Analysis of group behavior bias in financial markets using artificial market

Wang Yating[1], Toriumi Fujio[1]

[1]School of Engineering, The University of Tokyo

Abstract: In the past few decades, researchers have realized that human psychology can affect traders in decision-marking process and finally affect the financial market based on behavior finance theory and cognitive psychology. Group behavior bias is one of them. Group. Some studies have been done on group behavior bias from behavior finance viewpoint to tell the differences of group behavior bias. However they only qualitatively analyzed macro phenomenon without quantitatively measure the detail micro thinking process in individuals. In this paper, we proposed and validated three types of group behavior bias models including majority following, winner following and hub following models based on different nationalities. We also compared these models and figured out that the majority following bias is the easiest to form in the market, however the market impact is the least. On the other hand, hub following bias is the hardest to emerge but the market impact is the most. Besides, we introduced short selling regulation as well as multi rate regulation and find both of them can lead heavier market impact in the market with group behavior biases.

1, Introduction

1.1 Research Background

In the past 20 years, researchers have realized that human psychology can affect traders in decision-marking process and finally affect the financial market based on behavior finance theory and cognitive psychology. Group behavior bias is a kind of human psychologies. It refers to the psychology phenomenons that humans have a strong tendency to belong to a group and groups have influence on decision-making processes of individuals in a variety of ways, such as groupthink, deindividuation etc.

Recently, some researchers start to pay attention to group behavior bias because they think traders in the same group or the same market will share the same chart and the same channel even in the same dealer room should have more communication and affect each other in their decision-making process. They may be more likely to follow the groupthinking instead of their own thinking[1]. It is believed that group behavior bias varies in different groups, basing on different culture and different thinking mode in various countries.

However all previous analysis on group behavior biases are from behavior finance point of view. They are conducted from empirical literature and qualitative aspect, which can't measure the detail micro thinking process in individuals and reveal the mechanism about how individual thinking accumulate to affect the market. Besides there is no detail model for group behavior bias.

1.2 Research Objectives

Based on the problems on group behavior bias related researches, we conduct this research with three objectives:

1) To propose the models of group behavior bias which is never discussed in previous studies.

2) To figure out the differences in these group behavior biases.

3) To reveal the mechanism about how group behavior biases influent the market and how the asset price changes when the group behavior bias is engaged by using artificial market.

2, Artificial Market Model

To quantitatively measure the group behavior bias and the market impact of financial market based on each individual and their interaction, we use artificial market, which is one kind of multi-agent based models to simulate financial market. We also apply the CNN network model to describe the underlying structure of communication and relationship among traders in our artificial market model and then combined it with the mechanics behind the spread of interaction.

The whole artificial market model includes base model, which is created on the basic artificial market model, as well as group behavior bias models, which is based on agents' different decision-making processes, including the group behavior of majority following, winner following and hub following models.

2.1 Base model

The base model for usual agent of our simple artificial market is built on the basis of the model from Mizuta[2], in which agents follow the combination of fundamental strategy and technical strategy to decide whether to buy or sell.

$$r_{e,j}^t = \frac{1}{\sum_i w_{i,j}} \left(w_{1,j} \log \frac{p_f}{p^t} + w_{2,j} r_{k,j}^t + w_{3,j} \varepsilon_j^t \right)$$

The first term stands for fundamental strategy, the second term stands for technical strategy and the last term is the noise item.

Learning process is also engaged in this model by comparing the evaluation term with each strategy term separately. If the fundamental term or the technical term is the same signs with evaluation term, the weight of this term will increase, otherwise will decrease.

2.2 Group behavior bias models

For group behavior bias models, we propose three different types on different decision-making processes in different groups. These three kinds of models are: majority following, winner following and hub following policy based group behavior bias. Majority following bias represents the bias to follow the decision made by majority people in the group.This stands for thinking process in Japan. Winner following bias represents the bias to follow the decision made by the most profitable trader in the group.This kind of thinking mode matches the way of some result-driving countries such as America. Hub following bias represents the bias to follow the decision made by the authority trader in the group which is an important trading rule for traders in China.

Agents which employ majority following policy is to follow the most adopted decision by surroundings, like herding behavior. Traditional herding is defined as a switch in traders' decision into the direction of the crowd, however in our majority following model, agents make the decision based on both self-signal and others' signal. Agent will set a threshold and compares it to the result percentage of majority, then decide whether to follow the majority or insist his own decision. The agent observes the trading decision of neighbors within one step in the network, then calculate the buy ratio and sell ratio(Details in [4]).

For winner following model, we consider the agent with the most net assets within one step distance as ``winner". In winner following model, the agents will copy the decision made by winner agent. The agent observes the net assets of neighbors(including himself) within one step in the network and find the most profit agent, which we call it ``winner agent" here. If he earns the most, he will follow previous step to make the decision. The equation to calculate net asset is

$$V_i^t = \sum_{j=1}^{k} P_j^t \times S_{i,j}^t + C_i^t$$

where P_j^t is the market price of the asset. $S_{i,j}^t$ is the number of share for each asset, C_i^t means the amount of cash.

Hub following policy is a policy to follow the decision made by the agent who has the most resources or the most ways to gather information. We call this kind of agent the ``hub" agent. In the network, such kind of agent can be marked as the node with most links. The decision made by hub agent will be imitated by other agents.

3, Market Settings

In this part, we divide market settings into three parts: regulation settings, evaluation values and parameter settings. We also extend single risky asset market to multi-assets markets.

3.1 Regulation settings

We import short selling regulation and multi rate regulation to see how these regulation work when group behavior bias agents exist.

Short selling regulation stipulates the holding number of the asset that should not be less than one share when making a sell order, and the rest cash should not be less than the price of the asset when making a buy order.

The multi rate regulation means that each asset has a maximum threshold in the net asset of the agent who owns it. The equation to calculate threshold is

$$\frac{|P_j^t \times S_{i,j}^t|}{V_i^t} \le \theta$$

P_j^t is market price at time t of asset j, $S_{i,j}^t$ is the number of share hold by each agent. V_i^t means the total net asset.

Agent will check whether the holding asset ratio exceeds the maximum ratio before making order. When the rate of assets larger than maximum ratio, the order will be cancelled. Otherwise the order will be proceeded. If one asset ratio already exceeds the threshold θ due to abrupt price change, the following order will try to adjust the ratio to a reasonable range by selling the exceeding asset or buying the other asset until the ratio rebalances.

3.2 Evaluation Values

We introduce three features to explain how the markets are effected by group behavior biases. These features are group behavior bias coefficient, market impact and critical point.

3.2.1 Group Behavior Bias Coefficient

To measure group behavior bias phenomenon level in the market, we introduce group behavior bias coefficient. The Group behavior coefficient is an average measure of group behavior in the market during the whole simulation period T, it represents the synchronized level of decisions made by group agents in the artificial market. We calculate the group behavior bias phenomenon on the base of the coefficient described in [3]

$$\sigma = \frac{2}{N}\sqrt{\left(\frac{1}{T}\sum_{t=1}^{T}(N_{bt} - \frac{N}{2})^2\right)}, \sigma \in (0,1)$$

Here N means the total number of agents, and N_{bt} is the number of agents who decide to buy one unit at time t. T is the total simulation period. The bigger the value of σ is, the larger group behavior bias .If it becomes close to 1, it means that the action of the agents are synchronized to one direction. If it becomes close to 0, it means there is no group behavior bias phenomenon and the market is in a balance status.

3.2.2 Market Impact

we follow [2] and use the value of market impact to measure market efficiency. Market impact is defined to analyze how much the current price deviates the fundamental price of the risk asset. By calculating the value of it, we can check the efficiency of the market.

$$MI = \frac{1}{n_a}\sum_{j=1}^{n_a}\frac{p_a^j - p_f}{p_f}$$

Here n_a means the number of group behavior bias agents in a simulation period. P_a^j is traded price for each group behavior bias agent. The larger value of MI is, the heavier the market impact caused by group behavior bias agents.

3.2.3 Critical Point

Critical point is the maximum ratio of group behavior bias agents exist in the market to ensure the market efficiency. We only compare previous two evaluation values with the ratio of group behavior bias agents ranges from 5% to the critical point in the following experiments.

To figure out the limit action to keep efficient market, we carry on experiments and see how market impact changes. We define the maximum value of group behavior bias ratio which keeps the market efficient as the critical point r_{max}. When group behavior bias ratio is lower than it, the market is still efficient. We follow below steps to calculate the critical point:

1) To find the convergent time of each simulation run by locating the time where the price variations afterward are all lower than a threshold according to empirically set.
2) Mark the maximum value of group behavior bias ratio where 70% of simulation runs can finally get convergent as critical point.
3) For multi-assets market, the smallest critical point value among all the assets is considered as the critical point.

3.3 Parameter Settings

	Values
Agent Number	N = 1000
Maximum Size of Time	T_{max} = 2000
Fundamental Price of Single Market	P_f = 102
Fundamental Price of Multi Market	
Asset 1	P_1 = 102
Asset 2	P_2 = 102
Fundamentall Price after Jump	P_j = 80
Jump Time	T_j = 600
Tick Size	d_p = 0.1
Threshold of Most Trading Policy	Θ = 0.7
Maximum Ratio of Ownership Rate Regulation	θ = 0.5
Initial Share	100
Initial Cash	4000
Cancel Time	T_c = 10000
Probability in CNN model	P = 0.75

4, Simulation Results

4.1 Verification of the artificial market

In this part, we conduct experiment to confirm whether the models we built are valid or not. We calculate kurtosis, volatility and autocorrelation coefficients of squared return of the artificial market. As a result, the values of kurtosis and autocorrelation coefficients of squared return in all the markets are positive and are similar with actual markets. Meanwhile, autocorrelation coefficients of squared return decays as the lag interval goes by which is also like the actual market. Hence we reproduce the stylized facts including fat-tail and volatility clustering with different models. Therefore, the artificial markets we built with group behavior bias models are valid and the models replicate the characteristics of short term micro structure in real financial markets.

4.2 Experiment Results

We took 30 times simulation runs for each situation. The following result is the average of 30 simulation which runs for different markets on different random seeds.

4.2.1 Group Behavior Bias and Market Efficiency

We observe the price flow changes of the market, when with and without group behavior biases. We assume there is an abruptly jump on fundamental price of risky asset in the market. This experiment helps us to figure out whether group behavior biases can make the market inefficient or not.

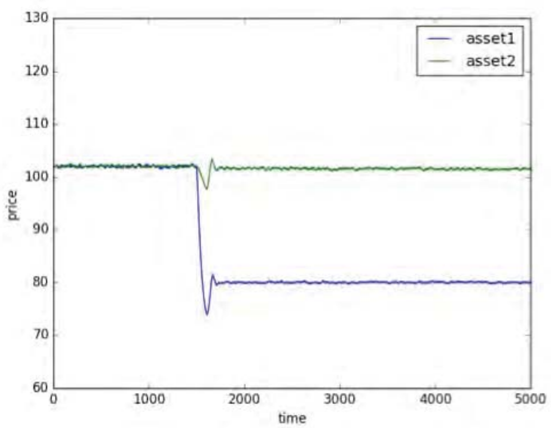

Fig.1(a) Price change figure of multi-assets market without group behavior bias agents

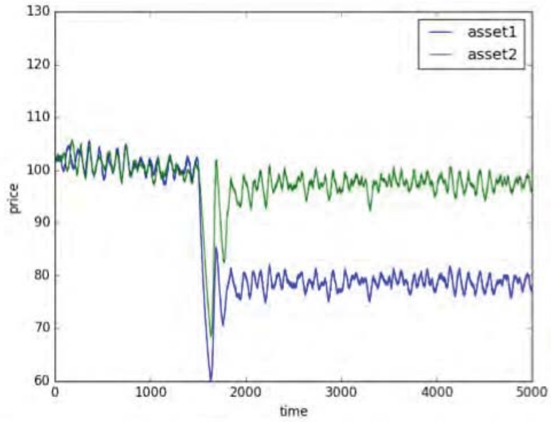

Fig.1(b) Price change figure of multi-assets market with group behavior bias agents

Fig.1 (a) and (b) show the price changes of assets without and with group behavior biases during a simulation run. X-axis is simulation time period. Y-axis is the market price of the asset. According to figures, we can see the price changes of asset will change more when group behavior bias exists.

4.2.2 Differences of group behavior bias models

We adjust the group behavior bias ratio in the market and compare the group behavior bias coefficient, market impact of different group behavior bias models to figure out the how each group behavior bias influents the market.

- Results of Group Behavior Bias Coefficient

We compare the group behavior bias coefficient of different group behavior bias models in the same market to figure out which kind of group behavior bias is more easy to form in the market.

Fig.2 shows group behavior bias coefficient of three kinds of group behavior bias models in the market basing on the CNN network. X-axis is bias agent ratio and y-axis is group behavior bias coefficient

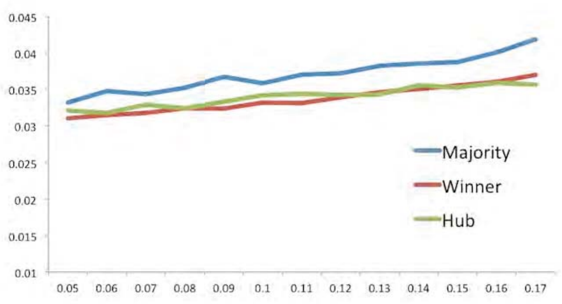

Fig.2 Group behavior bias coefficient of three kinds of group behavior bias model in single asset market without regulation.

- Group Behavior Bias and Market Efficiency

Fig.3 expresses the market impact with different group behavior bias models in the market. X-axis is the bias agent ratio in the market.Y-axis is the value of market impact. We only take the results within critical point to the validation of the results.

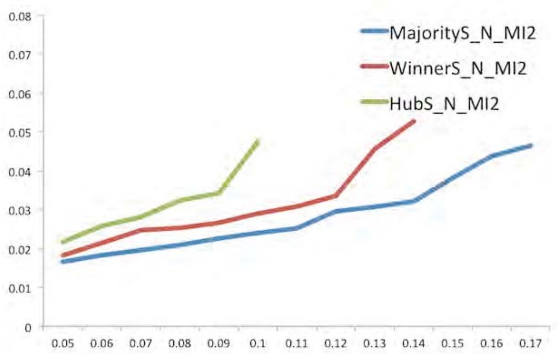

Fig.3 Market Impact by three group behavior bias models in single market without regulation

we can see that the group behavior bias coefficient with majority following model is the highest and lowest with hub following model. On the other hand, the market impact of hub following model is largest and majority is the smallest. We conclude that the majority following bias is the easiest to form in the market, however the market impact is the least. On the other hand, hub following bias is the hardest to emerge but the market impact is the most.

4.2.3 Regulation results

We compare the market impact of group behavior bias models when the market with or without different regulations respectively (Table Ⅰ and Table Ⅱ). Fundamental price jumps abruptly during the simulation run. In this way, we make clear how different regulations work with group behavior bias models.

TABLE Ⅰ

Market impact in different single assset markets with 10% hub following bias agent

	With short selling regualtion	Without any regualtions
Single Market	0.066	0.043

TABLE Ⅱ

Market impact in different multi-assets markets with 10% hub following bias agent

	With regulations	With short selling regulation	With multi rate regulation	Without any regulations
Asset 1	0.049	0.065	0.039	0.034
Asset 2	0.068	0.024	0.063	0.023

The group behavior biases show heavier market impact with short selling regulation exists and the market in which short selling is allowed is more stable. Hence we suggest that it will be better not to introduce short selling limitation in the market when group behavior biases exist to ensure the stability of financial market.

The multi rate regulation is the main factor to increase impact for non-risk asset. This is because agents will not take any action on non-risk asset to make sure the limitation number of risk asset within the threshold. In all the situations, the market impact will increase when multi rate regulation is engaged. Therefore, it is better not to employ multi-rate regulation to keep market efficiency. At last, no matter when the regulations exist or not, the market impact for hub following model is the largest and least for majority following model.

4.2 Conclusion

In this paper, we propose three different types of group behavior bias models based on different decision-making processes in various groups. We integrate these group behavior bias models to artificial markets and conduct experiments to figure out the differences among them. Besides, we reveal how the decision made by individuals get accumulated with group behavior biases and get reflect on the different markets.

We use KPI of group behavior bias coefficient, market impact to compare the differences of these group behavior bias models. We notice that it is the majority following bias is the easiest to form in the market, however the market impact is the least. On the other hand, hub following bias is the hardest to emerge but the market impact is the most. This matches the results of empirical analysis about financial markets which state financial market in China is more dramatic[5] and Japanese financial market is comparatively stable[6]. Therefore our models can reproduce the characteristics of group behavior biases in different countries.

we also figure out that group behavior biases show heavier market impact with short selling regulation exists. Hence we suggest that it will be better not to introduce short selling limitation in the market when group behavior biases exist to ensure the stability of financial market. The multi rate regulation is the main factor to increase impact for non-risk asset. This is because agents will not take any action on non-risk asset to make sure the limitation number of risk asset within the threshold. In all the situations, the market impact will increase when multi rate regulation is engaged. Therefore, we do not suggest market with multi rate regulation for market efficiency. At last, no matter when the regulations exist or not, the market impact for hub following model is the largest and least for majority following

References

[1] Masayuki Susai and Hiroshi Moriyasu. Consistency of risk attitude and other investment behavior of japanese professional fund managers: Questionnaire- based analysis. Waseda University Institute of Finance, Working Paper Series, pages 1–13, 2007.

[2] Takanobu Mizuta, Kiyoshi Izumi, and Shinobu Yoshimura. Price variation limits and financial market bubbles: Artificial market simulations with agents' learning process. In 2013 IEEE Conference on Computational Intelligence for Financial Engineering & Economics (CIFEr), pages 1–7. IEEE, 2013.

[3] Wang Yating, Toriumi Fujio. Market impact analysis on group behavior by artificial market. SIG-FIN-016-04, 2016

[4] Abhijit V Banerjee. A simple model of herd behavior. The Quarterly Journal of Economics, pages 797–817, 1992.

[5] Shujie Yao and Dan Luo. The economic psychology of stock market bubbles in china. The World Economy, 32(5):667–691, 2009.

[6] 高野陽太郎 and 纓坂英子. 日本人の集団主義 ”と “ アメリカ人の個人主義. 心 理学研究, 68(4):312–327, 1997.