571 (0.53)	0.000498 (0.70)	0.000668 (1.52)	-0.000357 (-0.39)	-0.000357 (-0.67)
Var*Raven test	0.0000233 (0.10)	0.00175 (1.18)	0.00157* (1.72)	-0.000275 (-0.15)	-0.000275 (-0.25)
Var*CRT	0.000136 (0.42)	-0.00370 (-1.65)	-0.00307** (-1.99)	0.000569 (0.21)	0.000569 (0.33)
Var*Loss aversion	-0.000773 (-1.26)	0.00659 (1.40)	0.00507 (1.45)	0.00443 (0.79)	0.00443 (1.17)
Var*Risk aversion	-0.000367 (-0.74)	-0.00249 (-0.86)	-0.00288* (-1.66)	-0.000640 (-0.16)	-0.000640 (-0.29)
Var*Age	-0.00000173 (-0.01)	-0.00143 (-1.09)	-0.000402 (-0.52)	-0.000364 (-0.21)	-0.000364 (-0.38)
Var*Male	0.00217** (2.33)	0.00235 (0.33)	0.00370 (0.72)	0.0122 (1.43)	0.0122** (2.16)
Cons	1.332 (1.09)	14.22** (2.30)	17.66*** (3.82)	11.55 (1.48)	12.58** (2.31)
N	1620	1620	1620	1620	1620
<i>pseudo/adj.R²</i>	0.021	0.022	0.012	0.002	0.009
t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01					

Table B9: This table reports the regression results of $y_{i,j} = c + b_7 \text{vol}_j / \rho_j / \text{Return}_{i,j-1} + b_8 Z_i + b_9 \rho_j * Z_i + \varepsilon_t$ in Model 1, *Absolute prediction error* $= c + b_7 \text{vol}_j / \rho_j / \text{Return}_{i,j-1} + b_8 Z_i + b_9 \rho_j * Z_i + \varepsilon_t$ in Model 2, $|E(\Delta p_{j,end})| = c + b_7 \text{vol}_j / \rho_j / \text{Return}_{i,j-1} + b_8 Z_i + b_9 \rho_j * Z_i + \varepsilon_t$ in Model 3, *Prediction error* $= c + b_7 \text{vol}_j / \rho_j / \text{Return}_{i,j-1} + b_8 Z_i + b_9 \rho_j * Z_i + \varepsilon_t$ in Model 4, $E(\Delta p_{j,end}) = c + b_7 \text{vol}_j / \rho_j / \text{Return}_{i,j-1} + b_8 Z_i + b_9 \rho_j * Z_i + \varepsilon_t$ in Model 5, where the notation of all variables are in Eq. (3.13). The main independent variable is autocorrelation of the stock series.

	Model 1	Model 2	Model 3	Model 4	Model 5
	$y_{i,j}$	<i>Absolute prediction error</i>	$ E(\Delta p_{j,end}) $	<i>Prediction error</i>	$E(\Delta p_{j,end})$
ρ	-3.165 (-0.42)	41.65 (0.88)	-6.725 (-0.23)	-21.12 (-0.36)	5.238 (0.15)
Social intelligence test	-0.102 (-1.10)	-0.294 (-0.48)	-0.424 (-0.92)	-0.124 (-0.17)	-0.124 (-0.24)
Raven test	0.174 (0.94)	-1.464 (-1.07)	-1.018 (-0.94)	-0.386 (-0.25)	-0.386 (-0.33)
CRT	-0.608** (-2.26)	4.160* (1.71)	2.338 (1.12)	0.487 (0.19)	0.487 (0.22)
Loss aversion	0.124 (1.02)	0.428 (0.50)	0.580 (0.96)	-0.207 (-0.20)	-0.207 (-0.30)
Risk aversion	0.753 (1.45)	-6.085 (-1.10)	-4.188 (-0.85)	-3.853 (-0.66)	-3.853 (-0.76)
Age	0.738* (1.77)	2.124 (0.84)	3.139 (1.62)	-1.531 (-0.50)	-1.531 (-0.73)
Male	-0.139 (-0.73)	0.979 (0.81)	-0.0828 (-0.09)	1.283 (0.88)	1.283 (1.21)
ρ *Social intelligence test	-1.461* (-1.89)	-2.521 (-0.31)	-3.031 (-0.42)	-14.81* (-1.70)	-14.81** (-1.97)
ρ *Raven test	-0.212 (-0.87)	1.720 (0.91)	1.220 (0.87)	-0.0942 (-0.04)	-0.0942 (-0.06)
ρ *CRT	0.777** (2.20)	-4.918 (-1.52)	-2.545 (-0.95)	0.412 (0.12)	0.412 (0.15)
ρ *Loss aversion	-1.117 (-1.63)	6.588 (0.91)	3.919 (0.62)	3.033 (0.39)	3.033 (0.47)
ρ *Risk aversion	-1.030* (-1.88)	-2.971 (-0.84)	-4.582* (-1.82)	2.317 (0.53)	2.317 (0.84)
ρ *Age	0.152 (0.61)	-1.378 (-0.82)	-0.0722 (-0.06)	-1.579 (-0.77)	-1.579 (-1.14)
ρ *Male	1.975* (1.93)	-0.176 (-0.02)	0.327 (0.04)	17.83 (1.53)	17.83* (1.85)
Cons	3.519 (0.62)	-14.17 (-0.42)	20.22 (0.91)	25.94 (0.63)	7.978 (0.31)
N	1620	1620	1620	1620	1620
$pseudo/adj.R^2$	0.030	0.043	0.011	0.027	0.010

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Table B10: This table reports the regression results of $y_{i,j} = c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 Return_{i,j-1} * Z_i + \varepsilon_t$ in Model 1, *Absolute prediction error* $= c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 Return_{i,j-1} * Z_i + \varepsilon_t$ in Model 2, $|E(\Delta p_{j,end})| = c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 Return_{i,j-1} * Z_i + \varepsilon_t$ in Model 3, *Prediction error* $= c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 Return_{i,j-1} * Z_i + \varepsilon_t$ in Model 4, $E(\Delta p_{j,end}) = c + b_7 vol_j / \rho_j / Return_{i,j-1} + b_8 Z_i + b_9 Return_{i,j-1} * Z_i + \varepsilon_t$ in Model 5, where the notation of all variables are in Eq. (3.13). The main independent variable is lagged subject's return of prediction task in each stock series.

	Model 1	Model 2	Model 3	Model 4	Model 5
	$y_{i,j}$	<i>Absolute prediction error</i>	$ E(\Delta p_{j,end}) $	<i>Prediction error</i>	$E(\Delta p_{j,end})$
<i>lagged return</i>	-0.0141 (-1.02)	0.133 (1.38)	0.0875 (1.39)	0.0782 (0.64)	0.113 (1.47)
Social intelligence test	-0.0288 (-0.94)	0.225 (1.07)	0.448*** (2.65)	-0.222 (-0.81)	-0.458** (-2.20)
Raven test	0.0874 (1.39)	0.252 (0.63)	0.636*** (2.64)	-0.252 (-0.51)	-0.377 (-1.18)
CRT	-0.226** (-2.54)	-0.292 (-0.51)	-0.751** (-2.12)	0.181 (0.25)	0.440 (0.97)
Loss aversion	-0.165 (-0.90)	2.908** (2.27)	1.624* (1.69)	0.505 (0.32)	0.414 (0.37)
Risk aversion	-0.206 (-1.45)	-0.653 (-0.85)	-1.036** (-1.98)	-0.451 (-0.43)	0.215 (0.32)
Age	-0.0373 (-0.58)	-0.111 (-0.33)	-0.610*** (-2.64)	0.0894 (0.19)	0.474 (1.53)
Male	-0.128 (-0.47)	-2.095 (-1.33)	-0.725 (-0.66)	4.522** (2.21)	2.482* (1.80)
<i>lagged return</i> *Social intelligence test	0.000138 (0.63)	-0.00123 (-0.79)	-0.00344*** (-2.77)	-0.000249 (-0.13)	0.00180 (1.20)
<i>lagged return</i> *Raven test	-0.000640 (-1.41)	-0.00292 (-0.89)	-0.00578** (-2.43)	-0.00115 (-0.29)	-0.00000204 (-0.00)
<i>lagged return</i> *CRT	0.00152** (2.38)	0.00508 (0.97)	0.00870** (2.05)	0.00395 (0.64)	0.00164 (0.35)
<i>lagged return</i> *Loss aversion	0.000599 (0.47)	-0.0300** (-2.50)	-0.0206** (-1.97)	-0.0142 (-1.04)	-0.0143 (-1.27)
<i>lagged return</i> *Risk aversion	0.00136 (1.34)	0.00373 (0.65)	0.00541 (1.32)	0.00278 (0.37)	-0.00199 (-0.39)
<i>lagged return</i> *Age	0.0000617 (0.13)	0.000306 (0.12)	0.00365* (1.93)	-0.000177 (-0.05)	-0.00352 (-1.49)
<i>lagged return</i> *Male	0.00145 (0.74)	-0.00161 (-0.10)	-0.0132 (-0.93)	-0.0470** (-2.45)	-0.0306** (-1.98)
Cons	3.242* (1.69)	-1.480 (-0.11)	3.512 (0.43)	0.389 (0.02)	-1.962 (-0.19)
N	1539	1539	1539	1539	1539
<i>pseudo</i> / <i>adj</i> . R^2	0.007	0.005	0.018	0.004	0.016

t statistics in parentheses * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table B11: This table reports the mean reaction and the statistical result (rank sum test) of the deviation from 0 for each sequence shape at each reversal level. Mirror is 1 if the image is a mirror image. The first number in last column is the z-statistics of rank sum test, and the number in parentheses is the p-value.

Sequence shape	Reversal category	mirror	Reversals	Reaction	Mean Reaction for category	Statistical result of difference from 0
low	0	0	18.5185
low	0	1	12.1605
low	0	1	-0.1728
low	0	1	20.5803	12.7716	10.043(0.0000)
moderate	0	3	7.9877
moderate	0	4	5.7037	6.8457	3.19(0.0014)
high	0	6	-4.8889
high	0	7	-22.8642	-13.8765	-7.806(0.0000)
low	1	0	11.5309
low	1	1	-26.5803
low	1	1	2.7160
low	1	1	0.6543	-2.9198	-2.317(0.0205)
moderate	1	3	6.9630
moderate	1	4	-2.9506	2.0062	1.721(0.0852)
high	1	6	-1.8889
high	1	7	25.5556	11.8333	5.77(0.0000)

Table B12: This table reports the regression results of $y_{i,j} = \text{logit}(c + b_1\#Reversals_j + b_2Z_i + b_3\#overreaction/\#underreaction/\#Overreaction - \#Underreaction + \varepsilon_j)$, where $y_{i,j}$, $\#Reversals_j$, Z_j are defined in Eq. (3.9). $\#overreaction$ is the number of overreaction to the random sequences in Stage 2, $\#underreaction$ is the number of underreaction to the random sequences in Stage 2, $\#overreaction - \#underreaction$ is the difference between the number of overreaction and number of underreaction to the random sequences in Stage 2.

	Model 1	Model 2	Model 3
Dep: $y_{i,j}$			
# Reversals	-0.00350 (-0.44)	-0.00350 (-0.44)	-0.00350 (-0.44)
# Overreaction	0.0107 (0.42)		
# Underreaction		-0.0107 (-0.42)	
# Overreaction - # Underreaction			0.00533 (0.42)
Social intelligence test	-0.00937 (-0.69)	-0.00937 (-0.69)	-0.00937 (-0.69)
Raven test	0.0152 (0.55)	0.0152 (0.55)	0.0152 (0.55)
CRT	-0.0252 (-0.66)	-0.0252 (-0.66)	-0.0252 (-0.66)
Loss aversion	-0.0758 (-1.00)	-0.0758 (-1.00)	-0.0758 (-1.00)
Risk aversion	-0.0345 (-0.57)	-0.0345 (-0.57)	-0.0345 (-0.57)
Age	-0.0227 (-0.80)	-0.0227 (-0.80)	-0.0227 (-0.80)
Male	0.0142 (0.12)	0.0142 (0.12)	0.0142 (0.12)
Cons	1.456 (1.09)	1.627 (1.23)	1.542 (1.17)
N	1620	1620	1620
$pseudoR^2$	0.002	0.002	0.002
t statistics in parentheses * p0.1 **p0.05 *** p0.01			

Table B13: This table reports the regression of $Prediction\ error = c + b_5\#Reversals_j + b_6Z_i + b_7\#overreaction/underreaction/\#Overreaction - \#Underreaction + \varepsilon_t$ in Panel A, $E(\Delta p_{j,end}) = c + b_5\#Reversals_j + b_6Z_i + b_7\#overreaction/underreaction/\#Overreaction - \#Underreaction + \varepsilon_t$ in Panel B, where $\#overreaction$ is the number of overreaction to the random sequences in Stage 2, $\#underreaction$ is the number of underreaction to the random sequences in Stage 2, $\#overreaction\#underreaction$ is the difference between the number of overreaction and number of underreaction to the random sequences in Stage 2. All other variables are defined in Eq. (3.12).

	Panel A			Panel B		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
# Reversals	0.0296 (0.49)	0.0296 (0.49)	0.0296 (0.49)	-0.0585 (-1.13)	-0.0585 (-1.13)	-0.0585 (-1.13)
# Overreaction	0.201 (0.90)			0.201 (1.37)		
# Underreaction		-0.201 (-0.90)			-0.201 (-1.37)	
# Overreaction-# Underreaction			0.101 (0.90)			0.101 (1.37)
Social intelligence test	-0.288** (-2.40)	-0.288** (-2.40)	-0.288** (-2.40)	-0.288*** (-3.58)	-0.288*** (-3.58)	-0.288*** (-3.58)
Raven test	-0.440* (-1.81)	-0.440* (-1.81)	-0.440* (-1.81)	-0.440*** (-2.72)	-0.440*** (-2.72)	-0.440*** (-2.72)
CRT	0.795** (2.01)	0.795** (2.01)	0.795** (2.01)	0.795*** (2.63)	0.795*** (2.63)	0.795*** (2.63)
Loss aversion	-1.492* (-1.83)	-1.492* (-1.83)	-1.492* (-1.83)	-1.492** (-2.34)	-1.492** (-2.34)	-1.492** (-2.34)
Risk aversion	0.147 (0.31)	0.147 (0.31)	0.147 (0.31)	0.147 (0.56)	0.147 (0.56)	0.147 (0.56)
Age	0.135 (0.58)	0.135 (0.58)	0.135 (0.58)	0.135 (0.91)	0.135 (0.91)	0.135 (0.91)
Male	-1.540 (-1.19)	-1.540 (-1.19)	-1.540 (-1.19)	-1.540 (-1.48)	-1.540 (-1.48)	-1.540 (-1.48)
Cons	4.151 (0.42)	7.368 (0.81)	5.759 (0.62)	17.24** (2.48)	20.46*** (3.36)	18.85*** (2.93)
N	1620	1620	1620	1620	1620	1620
adj.R ²	0.003	0.003	0.003	0.010	0.010	0.010
t statistics in parentheses * p<0.1 **p<0.05 *** p<0.01						

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