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Abstract

We investigate how individuals use measures of apparent predictability from price charts to predict future market prices. Subjects in our experiment predict both random walk times series, as in the seminal work by Bloomfield & Hales (2002) (BH), and stock price time series. We successfully replicate the experimental findings in BH that subjects are less trend-chasing when there are more reversals in the first task. We find that subjects also overreact less to the trend when there is less momentum in the stock price in the second task, though the momentum factor that is significant is the autocorrelation instead of the number of reversals *per se*. Our subjects also appear to use other variables such as amplitude and volatility as measures of predictability. However, as random walk theory predicts, relying on apparent patterns in past data does not improve their prediction accuracy.

Keywords: Asset Prices, Regime-switching, Price Prediction, Experimental Finance

JEL Classification: C91, D91, D84, G41

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1 Introduction

The use of charts and graphical displays has a long history in markets (Lo et al., 2000; Lo & Hasanhodzic, 2011). In financial markets, traders who look for price patterns and trends in historical information are called "chartists" and are widely considered the main driver of fluctuations in market sentiment and the subsequent price booms and busts (Frankel & Froot, 1990; Chiarella & He, 2003; Chiarella et al., 2006, 2009; Tedeschi et al., 2012). While one can disagree with their belief in "a picture is worth a thousand words", it is nevertheless very important to understand what specific patterns people may refer to in the charts and pictures.

In their influential paper, Barberis et al. (1998, BSV in below) argue that individuals make predictions based on the presumed predictability of past-price dynamics, namely, they tend to overreact to continuing trends in earnings while underreacting to earnings surprises. BSV propose that investors use the number of reversals in the sequence as an indicator of a change of earnings regime in the future. The primary experimental support of this model is provided by Bloomfield & Hales (2002, BH in below) through an experiment in which participants were shown the history of realization of some random walk time series and asked to predict the direction of next move of the series. They found that, in line with previous studies, e.g., Kahneman & Tversky (1973) and Griffin & Tversky (1992), participants do not regard random walk sequences as random even after they are told so. In addition, they find that participants tend to predict a price movement in the opposite direction to the direction in the previous period for sequences with more reversals and make a trend-following prediction for sequences with fewer reversals.

While BSV and BH generate many useful insights in understanding how people make forecasts in asset markets, there appears to be many unanswered questions that require further investigation: (1) The BH experiment was conducted in 2002 with 38 MBA students of the Johnson Graduate School of Management at Cornell University. Can the result be generalized to other samples from a different culture or background knowledge in finance? (2) The price time series in BH can only go up or down by a constant steplength, making the number of reversals the only observable pattern in the data. However, stock prices typically exhibit a much richer set of patterns, e.g., autocorrelation, seasonality, retreat, and volatility. Would subjects still mainly rely on the number of reversals as the main indicator of price momentum and basis of their forecasts? (3) Random walk time series are, by definition, unpredictable, and there is no way to evaluate subjects' forecasting accuracy in the BH experiment. However, whether the market participant can predict the direction and size of the next price movement is crucial for him or her in the stock market. Does making price forecasts like a chartist add to one's forecasting accuracy and profit in the stock market?

Motivated by the above questions, we run an experimental study to further examine financial forecasting based on patterns in past prices. The participants of our experiment are 81 undergraduate students from Singapore.

Our experiment consists of two parts. In Part 1 (Predicting Random Walk), participants go through the same set of tasks as in Part 1 of BH. Namely, after seeing a graph of price movements generated from a "random walk" model, participants submit their belief about the likelihood of the next price movement being up. We employ a Becker-DeGroot-Marschak (BDM) incentive-compatible mechanism (Becker et al., 1964). Participants repeat the task 16 times with different graphs. In Part 2 (Stock Price Prediction), participants are asked, after seeing a graph of daily stock price movements of a randomly selected stock over one year, to make a price prediction for 30 days after the last price shown on the graph (Bao et al., 2022). This task is similar to the task in (Glaser et al., 2007, 2019). Participants repeat this task 20 times. The payoff in Part 2 depends on the accuracy of the forecast. A smaller prediction error leads to a higher payoff. One methodological innovation of our paper is that we introduce moving average convergence divergence (MACD, Appel, 2005), a commonly used measure for momentum in technical analysis, and examine whether there is evidence that subjects use it to predict future price movements. Instead of the reversal of the sign of price changes in BH, we use the MACD reversal: a reversal is recorded if a bullish signal is followed by a bearish signal or the other way around. To the best of our knowledge, while MACD is widely used by chartists in financial markets, our work is the first to consider it in an experiment.

In general, the goal of Part 1 is to investigate whether the findings in BH can be replicated using a subject pool from a different cultural and professional background, and we add Part 2 to examine whether subjects will refer to other patterns in stock prices. We conducted a Lo-Mackinlay variance ratio test (Lo & MacKinlay, 1988) on stock price time series used in Part 2 and confirm that we cannot reject the null hypothesis that the underlying data generating process is a random walk. Thus, the time series in this part should be considered as unpredictable as those in Part 1.

Because the information display and task in Part 2 are similar to the situation faced by traders in financial markets, Part 2 should be associated with a higher degree of "representativeness of the situation" than Part 1 (List et al., 2021). To the best of our knowledge, we are the first to study how a broad range of statistical properties of stock asset prices such as autocorrelation, amplitude, and volatility impact forecasting behavior in a laboratory experiment. Moreover, our within subject design allows us to explore whether there is heterogeneity in subjects' type in momentum-chasing behavior, i.e., whether there is positive correlation between the same subject's level of overreaction in Part 1 and Part 2. Our findings are as follows:

For Part 1 of the experiment, i.e., the Random Walk Prediction task, we successfully replicate BH's findings. We observe that participants are more likely to overreact to the random walk sequences when there are fewer reversals and underreact to these sequences when there are more reversals. Additionally, participants tend to make their predictions closer to 50% for sequences with more reversals.

Our findings from the Stock Price Prediction task can be summarized as follows: first, as in the BH experiment, subjects overreact less to stock price time series with more reversals, though the coefficient for the number of reversals is not significantly different from zero in our regression, and the measure of price momentum that is significant is the autocorrelation of the price. Second, subjects are unable to predict price movements better than pure guessing. On average, their success rate is not significantly different from 50%. Third, the number of reversals appears to be a good indicator of the difficulty of forecasting future price movement. The chance for a subject to correctly predict the direction of the price movement is lower when the number of reversals is higher. Fourth, subjects pay attention to other price patterns such as volatility.

Furthermore, we do not observe any significant relation between overreaction behavior in the random walk prediction task and the stock price prediction task. This finding suggests that the overreaction behavior is driven mainly by the characteristics in the tasks/patterns in the time series instead of the subjects' personal idiosyncratic characteristics.

Our results show that BH's result is robust to changes in subject pool, though subjects may refer to different patterns when making price forecasts in the simulated random walk series and the stock price series. As in BH, this perceived predictability does not help them make more accurate price predictions in the stock market. Overall, our findings suggest prediction in financial markets is difficult. Although individuals try to play rationally by referring to different apparent patterns in different situations, stock prices are still largely unpredictable for them.

Besides BH, our paper relates to several strands of literature. 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 be more likely to buy. Moreover, J. Huber et al. (2010) conduct an experiment to evaluate the behavior of investors making decisions under risk. Subjects are asked to guess the outcomes of a series of coin tosses either by themselves or by relying on a prediction provided by 'experts'. The hot hand belief is observed when subjects choose to rely on experts who were successful in the past. Gambler's fallacy is observed in those subjects who rely on themselves. Specifically, the frequency of betting heads increases after streaks of tails. Rötheli (2011) examine how subjects extrapolate patterns in time series to provide expectations of stock prices and exchange rates. Loh & 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 to the literature on heterogeneous expectations and regime-switching in learning to forecast experiments (LtFEs), e.g., Marimon et al. (1993), Assenza et al. (2014), Colasante et al. (2017), Hanaki et al. (2018), Bao et al. (2019), Landier et al. (2019), Giamattei et al. (2020), Bao et al. (2021), Bordalo et al. (2020), Hommes (2013), Hommes (2021), Kopányi-Peuker & Weber (2021), Mokhtarzadeh & Petersen (2021) and Zhu et al. (2021). Different from BH, this literature usually does not impose an exogenous data generating process on the asset price but lets it be endogenously determined as a function of the average price forecast by the subjects. This literature usually finds that agents have difficulty learning the rational expectations equilibrium of the economy, and their trend chasing expectations can lead to persistent bubbles and crashes in asset prices. However, because asset prices are endogenously determined in LtFEs, it is difficult for researchers to study how exogenous patterns such as number of reversals, autocorrelation, and volatility influence forecasting behavior. Besides, our paper is also related to the literature on generalized trend chasing or hot hand fallacy, e.g., Camerer (1989), Offerman & Sonnemans (2004), Yuan et al. (2014).

Last, we explain whether the prediction behavior can be explained by other properties that are broadly related to the predictability of the data, e.g., Hommes & Zhu (2014). Our results suggest that the impact of price volatility of the stock series on individuals' prediction exhibits similarity to that of the reversals of the stock series. That is, the higher the volatility of the stock series, the less accurate the prediction is. By contrast, 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. (2016, 2019), the higher the autocorrelation, the lower the prediction error is, and the more accurate the prediction will be. However, our results indicate that when the autocorrelation coefficient is higher, subjects are indeed more trend chasing, but their forecasting accuracy does not become higher.

The remainder of this paper is organized as follows. Section 2 summarizes the experimental design. Section 3 and Section 4 present the analysis of the experimental data. Finally, Section 5 concludes.

2 Experimental Design

Our experiment consists of three parts. In Part 1, we elicited participants' predictions regarding movement in pure random walk sequences ([using the same random walk sequences as in BH). In Part 2, we asked participants to make price predictions about stock series. Finally, in Part 3 we asked participants to complete a battery of tests.[1] Part 1 and Part 2 are the main components of our experiment.

We recruited 81 undergraduate students from various majors from Nanyang Technologi-

[1]The following tests were included: the Mentalizing Skill Test (the reading mind in the eyes, RME test Baron-Cohen et al., 1997), the Raven test (Raven, 1936), the Cognitive Reflection Test (CRT Frederick, 2005), the Loss aversion (Kirchler et al., 2018), and the Risk aversion elicitation procedure (a variant of the multiple price list of (Holt & Laury, 2002), a similar method is used in (He & Hong, 2018)).

cal University. We incentivized all parts of our experiment, except the post-experiment questionnaire that contains demographic questions. The experiment lasted approximately 1.5 hours, and the average payment was approximately 20 SGD (approximately 15 USD). We describe Part 1 and Part 2 in detail in the following subsection. The timeline of our experiment is shown in Figure 1.

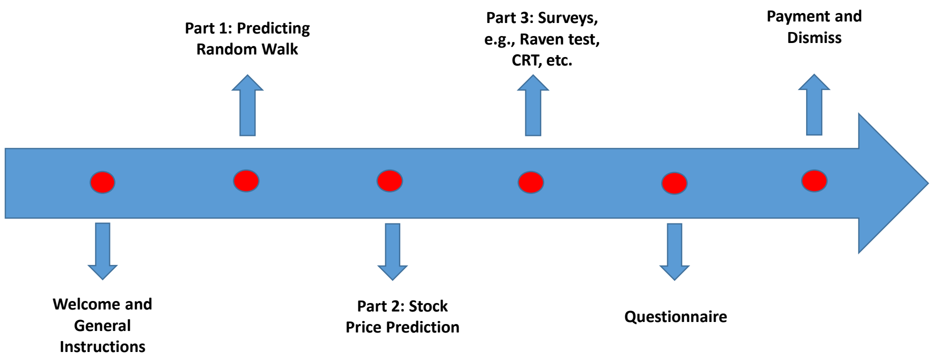


Figure 1: This figure depicts the timeline of our experiment.

2.1 Part 1: Predicting Random-Walk Time Series

We implement a slightly modified version of the experimental design of BH. Participants were told about a model of a random process that works much like flipping a fair coin. Based on this model, there are two possible outcomes. A "head" outcome indicates upward movement, and a "tail" outcome indicates downward movement. The subjects are exposed to the term "random walk", which we explain 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."

The participants were shown a set of 16 plots that were created as "random walks". Eight were mirror images of the other eight natural orientation price series (as in BH). Initially, the participants were given one unit of the asset (in our instruction, we use "bet" to make it easier to understand for the participants), whose value was either 0 or 100 points depending on the next movement (on how the series of the graph moved next). The asset generates 100 points if it moves upward and 0 points if it moves downward.

In line with BH, we elicited individuals' subjective beliefs about the probability of an upward change in the graph using the Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964). The participants were asked to name the price (in points) at which they were willing to sell this asset back to the experimenter. The range of prices should be between 0 and 100. The earnings for this part are calculated as follows. One of the 16 plots was selected randomly. Then, we generated a random number between 0 and 100 (each number was equally likely to be chosen). If the randomly generated number was less than or equal to the price set by the participant, then s/he kept the bet, and the payoff would be either 0 or 100 points depending on the next movement. If the randomly generated number was greater than the price set by the participant for the asset, then s/he received points equal to the randomly generated number.

Here are two numerical examples of how this payment mechanism works. First, if the price set for the asset was 60 points and the randomly generated number was 50, the subject kept the bet and the payoff would be either 0 or 100 points. Second, if the price set for the bet was 40 points and the randomly generated number was 50, the subject received 50 points. The lower (higher) the price the participant sets, the more pessimistic (optimist) s/he is. By contrast, the lower the price s/he sets, the more likely s/he is to receive a sure amount instead of keeping the asset whose value is either 0 or 100.

2.2 Part 2: Predicting Stock Prices

In Part 2, participants were presented with 20 graphs showing 12 months of the end-of-day prices of randomly selected stocks from the S&P 500 starting from a randomly selected day between January 1st 2008 and June 30th 2018. After seeing each graph, the individual was asked to forecast what the end-of-day price would be for this stock 30 days after the last price shown on the graph. The end-of-day prices were rescaled, and all starting prices were normalized to 100 for easy comparison. Thus, *a priori*, there were 1,916,250 possible charts. Because participants were informed that the stock series was randomly selected for each graph, and the starting day was also randomly chosen, it was difficult for them to guess the name of the selected stock and the chosen time window. We also did not tell participants about the name of the stock or the starting date.

We performed the Lo-Mackinlay variance ratio test (Lo & MacKinlay, 1988), where under the null hypothesis

$$\Delta p_t = \mu + \epsilon_t$$

The test statistic is $VR(q) = \frac{\hat{\sigma^2(q)}}{\hat{\sigma^2(1)}}$, and $\sigma^2(q) = \frac{1}{Tq}(p_t - p_{t-q} - q\hat{\mu})^2$.

We report the results in Table B4 and B5. The results confirm that we cannot reject that all the stock series used in Part 2 are random walks with drift. This result means that although stock price series have rich apparent patterns, they are, in general, as unpredictable as the artificial random walk series in Part 1.

Our experiment is essentially an individual decision-making experiment. Individuals were presented a different stock series in each period. The payoff for Part 2 depended on the accuracy of the prediction. Let p_i^e be the price prediction made by individual i, and let p_i^{obs} be the target price to be forecasted by i for the graph. The reward for Part 2 is given by Eq. (1) for a randomly chosen graph (out of 20):

$$\max\{200 - 1000 \times |\frac{p_i^e - p_i^{obs}}{p_i^{obs}}|, 0\} \tag{1}$$

If individual i's forecast p_i^e is exactly at the target price p_i^{obs}, then he/she receives 200 points. For each percentage point difference between p_i^e and p_i^{obs}, 10 points are subtracted. If the price forecast differs from the target price by more than 20 %, i would receive 0 points. The exchange rate in our experiment is 20 $points = 1\ SGD$ (0.73 USD).

3 Experimental Results for Random Walk Time Series Prediction

We follow BH and measure participant i's reaction to the past trend in series s as follows:

$$REACT_i^s = \begin{cases} p_i^s - 50 & \text{if orientation is natural} \\ 50 - p_i^s & \text{if orientation is mirror} \end{cases} \tag{2}$$

where p_i^s is the price subject i asked for the asset in series s; 50 is the expected value of the asset. Note that in BH, there are two types of orientations:

Natural orientation is the upward sequence, where the participants observe an upward change. All previous price movements are upward.

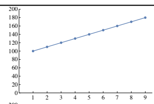
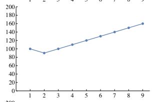
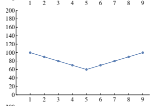
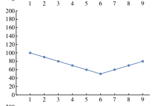
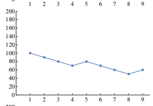
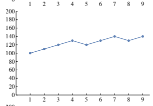
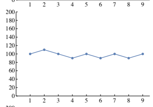
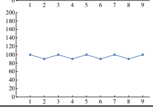
Mirror orientation is the downward sequence, where the participants observe a downward change. All previous price movements are downward.

$REACT_i^s > 0$ means that participant i believes that the last movement in the sequence will be repeated in the subsequent period (overreaction). By contrast, $REACT_i^s < 0$ demonstrates i's belief that the movement will be reversed in the subsequent period (underreaction). The stronger the belief is, the larger $REACT_i^s$ is.

BH used the number of reversals as the key variable to capture the momentum of the time series. A **reversal** is defined as an upward (downward) movement of the time series followed by a downward (upward) movement. A time series with fewer reversals is typically associated with stronger momentum, and *vice versa*.

Following BH, we categorize the random walk sequences as a **low**-reversal sequence if

Table 1: The mean reaction for each series.

Series	Reversal category	Number of Reversals	Sequence	Mean Reaction	Mean Reaction for category
1	low	0		15.02	
2	low	1		−7.21	
3	low	1		1.27	
4	low	1		10.62	4.93[a]
5	moderate	3		7.48	
6	moderate	4		1.38	4.43[a]
7	high	6		−3.39	
8	high	7		1.34	−1.02

Note: Significantly differently from zero (signed rank-sum test) at the 1% (a) and 5% (b) significance levels. Using subject within category average as an independent observation.

the number of reversals is less than 3, a **moderate**-reversal sequence if the number of reversals is between 3 and 4, and a **high**-reversal sequence if the number of reversals is greater than 4. According to the rank-sum test, we find that underreaction is significant in high-reversal sequences,[2] while overreaction is significant in low-reversal sequences.[3]

Table 1 shows the mean reaction across participants for the 16 series (pooling the 8 series of natural orientation and the 8 series of mirror orientation). Our findings are consistent with BH. We find that, on average, individuals tend to overreact to the sequence by, respectively, 4.9259 points with lower reversals and 4.4259 points with moderate reversals, and the difference is significant at the 5% level; by contrast, there is no significant over- or underreaction in sequences that have a high number of reversals. Unlike in BH, however, the average reactions in low and moderate-reversal sequences are similar, and those of high-reversal sequences are not significantly different from zero.

[2] z=7.852, p=0.0000 comparing high-reversal sequences with low-reversal sequences, z=6.401, p=0.0000 comparing high-reversal sequences with moderate-reversal sequences.

[3] z=7.852, p=0.0000 comparing low-reversal sequences with high-reversal sequences, z=1.105, p=0.2692 comparing low-reversal sequences with moderate-reversal sequences.

We further performed the following pooled logit regression to assess the relationship between the reaction to sequences and the number of reversals in sequences.

$$OVER_{i,t} = logit(a + b_1 \#Reversals_{i,t} + b_2 Category\ of\ sequence_{i,t} + b_3 Z_i + \epsilon) \quad (3)$$

where $OVER_{i,t}$ is a dummy variable that indicates whether individual i overreacts to the random walk sequence in period t. The relation between $OVER_{i,t}$ and $REACT_i^s$ is given below:

$$OVER_{i,t} = \begin{cases} 1 & \text{if } REACT_i^s > 0 \\ 0 & \text{if } REACT_i^s < 0 \end{cases}$$

$OVER_{i,t}$ is equal to 1 if $REACT_i^s$ is positive or the subject thinks that the direction of the next price movement will be the same as that in the last period, and 0 if there is underreaction. $\#Reversals_{i,t}$ is the number of reversals in the random walk sequence for individual i at period t. $Category\ of\ sequence_{i,t}$ is a set of dummy variables indicating whether the time series exhibits a low, moderate or high reversal sequence, with a low number of reversals as the baseline group. Note that low, moderate and high reversal sequences are defined in Table 1. Z_i is a vector of control variables, consisting of the score of the RME test, Raven's test, CRT, loss aversion and risk aversion attitude test, as well as demographic variables such as age and gender. Model 1 and Model 2 examine how the number of reversals affects the extent of overreaction to a random walk sequence. For every one unit change in the number of reversals, the log odds of overreaction to the sequence (versus underreaction) decreases by 0.094, as reported in Model 1. In other words, as the number of reversals increases, the overreaction to random walk sequences decreases significantly.

Model 3 and Model 4 test the relation between the number of reversals, which is represented by $Category\ of\ sequence_{i,t}$, and overreaction to a random walk sequence. The log odds of overreaction to the sequences (versus underreaction) decreases by 0.542 for low-reversal sequences versus high-reversal sequences. We do not observe a difference in overreaction to reversals between low-reversal sequences and moderate-reversal sequences. Our results suggest that individuals tend to overreact to random walk sequences with fewer reversals.

Further, we assess the deviation in the price offered by individuals from the expected price, which is 50. We run the following regression.

$$\begin{aligned} REACT_i^s = {} & a + b_1 \#Reversals_{i,t} + b_2 Category\ of\ sequence_{i,t} \\ & + b_3 Z_i + \epsilon \end{aligned} \quad (4)$$

where $REACT_i^s$ is the measure of reaction, as stated in Eq. (2). Positive (negative)

Table 2: The logit regression result of Eq. (3).

	Model 1	Model 2	Model 3	Model 4
Dep: $OVER_{i,t}$				
Reversals	-0.0944**	-0.0947***		
	(-2.57)	(-2.58)		
Default: Low-reversal sequence				
Moderate-reversal sequence			0.0989	0.0993
			(0.35)	(0.35)
High-reversal sequence			-0.542**	-0.544**
			(-2.49)	(-2.50)
Control (Z_i)	No	Yes	No	Yes
Cons	0.0384	1.020	-0.124	0.859
	(0.17)	(1.06)	(-0.53)	(0.91)
N	1296	1296	1296	1296
Cluster	Subject&Period	Subject&Period	Subject&Period	Subject&Period

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

Table 3: The regression result of Eq. (4).

	Model 1	Model 2	Model 3	Model 4
Dep: $REACT_i^s$				
Reversals	-1.163**	-1.163**		
	(-2.16)	(-1.98)		
Default: Low-reversal sequence				
Moderate-reversal sequence			-0.500	-0.500
			(-0.13)	(-0.13)
High-reversal sequence			-5.948*	-5.948*
			(-1.93)	(-1.91)
Control (Z_i)	No	Yes	No	Yes
Cons	6.658**	10.09	4.926	8.361
	(1.98)	(0.77)	(1.44)	(0.65)
N	1296	1296	1296	1296
Cluster	Subject&Period	Subject&Period	Subject&Period	Subject&Period

t-statistics in parentheses * p<0.1 **p<0.05 *** p<0.01
The main independent variables 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.

reaction means that participant i believes that the last movement in the sequence will (not) be repeated in the next period, hence overreacts (underreacts) to the sequence.

$\#Reversals_{i,t}$, $Category\ of\ sequence_{i,t}$ and Z_i are the same vectors of control variables in Eq. (3). The main independent variables are $\#reversals_{i,t}$ in Model 1 and Model 2, $Category\ of\ sequence_{i,t}$ in Model 3 and Model 4. Model 2 and Model 4 include all variables. The regression results are reported in Table 3.

We find that more reversals lead to less overreaction. The results remain consistent when we use the dummy variable about the category of sequences that is divided by the number of reversals in the sequence as the primary independent variable, as reported in Model 3 and Model 4 (although the results for moderate-reversal sequences are not significant).

Result 1: *Overall, individuals tend to overreact to random walk sequences when there are fewer reversals and to underreact to sequences when there are more reversals, which confirms the findings of BH.*

4 Experimental Results for Stock Price Prediction

In Section 3, we find that with more/fewer reversals in the "artificial" random walk sequences, individuals tend to underreact/overreact to the price movement. To further investigate whether the participant's forecasting behavior follows the same pattern when faced with stock series, we examine the results of Part 2, where subjects predict a true stock series. The participants made price forecasts for 20 stock time series in Part 2 of the experiment. The subjects were asked to predict the price of a randomly selected stock 30 days after the last price shown (price observed) in each period.

4.1 Overreaction to Trends in Stock Price Series

In this section, rather than using the number of reversals as the measure for momentum of the time series, we derive the moving average convergence divergence ($MACD$) to capture the trend momentum of the S&P500 in Part 2. The reason is that the reversals measured by BH are not obvious for subjects to capture the trend momentum of the S&P 500 stock series. The stock price time series contains daily price movement of 360 days, and the number of reversals defined on interday price change is typically more than 100 due to frequent fluctuation in stock prices. Thus, subjects are unable to count the number of reversals and keep them in mind when they see different time series.

$MACD$ is a momentum indicator that is commonly used by technical analysts (Appel, 2005). $MACD$ is equal to the difference between 2 exponential moving averages (EMAs) of different lengths: (a) a long-term EMA, usually of 26 days, and (b) a short-term EMA, usually of 12 days. $MACD$ is defined as

$$MACD = EMA_{12-days} - EMA_{26-days}$$

A third component is the signal line (SL), which is usually a nine-day EMA of the $MACD$.

$$SL = EMA_{9-days}$$

One could interpret $MACD$ in the following way: A "bullish" indicator occurs when the signal line crosses above the $MACD$, indicating an increase in stock price, and the investor should purchase the stock. A "bearish" indicator occurs when the signal line crosses below the $MACD$, implying a decrease in stock price, and the investor should sell the stock. Figure 2 illustrates the dynamics of $MACD$ lines and signal lines of Stock

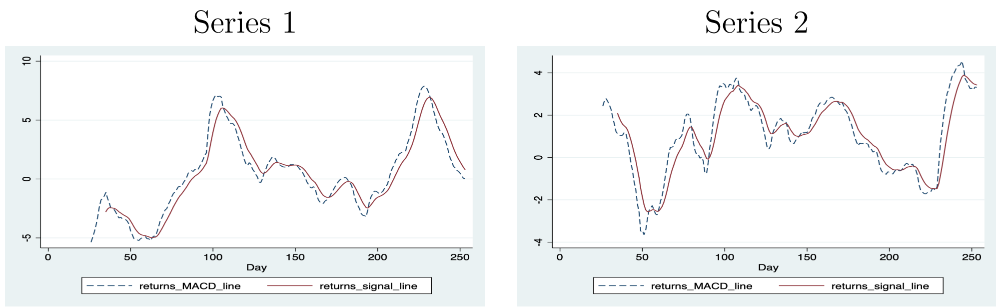


Figure 2: The dynamics of $MACD$ lines and signal lines of Stock series 1 and Stock series 2 in Part 2

series 1 and Stock series 2 in Part 2. Figure B1 and Figure B2 in Appendix B describe the dynamics of $MACD$ lines and signal lines of the other stock series in Part 2.

To capture the momentum of the time series, we consider the change in the bullish signal and bearish signal for a time horizon of a whole year, measured by $MACDreversals$ and defined as follows:

$MACDreversals$: a reversal is recorded if a bullish signal is followed by a bearish signal, or the other way around. $MACDreversals$ is the sum of the TOTAL number of reversals of a stock series for a whole year.

The mean $MACDreversals$ is 16 for all stock series in Part 2. The number of reversals for each stock series is shown in Table B1 of Appendix B.

To investigate subjects' overreaction behavior, we consider subjects' expected price change and the most recent change in the trend momentum of $MACD$. The excepted price change and most recent change in $MACD$ are defined as follows:

$$\text{Expected Price Change: } E(\Delta p_{j,f}) = p_j^e - p_{j,last} \tag{5}$$

$$\text{Most Recent Change in } MACD\text{: } \Delta MACD_j \tag{6}$$

where $j = 1, 2, \dots 20$ represents the stock series. p_j^e is the price prediction for the current series j, $p_{j,last}$ is the last price observed by the subjects for the current series j. $\Delta MACD_j$ is the last trend momentum of $MACD$ at the current series j. $\Delta MACD_j$ is positive if the last trend momentum exhibits a positive trend, vice versa.

We define the measure of overreaction of subject i to S&P stock series j as below:

$$OVER_{i,j} = \begin{cases} 1 & if \quad signE(\Delta p_{j,f}) = sign\Delta MACD_j \\ 0 & if \quad signE(\Delta p_{j,f}) \neq sign\Delta MACD_j \end{cases} \tag{7}$$

$OVER_{i,j}$ is one (overreaction) when the sign of $E(\Delta p_{j,f})$ is the same as the sign of $\Delta MACD_j$, and 0 otherwise.

Table 4: The regression results of Eq.(8).

	Model 1	Model 2
Dep: $OVER_{i,j}$		
MACDreversals	-0.0228	-0.0228
	(-1.12)	(-1.12)
Control(Z_i)	Yes	No
Cons	0.639	0.673***
	(0.89)	(2.04)
N	1620	1620
Cluster	Subject&Period	Subject &Period

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

We run the linear probability regression of Eq. (8) to examine the relationship between subjects' overreaction behavior and the number of reversals, $Reversals_j$, and other individual characteristics (Z_i). The results are reported in Table 4.

$$OVER_{i,j} = a + b_1 MACDReversals_j + b_2 Z_i + \epsilon_i \tag{8}$$

The dependent variable $OVER_{i,j}$ is defined in Eq. (7). The independent variables are the $MACDReversals_j$ and Z_i in Model 1 and $MACDReversals_j$ in Model 2. Z_i is defined in Eq. (3).

The estimated coefficients of $MACDreversals$ are reported in Table 4. The sign of the coefficients is negative, indicating that the subjects overreact (underreact) to stock series with fewer (more) reversals when the reversal is measured by $MACDreversals$. However, the coefficients are not significant at the 5% level. The nonsignificance of the coefficients suggests that the pattern of reversals of stock series might be harder to recognize for subjects than are patterns in random walk time series. These findings can be summarized as follows:

Result 2: *When we define reversals as changes between bullish and bearish markets according to MACD, our findings show that subjects overreact more to time series with more reversals, although the estimated coefficients for the number of reversals are nonsignificant.*

We try to investigate whether is heterogeneity exists among subjects, i.e., whether some have a stronger tendency to overreact to past price trends. We categorize subjects into momentum type, neutral type and reversal type. The definitions of these three types are as follows.

Momentum type : A subject is categorized as a momentum decision marker if s/he overreacts to the series more than 50% of the time.

Neutral type : A subject is categorized as a neutral decision maker if s/he overreacts

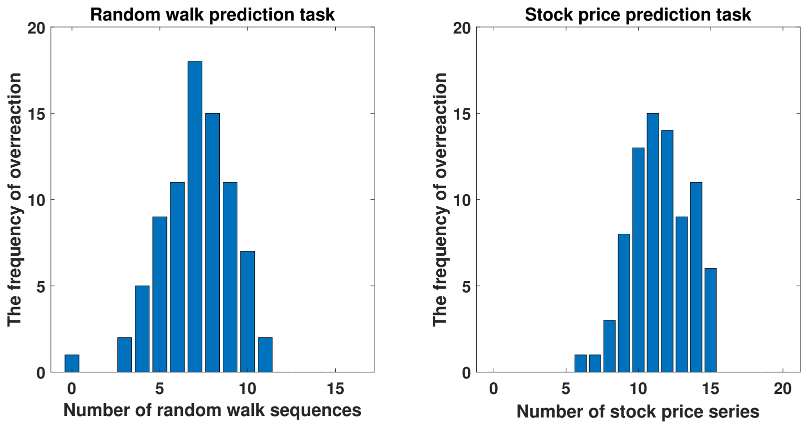


Figure 3: The frequency of subjects' overreaction to random walk sequences in the left panel and stock price series in the right panel.

to the series exactly 50% of the time.

Reversal type : A subject is categorized as a reversal decision marker if s/he overreacts to the series less than 50% of the time.

The fraction of reversal subjects is 56.79% in the random walk task and only 32.1% in the stock price prediction task. The fraction of momentum subjects is 24.69% in the random walk task and 67.9% in the stock price prediction task. Meanwhile, 18.52% of the subjects in the random walk task and 16.05% of the subjects in the stock price task cannot be categorized as either momentum or reversal types. This result shows that subjects behave in a very different ways in the two tasks. We perform a proportion test and confirm that subjects overreact more in the stock price task than in the random walk task ($Z = 5.8965, p - value = 0.0000$). Furthermore, we do not observe any significant relation between overreaction behavior in the random walk prediction task and the stock price prediction task ($\rho = -0.0140, p = 0.9015$), i.e., subjects of the momentum type in the random walk task are not more likely to be momentum type in the stock prediction tasks. This finding suggests that overreaction behavior is driven mainly by the characteristics of the tasks/patterns in the time series instead of the subjects' personal traits. More details of the results can be found in Table B2 in Appendix B.

Result 3: *Participants overreact less to the random walk sequence and more to stock series. There is a lack of correlation between subjects' frequency of correlation across the two tasks. Our finding suggests that the tendency to overreact is more related to the characteristics of the time series than those of the individual decision makers.*

4.2 Prediction of the Direction of Price Movement

To investigate whether the participants can predict the direction of the price movement correctly, we calculate both the expected price change and the actual realized price change for individual i and each stock price time series j. A subject is considered to make a correct prediction about the direction of price change if these changes are in the same direction. The price changes are defined as $E(\Delta p_{j,f})$ in Eq. (5). The actual price change $\Delta p_{j,f}$ is given by:

$$\text{Actual Price Change: } \Delta p_{j,f} = p_{j,f} - p_{j,last} \tag{9}$$

Where $p_{j,f}$ is the realized target price at the current series j, which the participants are required to make a prediction about, and $p_{j,last}$ is the last price observed by the subjects at the current series j. The price observed and the actual price in each period are independent across series.

We calculate the frequency with which the subject makes a correct prediction about the direction of future price movement, i.e., when the sign of $\Delta p_{j,f}$ equals the sign of $E(\Delta p_{j,f})$ (the absolute value is nonzero) for series j, to measure the correct prediction of price movement of stock series.

Let $y_{i,j}$ be the indicator variable of whether subject i correctly predicts the direction of the price movement for time series j:

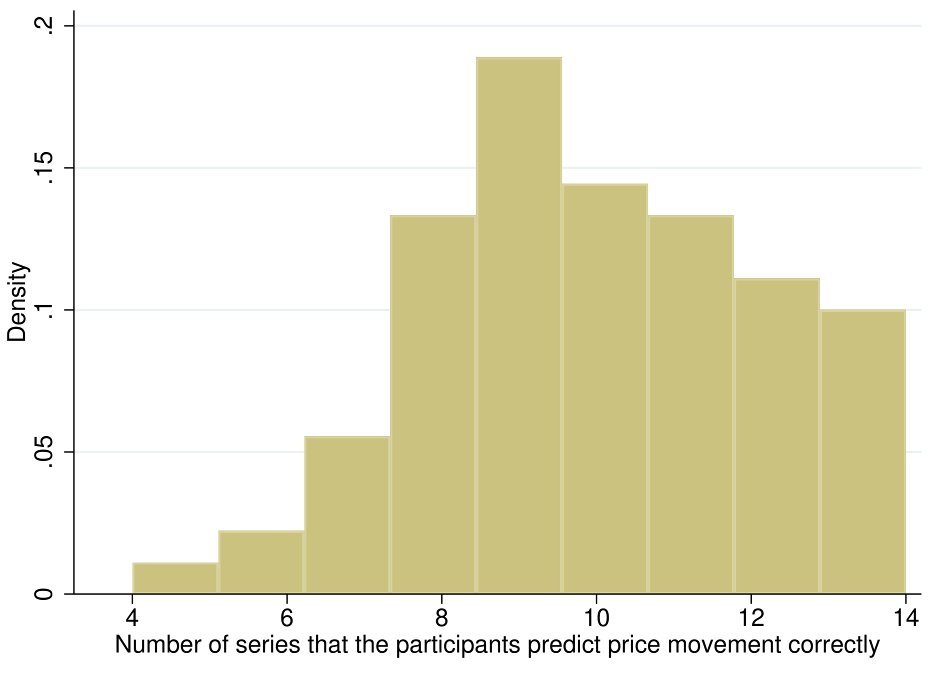
$$y_{i,j} = \begin{cases} 1 & \text{if } sign \Delta p_{j,f} = sign\ E(\Delta p_{j,f}) \\ 0 & \text{if } sign \Delta p_{j,f} \neq sign\ E(\Delta p_{j,f}) \end{cases} \tag{10}$$

Let $Y_i = \sum_j y_{i,j}$. The median Y_i is 10, and the mean is 9.87. Figure 4 shows the density of Y_i. The minimum is 4, and the maximum is 14.

Y_i is greater than 10 (half of the total number of predictions) for only 38.27% of the participants (31 out of 81). This finding suggests that most subjects did not do better than pure guessing. No participant correctly predicted the price movement of the stock series for all 20 series. A rank-sum test confirms that individuals make a correct prediction of price movement for less than 10 stock series (z=-0.909, p=0.3635).

We also count the number of participants who correctly forecast the direction of price movements for each price time series to see how often more than half of the participants did so correctly. The results consistently indicate that participants did better than pure guessing for only 7 of 20 stock price time series. Table B3 in Appendix B summarizes the number of participants who correctly forecast the price movements for each series.

Result 4: *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 when they predict the stock price.*



Note: The x-axis is the number of series for which the participants correctly predict the direction of price movement (Y_i),and the y-axis is the density.

Figure 4: Histogram of the number of series for which the participants correctly predict the price movement of the stock series.

4.3 Reversals and Stock Price Prediction

In the previous section, we found that subjects do not perform better than pure guessing. In this section, we further investigate the factors behind this result. We first check whether there is any relationship between the number of $MACDreversals$ of the stock price series and the directional prediction of the price movement. $MACDreversals$ is the same as that used in Section 4.1. The direction of the price movement can be either up or down.

We examine how the number of $MACDreversals$ of the stock series affect individuals' prediction of the price-movement direction by running the following regression.

$$y_{i,j} = logit(a + b_1 MACDReversals_j + b_2 Z_i + \epsilon_j) \tag{11}$$

where $y_{i,j}$ is a binary outcome variable defined in Eq. (10). We have $y_{i,j} = 1$ if individual i makes the correct directional prediction of the price-movement when facing series j, and $y_{i,j} = 0$ if individual i makes an incorrect prediction. Z_i is a vector of control variables. The regression results are reported in Table 5, where Model 2 excludes Z_i. Note that the standard errors of all regressions are corrected for clustering at the individual level.

Subjects are less likely to make a correct prediction about price movement when the stock series has more reversals. Compared to that of stock series with fewer reversals, the log odds of correct prediction of the price movement (versus incorrect prediction) decreases significantly by 0.126 for stock series with more reversals.

Table 5: The result of pooled logit regression of Eq. (11)

	Model 1	Model 2
Dep: $y_{i,j}$		
MACDreversals	-0.126***	-0.126***
	(-5.63)	(-6.09)
Control (Z_i)	Yes	No
Cons	3.191***	2.002***
	(2.61)	(5.95)
N	1620	1620
Cluster	Subject&Period	Subject &Period

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

Intuitively, time series with more reversals are harder to predict and/or are less predictable. Moreover, if subjects learn to overreact less to time series with fewer reversals and make more "calm" predictions, their predictions may become more accurate. Our findings show that the first effect dominates the second: subjects are less likely to correctly predict time series with more reversals because they are harder to predict.

The above findings are summarized in Results 5.

Result 5: *Participants are less likely to correctly predict the direction of price movement when the number of reversals is higher.*

4.4 Other Factors Influencing the Price Predictability and the Price Prediction

In their studies, BSV and BH focus on one type of pattern in the time series, the number of reversals. This is natural because the random walk time series in BH can only go up or down by a constant step-length, making the number of reversals the only observable pattern in the data. In Task 2 of our study, stock prices enable us to explore a richer set of patterns in price, e.g., size of the trend, seasonality, retreat, and volatility.

In this section, we further investigate whether the other patterns of the stock series affect the direction of the prediction of the stock price. The measurements of volatility (vol_j) used in this section are the variance (σ_j) and the amplitude of the stock series $Amplitude_j = p_j^{max} - p_j^{min}$. The measurement of the autocorrelation of the stock price series is the mean autocorrelation coefficient, ρ of the first 20 lags. We perform the pairwise correlation test and the results confirm that $MACDreversals$ is not correlated with volatility ($p-value = 0.2398$ $for\ variance$; 0.5691 $for\ amplitude$) and autocorrelation ($p-value = 0.3055$) in each stock series. Table B8 reports the figures of autocorrelation of each stock series. The mean ρ, the value of σ_j and $Amplitude_j$ are reported in Table B9.

We run the logit pooled regression of Eq. (12).

$$y_{i,j} = a + b_1 vol_j/\rho_j + b_2 Z_i + \epsilon_t \tag{12}$$

where $y_{i,j}$ and Z_i are defined in a similar fashion as in Eq. (11). The main independent variables are $Amplitude_j$ in Model 1, σ_j in Model 2, and ρ in Model 3. Panel A excludes Z_i, while Panel B does not. Table 6 reports the regression results.

The results are reported in Model 1 of Table 6. Our results suggest that with a one unit increase in the amplitude of the stock series, the log odds of correct prediction of the price movement (versus incorrect prediction) decrease by 0.0133, and the effect is significant at the 1% level. In other words, as the amplitude increases, the chance of correct prediction of the movement of a price decreases. Thus, as the gap between the maximum price and minimum price of the stock series increases, individuals tend to make a less accurate prediction of the price movement.

The result is consistent if we use the variance of the stock series as the main independent variable, as reported in Model 2 of Table 6. Increased variance of the stock series leads to fewer correct predictions of the price movement of the stock series. Our findings show that the second order patterns in the data, e.g. volatility also influences prediction behavior and prediction accuracy.

Additionally, the regression results of autocorrelation indicate that the log odds of correct prediction of the price movement (versus incorrect prediction) decrease significantly by 2.76, as reported in Model 3 of Table 6. In other words, as the autocorrelation of the stock series increases, the correct prediction of the price movement decreases. According to Anufriev et al. (2016, 2019), if a stock series has a high autocorrelation, then its previous values can be a good feature for predicting future values. Therefore, individuals are expected to make a more accurate prediction of the price movement when the stock series is highly autocorrelated.

Furthermore, we study whether there are interactions among the volatility, the autocorrelation of the stock series, one-period-lagged return and individual characteristics (e.g., the mentalizing skill test, loss aversion, and gender), we do not observe any consistent and significant influence of these interaction terms on the number of correct price predictions as reported in Table B10 in Appendix B.

Result 6: *Other patterns in the data also matter for individual prediction accuracy. Participants tend to make a less accurate predictions of price movement when the volatility of the stock series is high or when the autocorrelation of the stock series is high.*

Table 6: The regression results of Eq. (12).

	Model 1	Model 2	Model 3
Panel A			
Dep: $y_{i,j}$			
$Amplitude_j$	-0.0133***		
	(-4.04)		
σ_j		-0.00228***	
		(-5.72)	
ρ			-2.763***
			(-5.67)
Control (Z_i)	No	No	No
Cons	0.514***	0.287***	2.039***
	(3.97)	(4.41)	(5.60)
Panel B			
	Model 1	Model 2	Model 3
Dep: $y_{i,j}$			
$Amplitude_j$	-0.0134***		
	(-2.61)		
σ_j		-0.00229***	
		(-3.55)	
ρ			-2.770***
			(-5.72)
Control (Z_i)	Yes	Yes	Yes
Cons	1.674**	1.457	3.218***
	(1.78)	(1.49)	(3.35)
N	1620	1620	1620
Cluster	Subject&Period	Subject&Period	Subject&Period

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

The main independent variables are $Amplitude_j$ in Model 1, σ_j in Model 2, ρ in Model 3 and $Return_{i,j-1}$ in Model 4. The dependent variable is $y_{i,j}$. Panel B includes all independent variables in Eq. (12), while Panel A excludes Z_i.

5 Conclusion

In this study, we extend the seminal work by BH substantially by adding a prediction for stock time series and examining a larger set of patterns in the data. In general, subjects in our experiment behave in a similar manner as subjects in BH in that they tend to underreact to sequences with greater momentum.

When subjects predict the same random walk time series as in BH, we successfully replicated the finding by BH that more reversals in the price movement lead to less overreaction. When the subjects predict stock prices, they show a tendency (though not significant) to overreact to stock series with fewer reversals (measured by $MACD$) and underreact to stock series with more reversals. Meanwhile, subjects rely more on other patterns such as autocorrelation, amplitude and volatility.

Furthermore, using the patterns of past prices does not improve the prediction accuracy of subjects. The success rate of most of individuals is not statistically better than pure random guessing.

Our results lend support to the notion that people do not treat random walk time series as random. While the apparent patterns in the data, such as the number of price reversals and past trend, are indeed correlated with prediction performance, overall performance still does not exceed pure guessing, even though individuals try to extrapolate seemingly predictable patterns in the price data.

Our paper contributes to the literature on individual's prediction behavior in financial markets and the predictability of financial data. Given our finding that the number of reversals and the volatility of the stock series could be factors associated with the predictability of the stock series, trading platforms may consider providing more information about stock series to participants to help them make better decisions.

In future research, it would be interesting to examine the performance of professionals in predicting stock price movement and compare it with that of students to see if the results are robust. Indeed, C. Huber et al. (2021) investigate how an experimental volatility shock influences professional and student investment behavior, risk perception, and return expectations. They find that professionals changed their risk preference due to the shock, while the students did not. Weitzel et al. (2020) find that bubbles still occur in the market of professionals but less often than in the market of students. We leave these extensions to future research.

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Appendix A

Instructions

Part 1

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.

Part 2

Part 2

Welcome to Part 2 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 S&P 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.

$$\max\left[200 - 10 \times \left|\frac{\text{your forecast} - \text{realized price}}{\text{realized price}} \times 100\right|, 0\right]$$

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.

Part 3

Note for the readers. We have provided on-screen instruction before each task.

Task 1: Please select, among 8 options shown in the bottom, the one that is best suited to fill the blank part on the top. Specifically, you will see a pull-down menu allowing you to choose a number from 1-8. The selected number will then be displayed in the blank part. 10 cents is paid for each correct answer. If you answer all the questions correctly, you will get 1.6 SGD.

Task 2: Please select, among 4 words shown in the bottom, one that best describes the feeling of the person in the picture. 10 cents is paid for each correct answer. If you answer all the questions correctly, you will get 3.6 SGD.

Task 3: 10 cents is paid for each correct answer. If you answer all the questions correctly, you will get 0.7 SGD.

Task 4: In the 6 decisions below you have to decide whether you want to participate in a lottery where you can win or lose money. For this task, you receive an initial endowment of $18 ($ below stands for points). If you reject the lottery, you will only receive your initial endowment.

The initial endowment and one of your 6 decisions below will be randomly selected to calculate your payments. To determine your payment in case you chose the lottery, the program will randomly determine if you receive the loss or the gain. Note that gains and losses are equally likely. Since you do not know which decisions will be selected for payment, and each decision stands an equal chance of being selected, you should pay attention to the choice you make in each decision.

Please decide for each of the six rows below.

Task 5: In the 7 decisions below you have to decide between two options. One of your 7 decisions below will be randomly selected and you will be paid out according to the choice you have made for that selected decision, i.e. either the lottery or the sure payoff. To determine your payment in case you chose the lottery, the program will randomly determine if you receive the lower or the larger amount. Note that the lower and the larger amounts are always equally likely. Since you do not know which decisions will be selected for payment, and each decision stands an equal chance of being selected, you should pay attention to the choice you make in each decision.

Questionnaire at the end of the experiment

Financial Literacy

1) Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy:

- more than today with the money in this account
- exactly the same as today with the money in this account
- less than today with the money in this account
- Don't know
- Refuse to answer

2) Do you think that the following statement is true or false? "Bonds are normally riskier than stocks."

- True
- False

- Don't know
- Refuse to answer

3) Considering a long time period (for example 10 or 20 years), which asset described below normally gives the highest return?

- savings accounts
- stocks
- bonds
- Don't know
- Refuse to answer

4) Normally, which asset described below displays the highest fluctuations over time?

- savings accounts
- stocks
- bonds
- Don't know
- Refuse to answer

5) When an investor spreads his money among different assets, does the risk of losing a lot of money:

- increase
- decrease
- stay the same
- Don't know
- Refuse to answer

6) Do you think that the following statement is true or false? "If you were to invest $1000 in a stock mutual fund, it would be possible to have less than $1000 when you withdraw your money."

- True
- False

- Don't know
- Refuse to answer

7) Do you think that the following statement is true or false? "A stock mutual fund combines the money of many investors to buy a variety of stocks."

- True
- False
- Don't know
- Refuse to answer

8) Do you think that the following statement is true or false? "After age 55, you can withdraw the balances in your Special Account and Ordinary Account, if you have set aside your Full Retirement Sum in your Retirement Account. "

- True
- False
- It depends on the type of retirement scheme
- Don't know
- Refuse to answer

9) Do you think that the following statement is true or false? "A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less."

- True
- False
- Don't know
- Refuse to answer

10) Suppose you had $100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have on this account in total?

- More than $200
- Exactly $200

- Less than $200
- Don't know
- Refuse to answer

11) Which of the following statements is correct?

- Once one invests in a mutual fund, one cannot withdraw the money in the first year
- Mutual funds can invest in several assets, for example invest in both stocks and bonds
- Mutual funds pay a guaranteed rate of return which depends on their past performance
- None of the above
- Don't know
- Refuse to answer

12) Which of the following statements is correct? If somebody buys a bond of firm B:

- He owns a part of firm B
- He has lent money to firm B
- He is liable for firm B's debts
- None of the above
- Don't know
- Refuse to answer

13) Suppose you owe $3,000 on your credit card. You pay a minimum payment of $30 each month. At an Annual Percentage Rate of 12% (or 1% per month), how many years would it take to eliminate your credit card debt if you made no additional new charges?

- less than 5 years
- between 5 and 10 years
- between 10 and 15 years
- never
- Don't know

- Refuse to answer

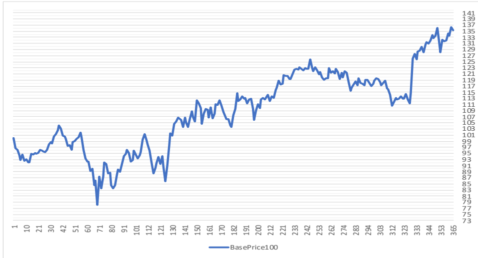
Demographics

1. What is your age?
2. What is your gender? Male Female
3. What is your GPA?
4. What is your major?
5. Which year are you in? Year1 Year2 Year3 Year4 Master Phd Others
6. Have you participated economic experiment before?
7. Have you learnt Investment, Finance in class?
8. Have you invested in financial market before?
9. What is your strategy?

The stock series used in Part 2

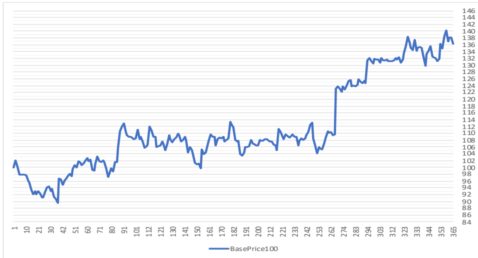
Series 1

Series 2



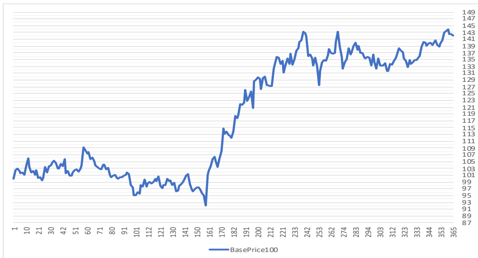
Series 3

Series 4

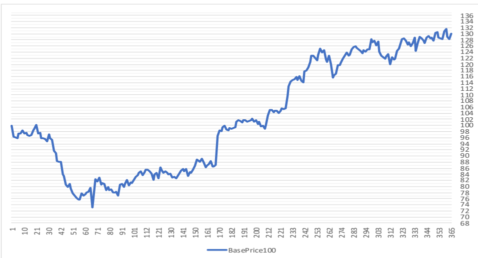


Series 5

Series 6

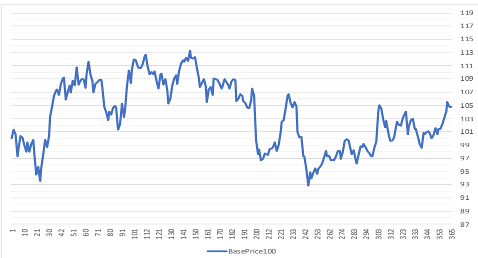


Series 7

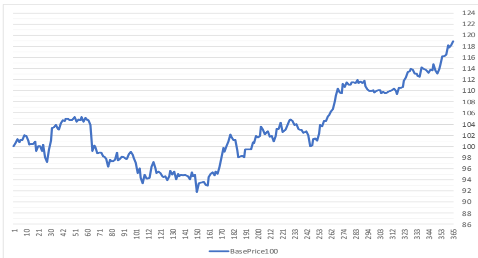


Series 8

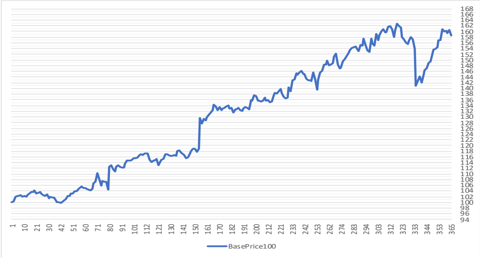
Series 9



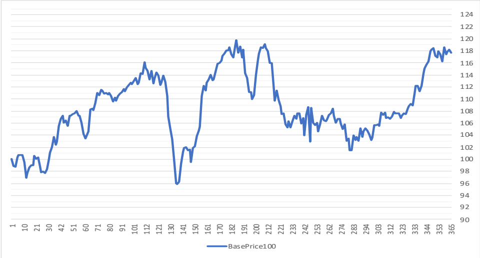
Series 10



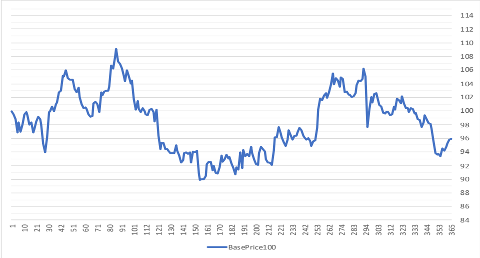
Series 11



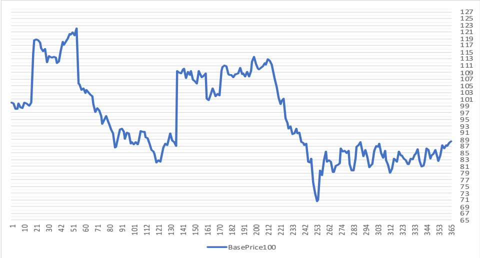
Series 12



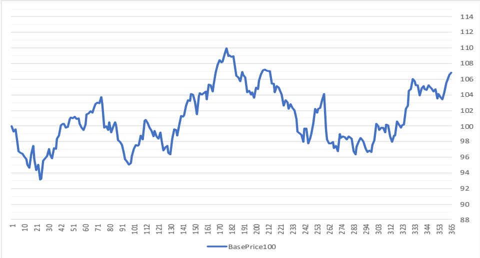
Series 13



Series 14

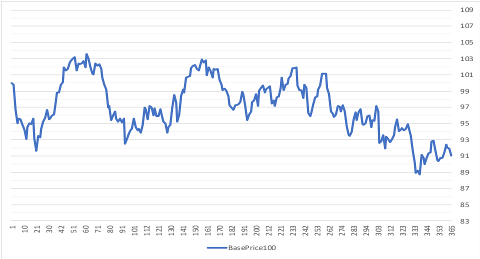


Series 15



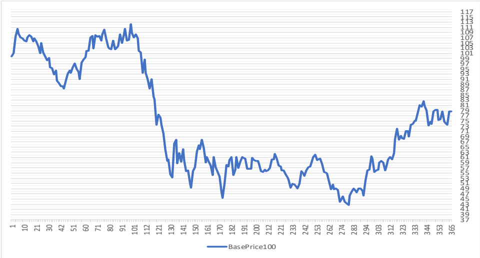
Series 16

Series 17

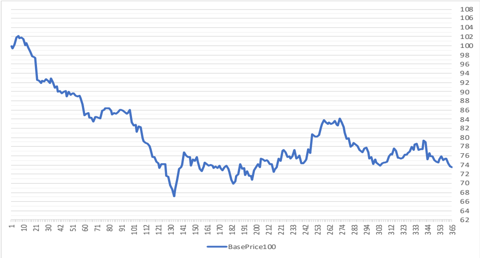


Series 18

Series 19



Series 20



Appendix B

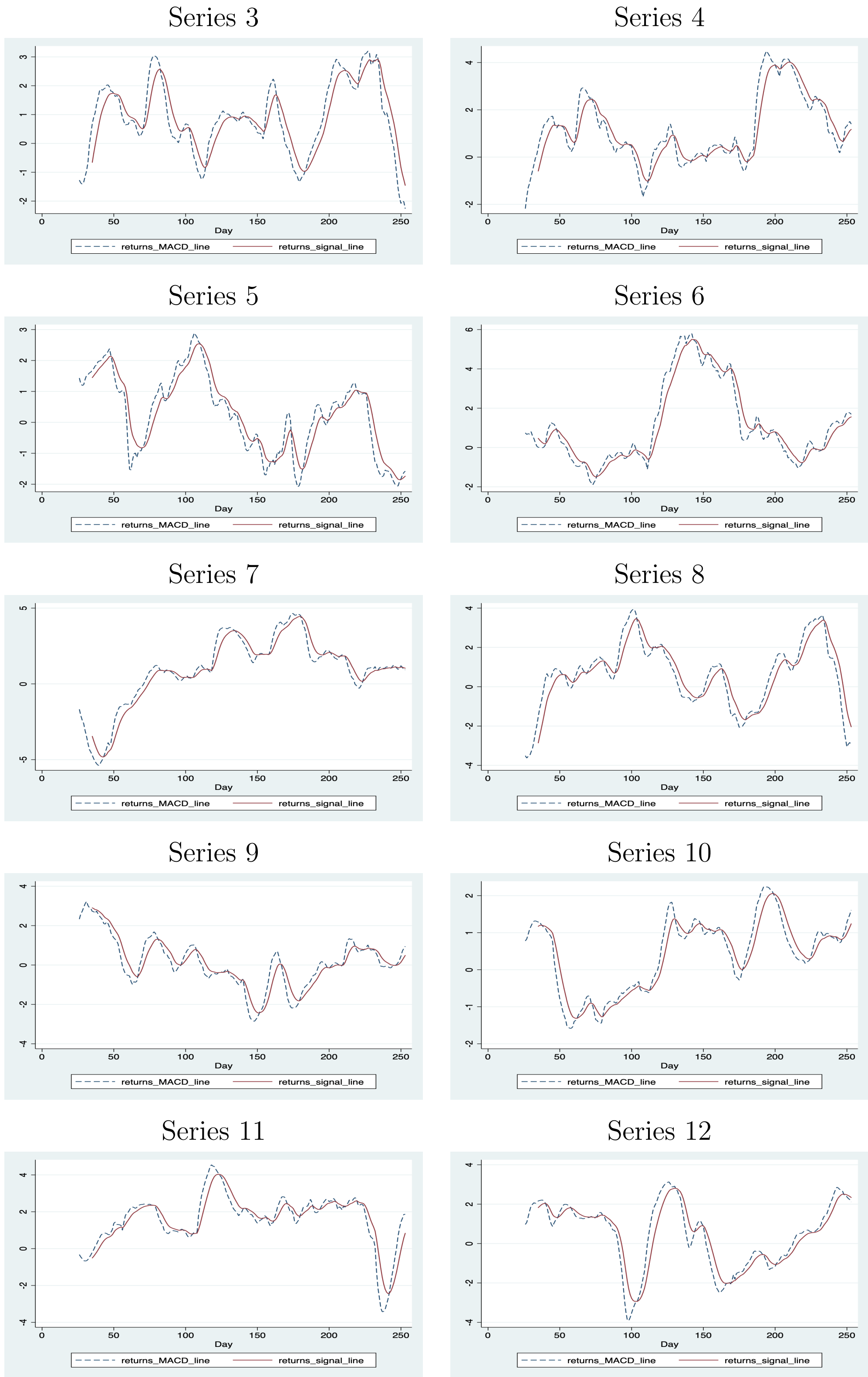


Figure B1: The dynamics of $MACD$ lines and signal lines of the stock series in Part 2

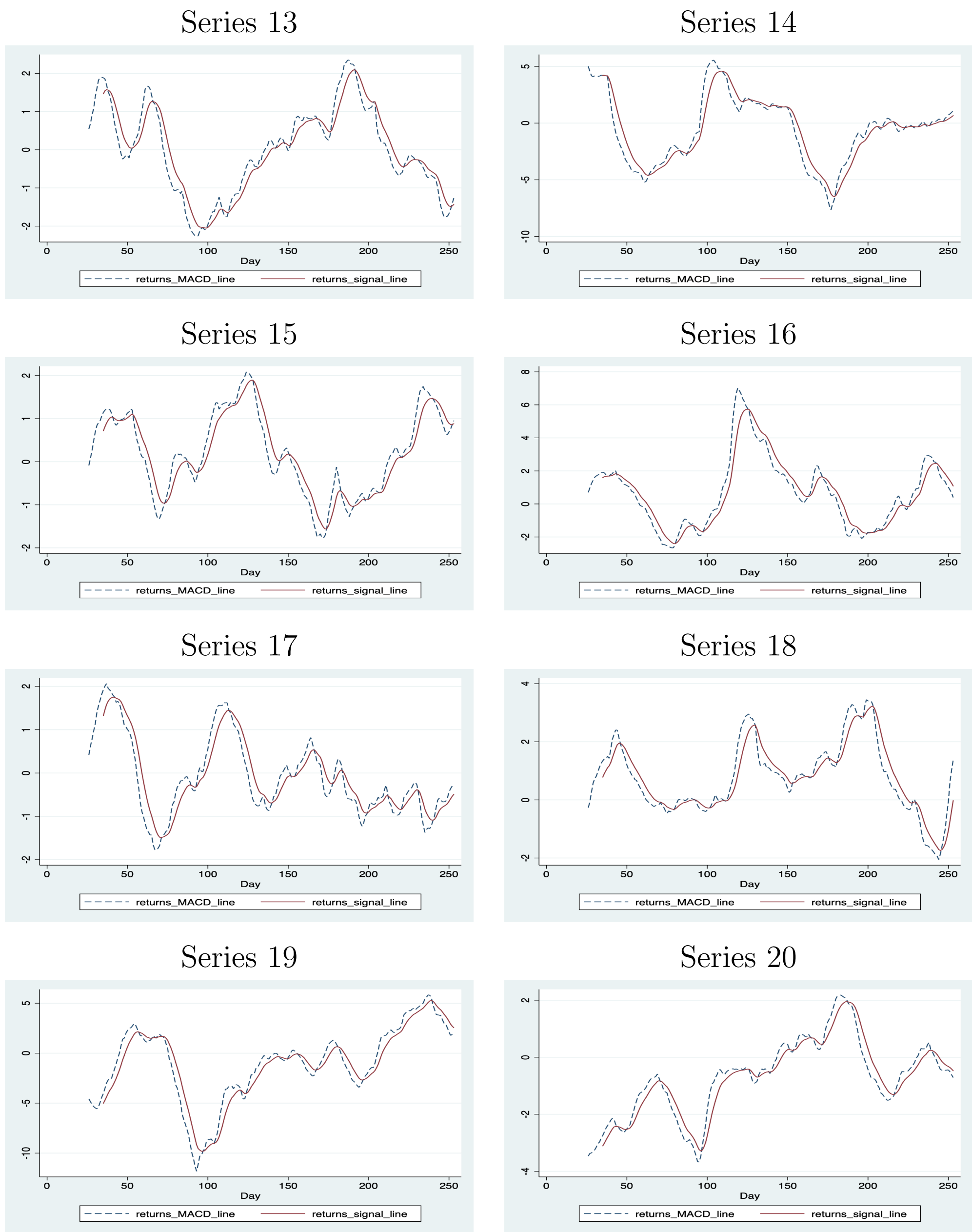


Figure B2: The dynamics of $MACD$ lines and signal lines of the stock series in Part 2

Table B1: The number of $MACDReversals$ in each stock series.

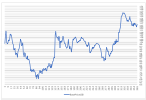
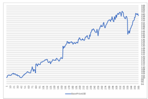
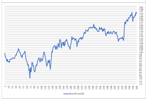
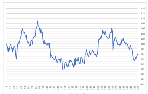
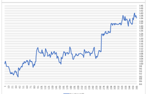
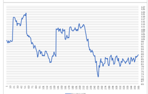
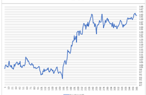
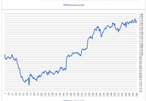
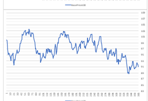
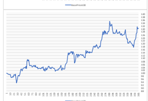
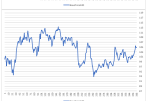
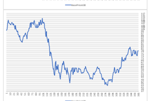
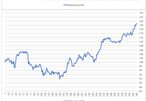
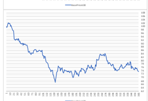
SeriesID	MACDreversals
1	11
2	14
3	17
4	20
5	14
6	19
7	22
8	17
9	19
10	18
11	20
12	13
13	14
14	17
15	16
16	11
17	16
18	16
19	13
20	15

Table B2: The frequency, probability and cumulative probability of the number of series that subjects overreact to for random walk prediction task in Panel A, and stock price prediction in Panel B.

Panel A: Random walk prediction			
The number of series that the subjects overreact to	Freq.	Percent	Cum.
0	1	1.23	1.23
1	0	0	1.23
2	0	0	1.23
3	2	2.47	3.7
4	5	6.17	9.88
5	9	11.11	20.99
6	11	13.58	34.57
7	18	22.22	56.79
8	15	18.52	75.31
9	11	13.58	88.89
10	7	8.64	97.53
11	2	2.47	100
12	0	0	100
13	0	0	100
14	0	0	100
15	0	0	100
16	0	0	100

Panel B: Stock price prediction			
The number of series that the subjects overreact to	Freq.	Percent	Cum.
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
5	0	0	0
6	1	1.23	1.23
7	1	1.23	2.47
8	3	3.7	6.17
9	8	9.88	16.05
10	13	16.05	32.1
11	15	18.52	50.62
12	14	17.28	67.9
13	9	11.11	79.01
14	11	13.58	92.59
15	6	7.41	100
16	0	0	100
17	0	0	100
18	0	0	100
19	0	0	100
20	0	0	100

Table B3: The number of participants correctly forecasting the price movements for each series.

Series ID	Original Fig	No. of Correct	Series ID	Original Fig	No. of Correct
1		64***	11		19***
2		33	12		57***
3		54***	13		61***
4		48	14		26***
5		28***	15		41
6		31**	16		61***
7		33	17		52**
8		35	18		21***
9		34	19		29**
10		24***	20		49*

significantly different from 40.5 (pure guess) according to binomial test, two sided, at 1, 5, 10% level (***, **, *)

Table B4: The Lo-Mackinlay variance ratio test for the stock price series in Part 2 of our experiment.

Series 1				Series 6			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	0.99	-0.19	0.85	2	0.89	-1.33	0.18
4	1.04	0.34	0.73	4	0.86	-0.98	0.33
8	1.22	1.16	0.25	8	0.73	-1.28	0.20
16	1.34	1.14	0.25	16	0.76	-0.77	0.44
Series 2				Series 7			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	0.95	-0.60	0.55	2	1.01	0.10	0.92
4	0.88	-0.74	0.46	4	1.01	0.07	0.94
8	0.79	-0.85	0.39	8	1.11	0.52	0.60
16	0.80	-0.61	0.54	16	1.41	1.43	0.15
Series 3				Series 8			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	1.04	0.48	0.63	2	1.09	1.45	0.15
4	1.06	0.42	0.67	4	1.14	1.10	0.27
8	1.07	0.29	0.77	8	1.25	1.22	0.22
16	0.96	-0.13	0.90	16	1.35	1.15	0.25
Series 4				Series 9			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	0.99	-0.29	0.77	2	1.10	1.36	0.17
4	0.85	-1.54	0.12	4	1.09	0.68	0.49
8	0.74	-1.67	0.10	8	1.19	0.92	0.36
16	0.65	-1.46	0.14	16	1.08	0.29	0.77
Series 5				Series 10			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	1.05	0.54	0.59	2	0.97	-0.42	0.68
4	1.00	0.01	0.99	4	1.05	0.41	0.69
8	0.74	-1.13	0.26	8	1.21	1.04	0.30
16	0.68	-0.95	0.34	16	1.32	1.13	0.26

Note: VR is the variance ratio, and R_s is the test statistic.

Table B5: The Lo-Mackinlay variance ratio test for the stock price series in Part 2 of our experiment.

Series 11				Series 16			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	0.96	-0.49	0.63	2	1.08	1.08	0.28
4	0.87	-0.88	0.38	4	1.09	0.65	0.52
8	0.87	-0.63	0.53	8	1.04	0.17	0.86
16	0.82	-0.61	0.54	16	1.13	0.44	0.66
Series 12				Series 17			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	1.00	0.00	1.00	2	1.04	0.74	0.46
4	1.25	1.39	0.16	4	1.02	0.16	0.87
8	1.47	1.80	0.07	8	0.93	-0.37	0.71
16	1.64	1.84	0.07	16	1.03	0.11	0.91
Series 13				Series 18			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	0.99	-0.07	0.95	2	0.99	-0.10	0.92
4	0.95	-0.29	0.77	4	0.97	-0.24	0.81
8	0.88	-0.52	0.60	8	0.96	-0.18	0.86
16	0.96	-0.15	0.88	16	0.89	-0.38	0.70
Series 14				Series 19			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	1.01	0.26	0.79	2	0.93	-1.06	0.29
4	1.01	0.09	0.93	4	0.90	-0.77	0.44
8	1.05	0.39	0.70	8	0.98	-0.11	0.91
16	1.28	1.26	0.21	16	1.29	0.87	0.38
Series 15				Series 20			
lags	VR	R_s	$p > z$	lags	VR	R_s	$p > z$
2	1.06	1.01	0.31	2	1.01	0.23	0.82
4	1.14	1.22	0.22	4	1.15	1.18	0.24
8	1.20	1.14	0.25	8	1.28	1.38	0.17
16	1.16	0.59	0.56	16	1.58	1.95	0.05

Table B6: The descriptive statistics of the results of the mentalizing skill test, raven test, crt, loss aversion and risk aversion.

Mentalizing skill Test				
	Low	Medium	High	Whole sample
Obs.	27	29	25	81
Mean	19.93	24.52	28.76	24.30
Median	20	25	28	25
Std	2.04	1.09	1.79	3.93
Min	15	23	27	15
Max	22	26	34	34
Raven Test				
	Low	Medium	High	Whole sample
Obs.	23	22	36	81
Mean	8.87	11.27	13.56	11.60
Median	9	11	13	12
Std	1.18	0.46	0.84	2.15
Min	6	11	13	6
Max	10	12	16	16
CRT				
	Low	Medium	High	Whole sample
Obs.	24	35	22	81
Mean	3.17	5.63	7	5.27
Median	3.5	6	7	6
Std	1.01	0.49	0	1.61
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	5.06	3.90
Median	3	4	5	4
Std	0	0	0.25	0.73
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	5.48	4.25
Median	3	4	5	4
Std	0	0	0.59	0.92
Min	3	4	2	3
Max	3	4	2	7

Note: 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.

Table B7: The correlation coefficients among the profiles of subjects.

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

Note: 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.

Table B8: The auto-correlation figures for each series.

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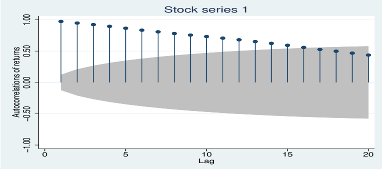
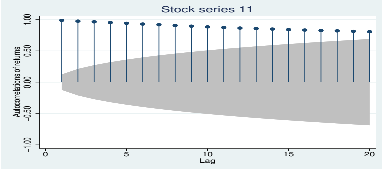
<tr><td>1</td><td>
</td><td>11</td><td>
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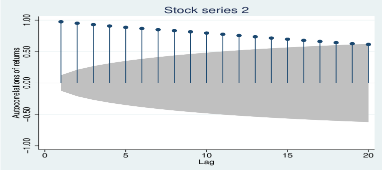
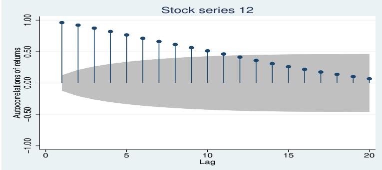
<tr><td>2</td><td>
</td><td>12</td><td>
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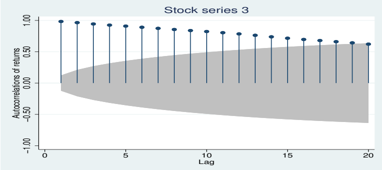
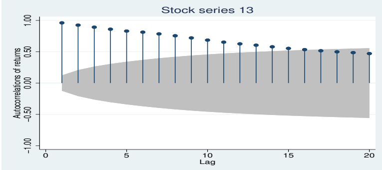
<tr><td>3</td><td>
</td><td>13</td><td>
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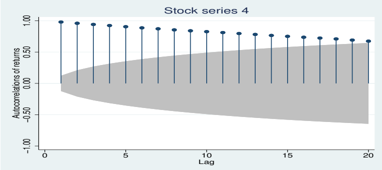
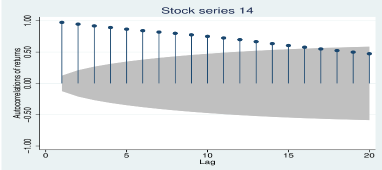
<tr><td>4</td><td>
</td><td>14</td><td>
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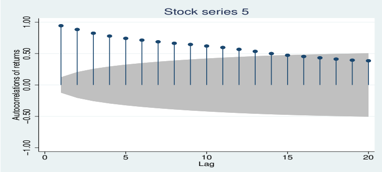
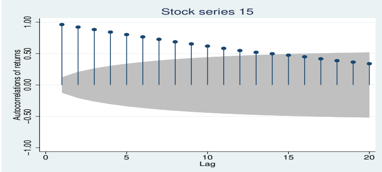
<tr><td>5</td><td>
</td><td>15</td><td>
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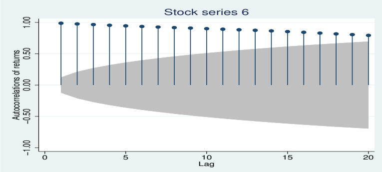
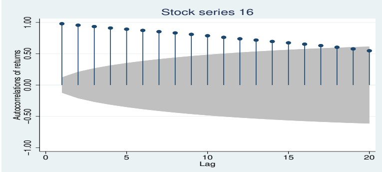
<tr><td>6</td><td>
</td><td>16</td><td>
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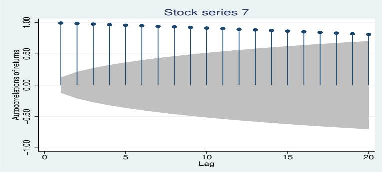
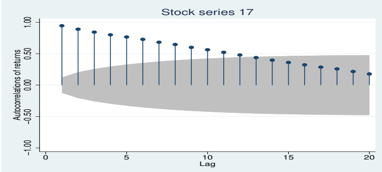
<tr><td>7</td><td>
</td><td>17</td><td>
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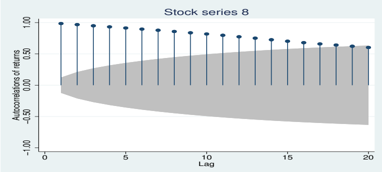
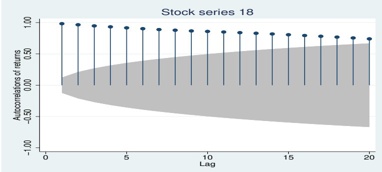
<tr><td>8</td><td>
</td><td>18</td><td>
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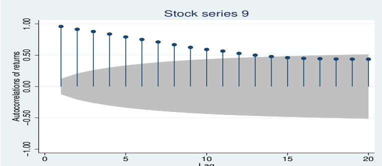
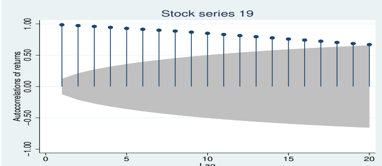
<tr><td>9</td><td>
</td><td>19</td><td>
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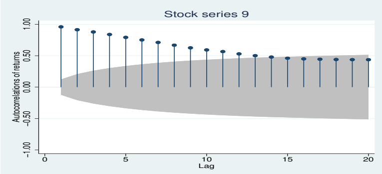
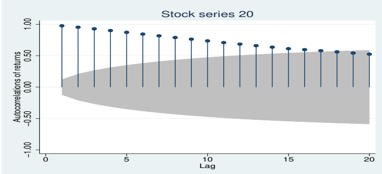
<tr><td>10</td><td>
</td><td>20</td><td>
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Table B9: The mean auto-correlation coefficient that is calculated from 20-periods lagged auto-correlation coefficients, the value of amplitude and variance of each stock series.

Stock series	$\overline{\rho}$	$Amplitude_j$	σ_j
1	0.7130	55.88	163.12
2	0.7855	58.25	171.66
3	0.8059	45.40	98.11
4	0.8219	50.46	167.18
5	0.6128	25.22	29.53
6	0.8939	51.81	292.95
7	0.9045	58.44	328.72
8	0.7995	42.30	90.53
9	0.6238	20.47	25.32
10	0.8085	27.09	42.08
11	0.8861	62.94	401.36
12	0.4948	23.92	33.52
13	0.6879	19.20	18.98
14	0.7270	51.34	153.52
15	0.6222	16.84	13.31
16	0.7714	38.52	107.32
17	0.5468	14.86	11.44
18	0.8561	41.79	108.79
19	0.8356	69.75	441.27
20	0.7344	34.95	58.82

Table B10: The regression results of $y_{i,j} = c + b_7 vol_j/\rho_j + b_8 Z_i + b_9 vol_j/\rho_j * Z_i + \epsilon_t$.

	Model 1	Model 2	Model 3
Dep: $y_{i,j}$			
$Amplitude_j/\sigma_j/\rho_j$	-0.00406	-0.00132	-3.165
	(-0.08)	(-0.20)	(-0.42)
$Amplitude_j/\sigma_j/\rho_j$ $\times$ *Social intelligence test*	0.000338	0.0000571	-1.461*
	(0.41)	(0.53)	(-1.89)
$Amplitude_j/\sigma_j/\rho_j$ $\times$ *Raven test*	-0.000104	0.0000233	-0.212
	(-0.06)	(0.10)	(-0.87)
$Amplitude_j/\sigma_j/\rho_j$ $\times CRT$	0.00180	0.000136	0.777**
	(0.76)	(0.42)	(2.20)
$Amplitude_j/\sigma_j/\rho_j$ $\times$ *Loss aversion*	-0.00657	-0.000773	-1.117
	(-1.42)	(-1.26)	(-1.63)
$Amplitude_j/\sigma_j/\rho_j$ $\times$ *Risk aversion*	-0.00303	-0.000367	-1.030*
	(-0.81)	(-0.74)	(-1.88)
$Amplitude_j/\sigma_j/\rho_j$ $\times$ *Age*	0.000210	-0.00000173	0.152
	(0.12)	(-0.01)	(0.61)
$Amplitude_j/\sigma_j/\rho_j$ $\times$ *Male*	0.0144**	0.00217**	1.975*
	(2.06)	(2.33)	(1.93)
Control (Z_i)	No	No	No
Cons	1.303	1.332	3.519
	(0.59)	(1.09)	(0.62)
N	1620	1620	1620
Cluster	Subject&Period	Subject&Period	Subject&Period

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

Note: the main dependent variable is $y_{i,j}$. The main independent variable is $Amplitude_j$ in Model 1 and σ_j in Model 2, ρ in Model 3.