Masaki Nakagome, Kazuo Maki, Hiromi Fujimori, and Hideto Ide (2013), "Our Free Choice of Reason-based Actions Can Produce Herd Behavior in Financial Markets: A Neuroeconomic Study Using Brain Decoding Methods,"Working Paper Series, Institute of Economic Research, Aoyama-Gakuin University, no.2013-1.

Our Free Choice of Reason-based Actions Can Produce Herd Behavior in Financial Markets:
A Neuroeconomic Study Using Brain Decoding Methods

By Masaki Nakagome*, Kazuo Maki*, Hiromi Fujimori*, and Hideto Ide**

Affiliations: * College of Economics, Aoyama Gakuin University
** College of Science and Engineering, Aoyama Gakuin University

Corresponding Author: Masaki Nakagome, College of Economics,
Aoyama Gakuin University, 4-4-25, Shibuya, Tokyo,
150-8366 Japan
TEL:+81-3-3409-7924
FAX:+81-3-5485-0698
Email: nakagome@cc.aoyama.ac.jp

Keywords: brain decoding, herd behavior, framing effects,
neuroeconomics, laboratory financial markets

Classification Codes: D87, G02

Acknowledgements：This study was supported in part by The Ministry of Education, Culture, Sport, Science, and Technology of Japan (Grant in Aid for Scientific Research, No.2020002) awarded to Masaki Nakagome and by the Research Institute at Aoyama Gakuin University (Grant in Aid for Research in Social Science Areas) awarded to Masaki Nakagome and Hideto Ide. Many thanks to Tetsuji Oyama for his technical support for executing the experiment with scanning.

Our Free Choice of Reason-based Actions Can Produce Herd Behavior in Financial Markets: A Neuroeconomic Study Using Brain Decoding Methods

By Masaki Nakagome, Kazuo Maki, Hiromi Fujimori, and Hideto Ide

Abstract

The introduction of a brain decoding method enabled us to extend the analytical framework for the possibility of herd behavior, including realistic cases in which traders decided herd behavior according to the free choice of frames for reason-based actions. In the extended experimental study, we confirmed the effectiveness of the extended version of the reason-based model and observed that reason-based actions were compatible with the birth of herd behavior in a financial market with decisions of buying risky stock. We obtained more implications for the relationship between herd behavior and reason-based actions. The accelerated experimental game drastically changed the result of brain decoding. Differing from earlier studies of the reason-based model, the emergence of emotions and intuitions for quick judgments in the accelerated game was expected to construct a new type of reason-based action to change the characteristics of herd behavior, more emotional and intuitive, in a laboratory financial market. In this emotional type of herd behavior, traders may be occasionally deprived of rational judgment to blindly follow other traders without careful examinations.

1.Introduction

1.1 The Aim of Our Study

The aim of our study is to explore the possibility of whether our free choice of reason-based actions can produce herd behavior in financial markets using the brain decoding method. This study implies that the theoretical framework for investigating herd behavior should be extended to include the analysis of bounded rational traders who have imperfect cognitive capacities to understand the complicated world, whereas traditional economics has assumed only perfectly rational traders for their theoretical basis. For bounded rational traders, the reason-based choice is necessary to assist and support their imperfect capacities to decide adaptive behaviors in the world. The traders can focus their attention on a specialized world restricted by the reasons and context-sensitive implications to more efficiently determine their adaptive behaviors.[1] When we examine the possibility of herd behavior in financial markets with bounded rational traders, we cannot ignore the problem of how reason-based choice affects the generation of herd behavior.

The reason-based model was presented by Shafir (1993) and Shafir-Simonson-Tversky (1993). These authors claimed that the model had attractive features. Thinking of choices guided by reasoning appears to be a natural method for us when we face a difficult choice in the complicated real world. Therefore, we can expect that the reason-based model will provide a new idea to explain the possibility of herd behavior in financial markets with bounded rational agents in an innovative manner. The author's famous example was the model with "pros and cons" in which one of two alternative options must be chosen. The first was an enriched option that possessed great merits and demerits, and the second was an impoverished option that had small merits an demerits. According to their expectations, if the agents were likely to focus on reasons for rejecting an option, i.e., they

[1] Consider an example of the frame problem whose philosophical implications were examined by McCarthy-Hayes (1969) and Dennett (1984). Cognitive framings or the limited beliefs of reasons maintained by human beings can avoid a state of frozen action such as that described by Dennett in the context of robots.

had the cognitive frame of "scoring by deducting points" or "the demerit mark method," they would choose the option with small merits and demerits. However, if the agents focused on reasons for accepting an option, i.e., they had the cognitive frame of "merit mark method," they would choose the option with great merits and demerits. Shafir (1993) and Shafir-Simonson-Tversky (1993) claimed that the effect of reason-based choices was sufficiently strong and robust, and the effect was confirmed to be statistically significant in their experiments. Using a statistical algorithm for brain decoding and functional near-infrared spectroscopy (fNIRS), we will confirm the effectiveness of the reason-based model and examine whether the reason-based actions can produce the possibility of herd behavior in financial markets.

1.2 The Necessity of Brain Decoding Methods in Neuroeconomic Studies of Herd Behavior

The use of brain decoding provides the following two advantages to attain the aim of our study. First, we obtain large technological possibilities to extend the research framework for exploring the possibility of herd behavior. Brain decoding is a type of so-called brain reading, enabling us to directly explore agents' mental states and internal decision-making processes. Earlier studies of herd behavior assumed psychological and behavioral patterns of traders and then competitively analyzed what explanatory power these assumptions had in examining the possibility of herd behavior. Without requiring specific assumptions in advance regarding psychological and behavioral patterns of agents, we can conduct neuroeconomic experiments to examine what psychological factors have the greatest effects on the phenomenon of herd behavior.[2]

Second, we obtain more fundamental advantages over earlier studies. The framing effect and reason-based choice have been studied since the seminal studies by Tversky-Kahneman (1981, 1986), Kahneman-Tversky (1984), Shafir (1993) and Shafir-Simonson-Tversky (1993). However, in the development after the initial studies, various types of reasons /frames of subjects in controlled experimental tasks have been assumed, i.e., the subjects have not been permitted to voluntarily choose their reasons/frames in the experiments. Under restrictive assumptions, these studies have investigated how the effect of reasons /frames would distort the subjects' decision-making. There is no economic study that has intensively analyzed the free and voluntary choice of reasons/frames by the subjects.

Figure 1 illustrates the case in which the effects of reasons/frames F1, F3 and F4 have been previously investigated but the effects of F2 and F5 have not yet been investigated. In the development of reason-based models, the subjects were required to have the reasons /frames of F1, F3 and F4 in controlled tasks, and it was demonstrated that these different reasons/frames would change decision-makings: D1, D2 or D3. The analysis of the free choice of reasons/frames by the subjects is essentially required to determine the relative importance of the effect produced by reasons and frames. Figure 1 illustrates that if there were an analysis of the free choice of reasons/frames, and if it was demonstrated that only the reasons/frames F3 and F5 would be frequently chosen by the subjects and F1, F2 and F4 would be less frequently chosen, the earlier study of F3 would then be determined to be more valuable than the studies of F1 and F4. The free choice analysis would also suggest the presence of the unexplored problem, the study of F5, to be more valuable than the previously investigated studies of F1 and F4. Using the analysis of free choice of reasons/frames, we can improve the inefficient allocation of research efforts among various types of effects produced by reasons/frames.

---

[2] The seminal studies on herd behavior are those by Glosten-Milgrom (1985), Banerjee (1992), Bikhchandani et al. (1992), Welch (1992) and Avery-Zemsky (1998). However, as Cipriani-Guarino (2005) correctly noted, it is difficult to test the theoretical results of herd behavior with earlier empirical study methods. Because of the absence of data on the private information available to traders, it cannot be determined whether traders would disregard private information in favor of imitation. The studies by Cipriani-Guarino (2005, 2009) and Drehmann-Oechssler-Rider (2005) overcame these difficulties by conducting experimental studies. However, there is no current neuroeconomic study of herd behavior that uses brain decoding methods without requiring specific assumptions in advance about psychological and behavioral patterns of agents. Our study presents a new type of research on herd behavior that does not have any restricted framework for examining the possibility of herd behavior.

Figure 1 The Free Choice of Reasons/Frames and Their Effect on Decision-making

Brain decoding provides a new technological possibility of analyzing subjects' free choice of reasons/frames. Examining the neural data obtained from the experiment, we previously demonstrated (Nakagome et al. (2012)) that the brain decoding method enabled us to directly investigate the subjects' mental states to determine what types of reasons/frames were used by the subjects when playing experimental games. Using the neuroeconomic method of brain decoding, we will strengthen the effectiveness of the earlier studies that have analyzed the effect of reasons/frames. We will design an experiment in which the subjects are permitted to freely choose their reasons/ frames and investigate what types of reasons/frames can produce the possibility of herd behavior in a financial market.

The structure of our paper is as follows. Section 2 describes the experimental methods and design, section 3 presents the results of the experiment, section 4 discusses the implications of our results, and section 5 provides the concluding remarks.

2. Methods

Brain decoding is a brain-reading method that interprets the data of neural activities. In this study, we used a statistical algorithm for interpretation and fNIRS to classify the neural activity data into two groups with different mental states to predict which reason-based choice, either the merit mark method or the demerit mark method, was used by the subjects to decide their behavior in the laboratory market. The introduction of this method extended the analytical framework for the study of herd behavior to include the analysis of realistic cases in which traders decided herd behavior according to reasons and cognitive frames.

Our experimental method is explained in detail. We will initially explain the subjects and the tools to be employed for our brain decoding. We will then illustrate the experimental tasks presented to the subjects.

2.1 The Subjects and Tools for Brain Decoding

The experimental games were played by six healthy right-handed subjects (three males; three females) who were 20-23 years of age. During each subject's games, we obtained the necessary data for brain decoding 10 different times, giving us enough data to execute brain decoding 60 times. The subjects were not allowed to eat for two hours before playing to provide clear neural reactions to the experimental tasks. Before beginning the experiment, we explained to the subjects the experimental procedure, experiment's safety, information on data security and instructions on how to receive payment for participation. Then, we obtained informed consent from the subjects. Our experimental plans and procedures were endorsed by the Research Ethical Committee of Aoyama-Gakuin University, Tokyo, Japan.

As Figure 2 illustrates, we used fNIRS, a simpler and more convenient tool for examining brain activation than the widely used method of functional magnetic resonance imaging (fMRI). As the use of fNIRS results in only minimal stress to the subjects, we were able to ask the subjects to execute lengthy and complex tasks. We used the Spectratech OEG-SpO2 model (updated from the OEG-16 model, sampling rate 6.10Hz) of fNIRS, based on the modified Beer-Lambert law, to scan the frontal cortex of the brain.[3] The fNIRS uses small, lightweight, 16-channel digital sensors on a headband to obtain event-related fNIRS data through a dynamically changing, high-sensitivity

[3] This model has previously been employed in scientific studies (Kita et al. (2011)).

optical signal. The signal reflects how the in vivo hemoglobin combines with oxygen in the blood vessels with high or low cortical activation. Our fNIRS method provided three types of event-related neural data: changes in oxyhemoglobin (ΔCoxyHb), changes in de-oxyhemoglobin (ΔCdeoxyHb) and aggregate changes in the two types of hemoglobin (ΔCoxyHb + ΔCdeoxyHb). We selected the changes in oxyhemoglobin to use for brain decoding. Strangman et al. (2002) found a strong correlation between fMRI variables and fNIRS measures with oxyhemoglobin data providing the strongest correlation. Therefore, by using the oxyhemoglobin data, our results of fNIRS brain decoding will correspond to those of the fMRI studies. We claim that this method enables us to perform efficient and low-stress experiments without the loss of generality in brain decoding.

Figure 2 The fNIRS Multi-channel Digital Sensors on a Headband

The locations of the 16-channel digital sensors were fixed by a headband during the experiment. After each subject completed the experiment, the locations of the sensors were measured using a 3D position measuring method with a digital camera (Nikon D5100) and NIRS-SPM software to allow the statistical analysis of the fNIRS signals and confirm that the channels were properly located on the frontal cortex of the brain.[4] For example, Figure 3 illustrates the locations of the sensors in the initial subject, as registered to a compatible canonical brain optimized for NIRS analysis. We obtained event-related, high-sensitivity optical signals from these channels.

Figure 3 The Locations of the16 fNIRS Channels in the Initial Subject as Registered to a Canonical Brain

2.2 Experimental Tasks

We presented the subject with tasks to be executed on a computer monitor. We obtained neural data when the subject decided his/her herd behavior in the task using reason-based choice. Figure 4 illustrates that our experiment was composed of three sections, Games, A1, A2 and B. After Game B, each subject was required to play an accelerated version of Game B, called B+. We planned the initial section of Game A1 to obtain data on the subject's typical neural activity pattern when using the reason-based choice of the demerit mark system to decide his/her behavior in the laboratory market. Our learning process for the typical neural pattern was executed by employing the brain decoding software Neural Network Tool Box, run on MATLAB. Game A2 was planned to obtain data on the typical neural pattern of the subject when using the reason-based choice of the merit mark system in the laboratory market. The third game, B, was the essential section of the experiment in which we obtained neural data to execute our brain decoding. In Game B, the subject could freely choose either the demerit or merit mark method as the frame for reason-based choice. After obtaining the neural data of the free choices, we use brain decoding to judge which reason-based choice was used by the subject. In the brain decoding method that used the Neural Network Tool Box, the data obtained from Game B were matched to the two neural patterns previously identified in Games A1 and A2. Game B+ was planned to investigate how to change the use of reason-based choice. We compared the analytical results of the accelerated Game B+ with those of the normal Game B. The change in the reason-based choice shows essential information regarding the role of reasons and frames in the subjects' decision-making involving herd behavior.

---

4 There were slight differences in the channel locations among the different subjects. However, the differences in the locations were not large, and we ensured that the channels were properly located on the frontal cortex using the 3D position measuring method. The neural data obtained from the fixed channel locations in each individual experiment suggested that the data can be successfully decoded without inconsistencies.

Figure 4 The Games Performed by Each Subject in Our Brain Decoding Experiment

Games A1, A2, B and B+ were each composed of short tasks. The short tasks were repeated 30 times in each section of A1, A2, B and B+. Figure 5(a) and Figure 5(b) illustrate a short task repeatedly executed in Games B and B+. In Game B, each screen was switched every 4 seconds but was switched every 2.5 seconds in the accelerated Game B+. Other short tasks in Games A1 and A2 were simplified versions of this task. Therefore, we initially explain the task of Games B and B+.

The short task of B and B+ was arranged in a reversed oddball pattern to maintain the subjects' vigilance to execute the task. The short task, as illustrated by Figures 5(a) and 5(b), was composed of main and sub-tasks. The main and sub-tasks were randomly presented to the subject to maintain his/her awareness to execute the games. The probability of the main task was 2/3, and the probability of the sub-task was 1/3. We obtained the data only from the main task.

Both the main and sub-tasks contained problems of whether the subject would buy one unit of risky stock. For simplicity, the problems assumed that buying the risky stock would cause the subject to gain or lose \$10; by not buying the stock, the subject would gain \$ 0.

Figure 5(a) The Short Task Repeatedly Executed in Games B and B+
Figure 5(b) The Short Task Repeatedly Executed in Games B and B+ (Continued)

The first screen of the computer monitor displayed the message "Let's Start." After 4 seconds, either the main or sub-task randomly started at probabilities of 2/3 and 1/3, respectively. If the main task started, the computer monitor displayed private information that was only available to the subject. The private information was "If You Buy, You May Get \$10 (Credibility 60%)." However, if the sub-task started, two types of private information were randomly presented to the subject at probabilities 1/2 and 1/2. The two types of private information were "If You Buy, You May Lose \$10 (Credibility 20%)" and "If You Buy, You May Lose \$10 (Credibility 80%)."

After these private information messages were presented, the third screen appeared. On the monitor, the subject received public information that was available to all of the agents. In the main task, the message was "Only 40% of the Traders Buy," whereas in the sub-task, the message was "60% of the Traders Buy."

It is noteworthy that the private information and the public information in the main task suggested adverse profit opportunities in the market. According to the private information, the subject would obtain a higher expected profit by purchasing the risky stock, whereas the public information suggested that the purchase of the stock could generate poor returns. When the subject rejected the private information or accepted the public information, he would perform the identical action as those who performed no trade.

However, in the sub-task, the probability was 1/2 when the private and public information suggested adverse opportunities for profits. In process B of the sub-task, as illustrated in Figure 5(a), both the private and public information suggested that the subject would have higher opportunities for profits by purchasing the stock. However, in process C of the sub-task, the private and public information suggested adverse profit opportunities. The asymmetric contents of the main and sub-tasks provided the subject with the appropriate psychological stimulus to maintain a strong awareness to execute the experimental tasks.

After 4 seconds, the message on the fourth screen was "Buy or Not? Push One of Two Buttons." The subject was required to push one of the two buttons to buy or not to buy the stock.

The result was immediately shown when the subject pushed the button. In the main task, as illustrated in Figure 5(b), the result was uncertain. We controlled the probability of uncertainty to be exactly even, i.e., 50%, but the subject was not informed about the probability of uncertain returns. This state is ambiguous for the subject because the probability is not known, whereas the risk is a different uncertainty state when the probability is known (following F. Knight (1921), who ascribed different definitions to risk and ambiguity). Recent neuroeconomic studies empirically demonstrate that the effect of ambiguity on neural activities is significantly different from that of risk.[5]

In an ambiguous state without information, the subject's decision-making was expected to fluctuate because he might repeatedly doubt his present expectations of probability and feel insecure. Therefore, in our experiment, we expected the subject to repeatedly change his decisions, either herd or non-herd behavior. However, in the sub-task, the result was not required to be uncertain, and we did not obtain data from the sub-task.

After the result was shown, the final message of "Rest" was displayed, and the monitor returned to the start screen.

It was previously explained that the tasks in Games A1 and A2 were simplified versions of the typical tasks executed in Games B and B+ because Games A1 and A2 were preliminary activities for brain decoding. In A1, we obtained data on the subject's typical neural activities when he/she used the reason-based choice of the demerit mark method. In A2, we obtained the data on the typical neural activities for the use of the merit mark method. In the simplified task for Game A1, the subject only received private information on the second screen, and the third screen for public information was abbreviated. In the simplified task for Game A2, the subject only received public information on the third screen, and the second screen for private information was abbreviated.

2.3 Random Sampling of Neural Data for Brain Decoding

We focused on the examination of herd behavior in the non-trade decision-making manner produced by either the rejection of private information or the acceptance of public information. The rejection of private information would be decided by using the reason-based choice of the demerit mark method. The acceptance of public information would be decided by using the merit mark method. We empirically investigated how herd behavior was actually determined by the subjects using the two types of reason-based choice: the merit and demerit mark methods.

For brain decoding, we randomly sampled the neural data on non-trade decision-making from the experimental data obtained by fNIRS. It is notable that the experimental task was arranged in the reversed oddball pattern to maintain a strong awareness of the subject to execute the tasks, as illustrated by Figures 5(a) and 5(b). We randomly sampled the neural data only from the main task.

First, we randomly sampled 40 pieces of neural data from non-trade cases in the main task of Games A1 and A2 played by each subject to identify the typical neural patterns in the rejection of private information and acceptance of public information. We conducted this random sampling of the experimental data for a specific time frame: 4 seconds $< t <$ 12 seconds from the beginning of each task. Thus, all of the neural data to identify the typical neural patterns were obtained from this specific period during which the subjects had previously received available information on the screen (either private or public information) but while they were still waiting for the screen to allow them to push one of the buttons to buy or not. The data obtained during this period were expected to clearly show the neural activity characteristics in each subject's consideration of decision-making.

The second random sampling was conducted to obtain the necessary neural data for brain decoding from the main task in Games B and B+. We selected the non-trade cases from the experimental data in Games B and B+ and randomly sampled 10 pieces of data from each subject's non-trade cases. The time frame for random sampling was also the time after the subjects had previously obtained all of the available information but before they were allowed to push one of the

---

[5] Hsu et al. (2005), Huettel et al. (2006) and Bach et al. (2009) are seminal papers to explore the neural processing of risk and ambiguity in the brain. They presented neurological evidence that the human brain perceived risk and ambiguity differently. The neurological responses to ambiguity, particularly the higher activation of the posterior inferior frontal sulcus (pIFS), come from the anticipation of subjects that hidden information under ambiguity is searched for to reduce to risk (uncertainty with known probabilities). We also examined the effects of ambiguity on the brain wave by analyzing the contingent negative variation (CNV). See Nakagome et al. (2011).

buttons to indicate their decision (i.e., the period after the third screen but before the fourth screen, shown in Figures 5(a) and 5(b)).

In Game B, the screens were switched every 4 seconds, but in the accelerated version of Game B+, the screens were switched every 2.5 seconds. Therefore, the period for random sampling was 8 seconds $< t <$ 12 seconds in Game B and 5 seconds $< t <$ 7.5 seconds in the accelerated Game B+. Six subjects participated in the experiment, providing the neural data required for 60 instances of brain decoding from the normal speed Game B and the accelerated Game B+.

2.4 The Incentives for the Subjects to Execute the Experimental Games

We presented an incentive plan to the subjects to make our experiment effective. The subjects were informed about the possibility that their paycheck from participating in the experiment would be changed with the results of their decisions during the games. After each subject finished all of the games, we randomly selected two results from all the results to determine his/her final paycheck. This changeable bonus paycheck was added to (or deducted from) the basic paycheck previously determined in the contract. The luckiest bonus was \$20, and the unluckiest bonus was -\$20.

The incentive plan was jointly explained with an overview of playing the games before the start of the experiment. We explained to each subject the possibility that the two types of information, private and public, would have occasionally inconsistent and adverse meanings, for example, one might encourage his buying the risky asset but the other might not. This prior explanation increased the effectiveness of the incentive plan. The subjects became more concerned with the contents of the experimental game and intensely considered the problem of which information, private or public, was more appropriate (or less appropriate) to maximize their paycheck.

3. Results

Figure 6 illustrates the neural images generated by fNIRS that showed the typical patterns of neural activity at the 16 channels located on the frontal cortex. The images were obtained by calculating the cumulative means of the data in Games A1 and A2. The left side of the images showed the typical patterns in neural activity obtained in Game A1, and the right side of the images showed the typical patterns in neural activity obtained in Game A2. These neural images illustrate the changes in oxyhemoglobin (ΔCoxyHb) measured using the standard unit of mMmm. It was previously explained that following the procedures described by Strangman et al. (2002), we selected the changes in oxyhemoglobin (ΔCoxyHb) for use in brain decoding to retain strong correlations between the fMRI variables and fNIRS measures. By using the Neural Network Tool Box, the event-related data obtained from Games B and B+ were matched to the typical neural activity patterns seen in Games A1 and A2, to determine which reason-based choice was used by the subjects.

Figure 6 The fNIRS Images of Typical Neural Activity in the Frontal Cortex in Games A1 and A2

Figures 7 to 10 illustrate the primary results provided by our 60 brain decoding values of the normal game B and the accelerated game B+, respectively. In the scatter diagrams, each datum of neural activity is interpreted to have two types of plausibility for using the alternative reason-based choice. The horizontal axis measures the plausibility of using the demerit mark method to reject private information. The vertical axis measures the plausibility of using the merit mark method to accept public information. The two types of plausibility for using the reason-based choice were represented by the values of the sigmoid function calculated by Neural Network Tool Box, run on MATLAB. The points located in the lower right section had larger values on the horizontal axis than on the vertical axis and could be categorized as those cases in which the subjects used the demerit mark method to reject private information. On the other hand, the points located in the upper left section could be categorized as those cases in which the subjects used the merit mark method to accept public information.

Figure 7 A Scatter Diagram of the Type 1 Herding Cases Obtained by Brain Decoding in Game B
Figure 8 A Scatter Diagram of the Type 2 Herding Cases Obtained by Brain Decoding in Game B
Figure 9 A Scatter Diagram of the Type 1 Herding Cases Obtained by Brain Decoding in Accelerated Game B+
Figure 10 A Scatter Diagram of the Type 2 Herding Cases Obtained by Brain Decoding in Accelerated Game B+

In Figures 7 and 9, the plausibility of using the demerit mark method to reject private information was larger than the plausibility of using the merit mark method to accept public information. By contrast, in Figures 8 and 10, the plausibility of using the demerit mark method was lower than the plausibility of using the merit mark method. The rejection of private information and acceptance of public information arose from different reason-based actions but resulted in the identical decision, i.e., herd behavior in the non-trade decision-making manner. Figures 7 and 9 illustrate the herding cases in which the rejection of private information by the use of the demerit mark method was more plausible than the acceptance of public information by the use of the merit mark method. We denote this type of herd behavior "type 1 herd behavior." Figures 7 illustrates that there were 41 type 1 herding cases in the 60 brain decoding values in Game B, whereas Figure 9 illustrates that there were only 26 type 1 herding cases in the accelerated Game B+. The number of type 1 herding cases decreased with an increase in the speed of playing the games. Figures 8 and 10 illustrate the herding cases in which the acceptance of public information by the use of the merit mark method was more plausible than the rejection of private information by the use of the demerit mark method. We denote this type of herd behavior "type 2 herd behavior." Figures 8 illustrates that there were only 19 type 2 herding cases in the 60 brain decoding values in Game B, whereas Figure 10 illustrates that there were 34 type 2 herding cases in the accelerated Game B+. The number of type 2 herding cases increased with the acceleration of playing the games. Therefore, the following results were determined.

Result 1

We compared the plausibility of using the demerit mark method to reject private information with the plausibility of using the merit mark method to accept public information. The results of brain decoding were that the number of type 1 herding cases with the demerit mark method decreased from 41 to 26 but that the number of type 2 herding cases with the merit mark method increased from 19 to 34, when the original game B is changed to the accelerated game B+.

We additionally examine the possibility of the two types of herding cases (type 1 and 2). In these scatter diagrams, there were multiple herding cases that could not be clearly categorized into the two types. Therefore, we adopted the following 5% rule to determine whether the decoding was sufficiently successful to clearly categorize each of the neural data into one of the different groups. The sigmoid values on the horizontal and vertical axes, denoted by $x(t)$ and $y(t)$ respectively, were obtained by decoding the t'th neural datum: therefore, we defined the following rule for judgment.

(i) if $x(t) > y(t)$ and $y(t)/[x(t) + y(t)] < 0.05$,
the t'th datum was successfully judged by decoding to be a case in which the demerit mark method was used to reject private information to determine herd behavior

(ii) if $x(t) < y(t)$ and $x(t)/[x(t) + y(t)] < 0.05$, the t'th datum was successfully judged by decoding to be a case in which the merit mark method was used to accept public information to determine herd behavior

(iii) if $x(t) > y(t)$ and $y(t)/[x(t) + y(t)] > 0.05$ or if $x(t) < y(t)$ and $x(t)/[x(t) + y(t)] > 0.05$, the t'th datum was not successfully judged by decoding

Using these judgment rules, we counted the cases of successful and unsuccessful decoding. Table 1 shows that 36.6% and 31.6% of decoded cases were interpreted to be unsuccessful when we adopted the 5% rule for judgment. However, even when we excluded these unsuccessfully decoded cases from our analysis, we found that the empirical implications of Result 1 were also identically maintained in the group of successfully decoded cases. Table 1 shows that in the successfully decoded cases, type 1 herding decreased from 27 to 15, but type 2 herding increased from 11 to 26 when the original game B was changed to the accelerated game B+. We indicate this result as Result 2 that has the identical empirical implications as Result 1.

Result 2

We adopted the 5% rule to judge whether the decoding was successful to clearly distribute the neural data into the two groups in which the two different types of reason-based choice were used. In the group of the successfully decoded cases, type 1 herding decreased from 27 to 15, but type 2 herding increased from 11 to 26 when the original game B was changed to the accelerated game B+.

Table 1 The Number of Successful and Unsuccessful Brain Decoding in Game B and Accelerated Game B+

4. Discussions

The purpose of our study is to examine the possibility of whether traders' free choice of frames for reason-based actions can produce herd behavior in financial markets. To attain our purpose, we applied the reason-based model by Shafir (1993) and Shafir-Simonson-Tversky (1993) to our examination of herd behavior. These studies expected that if agents used the demerit mark method, they would choose an impoverished option with small merits and demerits; however, if agents used the merit mark method, they would choose an enriched option with great merits and demerits.

In our experiment, we defined an impoverished and enriched option for the subjects. The non-trade decision-making was an impoverished option without any gains or losses, whereas the purchase of risky stock was an enriched option with great gains and losses. It was previously explained in the methods section that we focused on herd behavior in the non-trade decision-making manner that was produced by either using the demerit mark method to reject private information or using the merit mark method to accept public information. Because non-trade decision-making was an impoverished option, following the expectation by Shafir (1993) and Shafir-Simonson-Tversky (1993), the subjects were expected to use the demerit mark method to reject private information when they decided on the non-trade decision-making. Our expectation was justified by the result of brain decoding in the normal game B. Result 1 showed that in the brain decoding results of Game B, the number of type 1 herding cases using the demerit mark method was 41, and the number of type 2 herding cases using the merit mark method was only19. Result 2 also justified our expectation by demonstrating that the number of type 1 herding cases using the demerit mark method was 27, and the number of type 2 herding cases using the merit mark method was only 11 in the brain decoding results of Game B when we adopted the 5% rule to determine whether decoding was successful. Both Results 1 and 2 showed that the usage of the demerit mark method was more plausible than the merit mark method when the traders chose non-trade decision-making as herd behavior. The emergence of reason-based actions could be compatible with the birth of herd behavior in the financial market.

However, Results 1 and 2 provided more information about the possibility of herd behavior caused by reason-based actions. The accelerated game B+ drastically changed the result of brain decoding. Results 1 and 2 illustrated that the type 1 herding cases sharply decreased, but by contrast, the type 2 herding cases remarkably increased when the original game B was changed to the accelerated game B+. This result obtained in Game B+ implies that the reason-based actions are context-sensitive, and that the expectation of Shafir (1993) and Shafir-Simonson-Tversky (1993) will not always occur. We expect that a new type of reason-based action would arise in the accelerated game B+, and the characteristics of herd behavior would change with the emergence of the new reason-based action.

We should consider the effect of emotions and intuitions on the new type of reason-based action. Opposed to the traditional consequentialism view that Loewenstein et al. (2001) and Slovic et al. (2004) have criticized, feelings and emotions are not simple noises that disturb the function of reason. Damasio (1994, 1999, 2003) claims that emotions can intuitively help the function of reason. In the accelerated game B+ in which quick judgments were required, feelings and emotions had to intuitively assist imperfect reason and limited capacities to adaptively make decisions. This emergence of emotions and intuitions was expected to construct a new type of reason-based action. Therefore, the new reason-based action used in the accelerated Game B+ would be more emotional than the previous one in Game B. Results 1 and 2 can be interpreted that the emotional reason-based action increased the usage of the merit mark method to aggressively accept public information and changed the characteristics of herd behavior to be more emotional; however, the new reason-base action decreased the usage of the demerit mark method to carefully reject private information.

5. Concluding Remarks

Brain decoding is a type of so-called brain reading. From the results of the subjects' decisions, we can investigate which frame for reason-based action was used by the subject to make the decision. Using brain decoding, we obtained the following two implications in our study.

First, we extended the experimental framework to permit the subjects to freely choose their reason-based actions. In the extended framework, we reinterpreted the expectation by Shafir (1993) and Shafir-Simonson-Tversky (1993) and confirmed the effectiveness of their expectation. Figure 11 illustrates the extended reason-based model with impoverished and enriched options, permitting the subjects the free choice for frames of reason-bases actions. In this figure, we also illustrate additional explanations in the parentheses. We formulated the extended reason-based model as a financial experimental game with the option of buying risky stock. The purchase of risky stock was an enriched option, and no-trading decision was an impoverished option. In the experimental game, we examined the relationship between the possibility of herd behavior and the free choice of a frame for reason-based actions. It was previously explained in the methods section that we focused on the examination of herd behavior of the non-trade decision-making that was produced by either using the demerit mark method to reject private information or using the merit mark method to accept public information.[6] The brain decoding demonstrated that the extended version of the expectation by Shafir (1993) and Shafir-Simonson-Tversky (1993) was effective in the normal speed game of the neuroeconomic experiment. The usage of the demerit mark method was judged to be more plausible in subjects' free choice of reason-based actions than the merit mark method. Confirming the effectiveness of the extended reason-based model in our financial experimental

[6] The other case of herd behavior is the purchasing behavior of risky stock, which can be symmetrically discussed. Therefore, we abbreviate this case in this study. More general analyses, including the examination of mutiple types of herd behavior should be studied in the future.

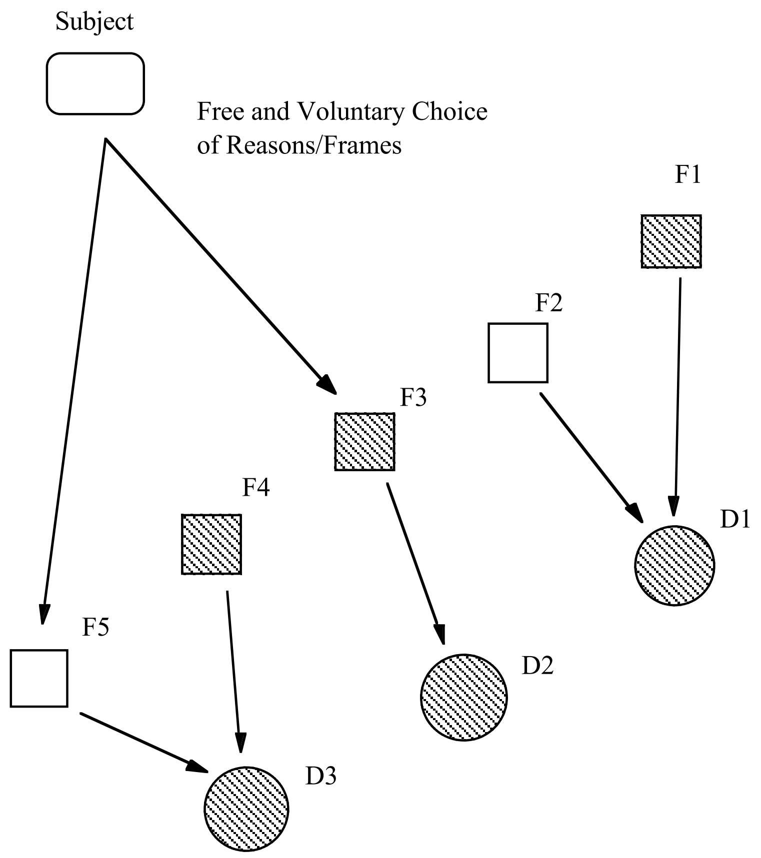
games with herd behavior, we claim that free choice of reason-based actions is compatible with the birth of herd behavior in this financial market.

Figure 11 An Explanation for the Extended Reason-based Model with the Free Choice of Frame for Reason-based Actions

Second, examining the neural data obtained in the abnormally accelerated experimental game, we demonstrated, using brain decoding, that the choice of frames of reason-based actions changed in a context-sensitive manner. Differing from the expectations by earlier reason-based models, as illustrated by Figure 11, the type 1 herding cases using the demerit mark method sharply decreased, but the type 2 herding cases using the merit mark method remarkably increased. We consider that this unexpected change in reason-based actions derived from the emergence of new emotions and intuitions required for quick judgments in the accelerated game. As Damasio (1994, 1999, 2003) claimed that emotions and feelings can intuitively help the function of reason and limited capacities to understand the world or to decide adaptive behaviors. The emergence of emotions and intuitions was expected to construct a new type of reason-based action. The increase in the use of the merit mark method implied that its use in the type 2 herding cases was more suitable than other types of cognitive frames to collaborate with the new emergence of emotions and intuitions to make quick decisions in the accelerated game. It is noteworthy that the characteristics of herd behavior would change with the emergence of the new type of reason-based action using the merit mark method. We expect that the characteristics of type 2 herd behavior would be more emotional than the previous type 1 herd behavior. The traders seemed to decide to accept public information in a more emotional and intuitive manner for quick judgments in the accelerated game. In this emotional type of herd behavior, the traders may be occasionally deprived of rational judgment to blindly follow other traders without careful examination.

This consideration regarding the change in the herd behavior characteristics will provide a criticism to earlier theoretical studies of herd behavior that have only analyzed herd behavior produced by traders' perfectly rational decisions. In general, herd behavior will be produced by not only rational decisions but also emotional and intuitive decisions following other traders blindly without careful examination. The earlier studies have been restricted in their analytical tools for investigating herd behavior with emotions and intuitions. However, the brain decoding method will provide a new possibility to open a new research field toward a general theory of herd behavior, including the study of emotions and intuitions. It was previously mentioned in the introduction that we do not require any specific assumptions in advance about the psychological and behavioral patterns of the agents before conducting the brain decoding experiment. We can extend the effectiveness of the reason-based model, adding the necessary revisions to further examine whether free choices of frames for reason-based actions can produce the possibility of various types of herd behavior, either emotional or rational, in financial markets.

Figure 1 The Free Choice of Reasons/Frames and Their Effect on Decision-making



F1 to F5 … Reasons/Frames
D1 to D3 … Decisions

Figure 2 The fNIRS Multi-channel Digital Sensors on a Headband

Figure 3 The Locations of the 16 fNIRS Channels in the Initial Subject as Registered to a Canonical Brain

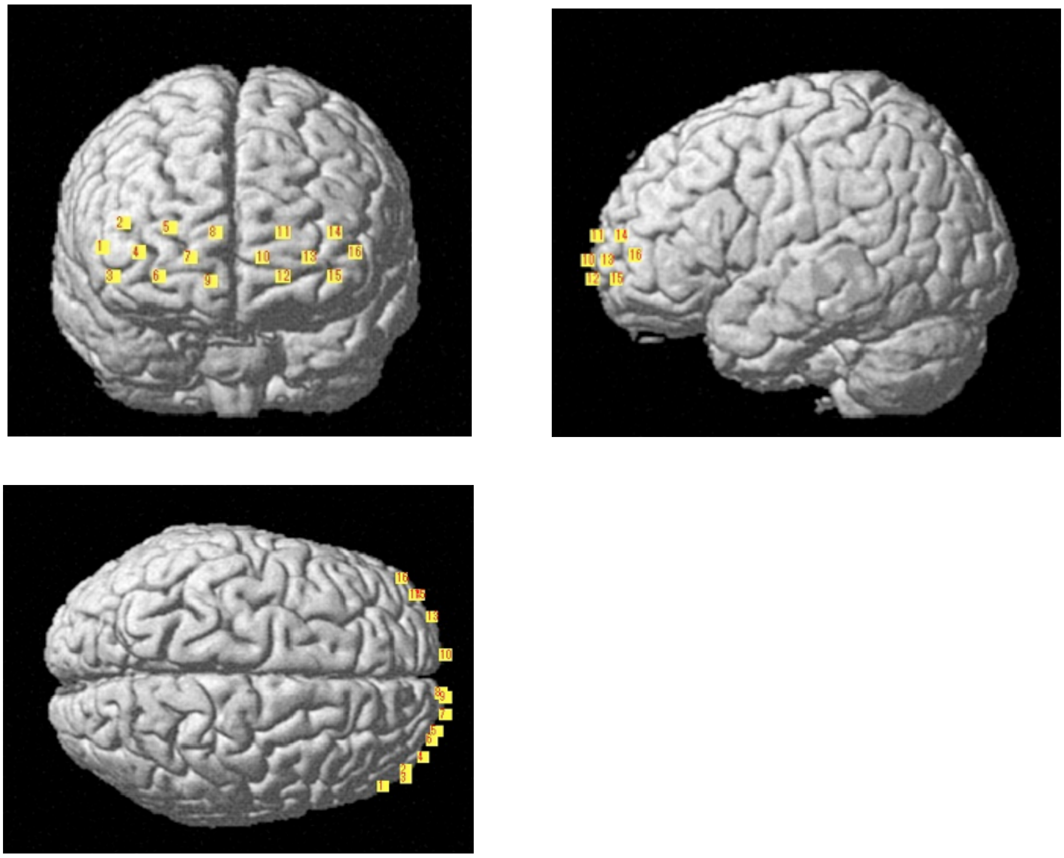


Figure 4 The Games Performed by Each Subject in Our Brain Decoding Experiment

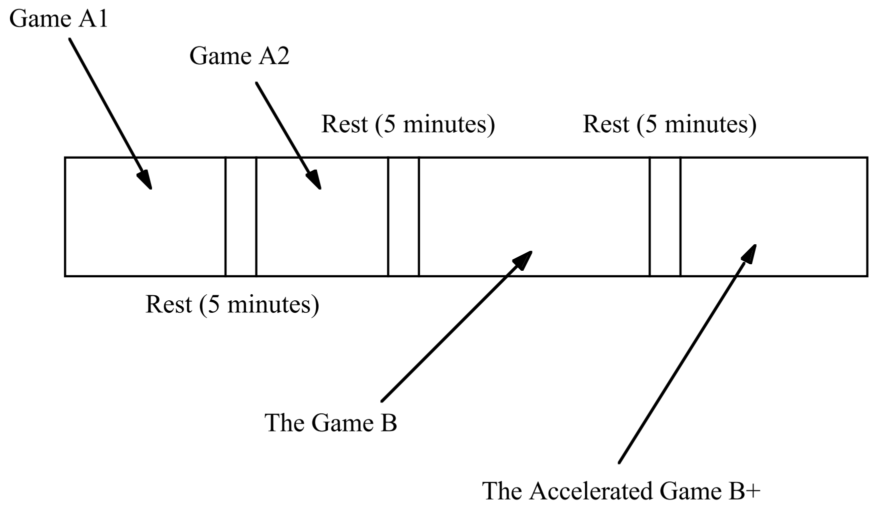


Figure 5(a) A Short Task Repeatedly Executed in Games B and B+

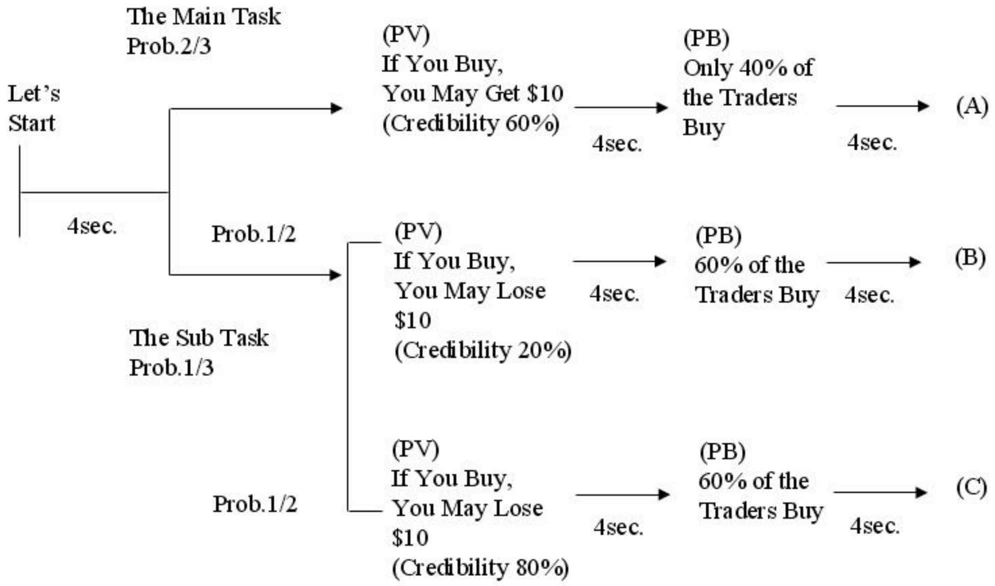


Figure 5(b) A Short Task Repeatedly Executed in Games B and B+ (Continued)

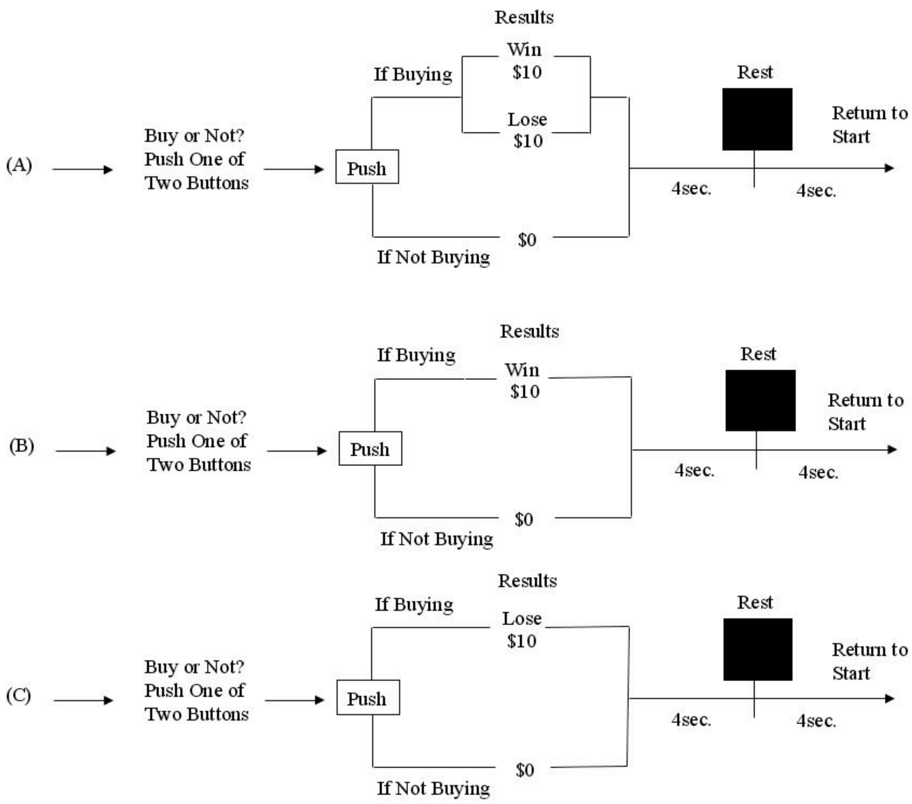


Figure 6 The fNIRS Images of Typical Neural Activity in the Frontal Cortex in Games A1 and A2

The typical neural changes in Game A1 The typical neural changes in Game A2

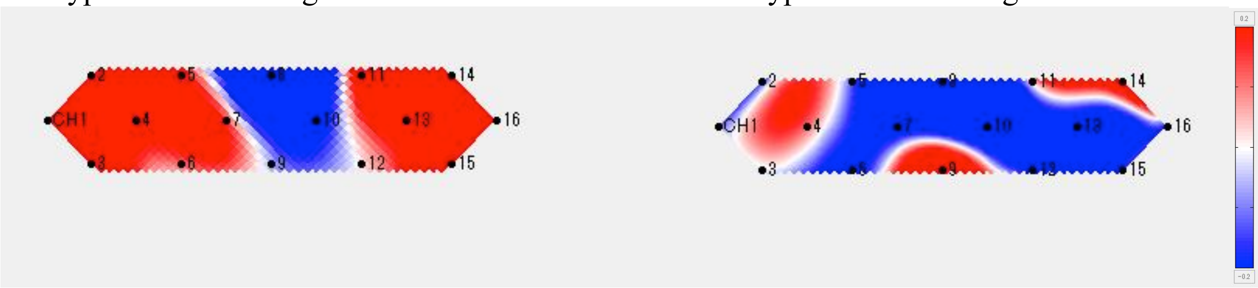
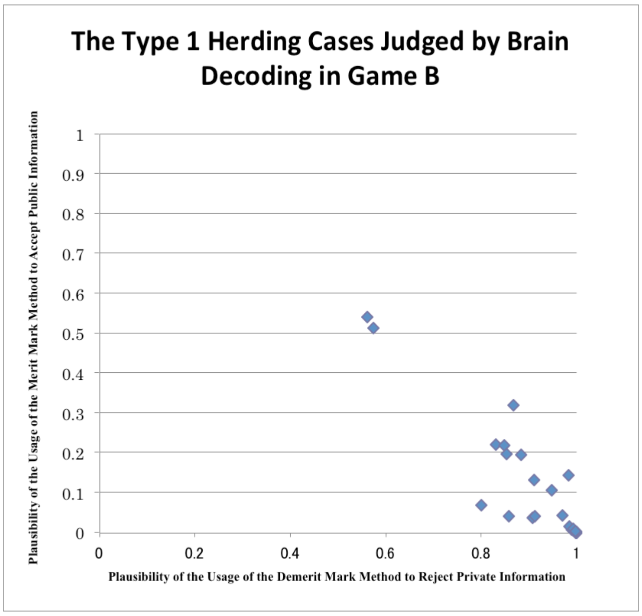
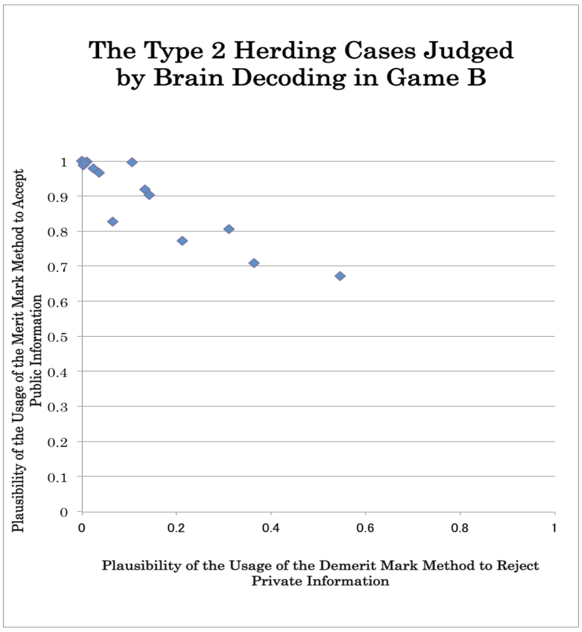


Figure 7 A Scatter Diagram of the Type 1 Herding Cases Obtained by Brain Decoding in Game B



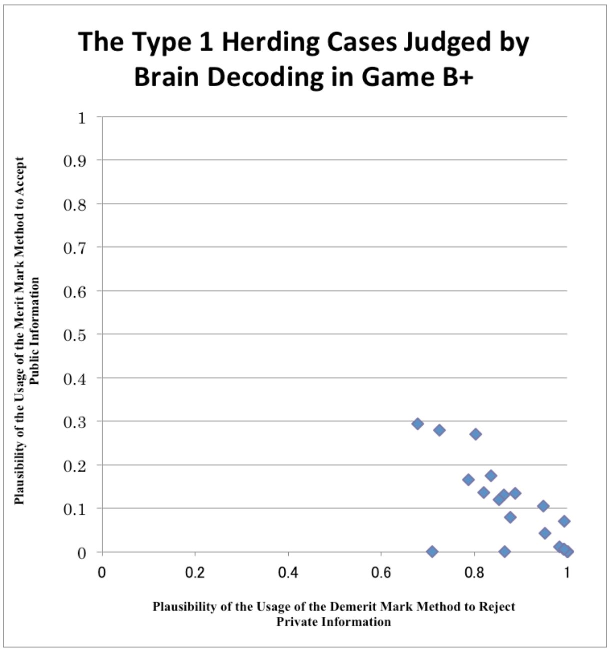
	Plausibility of the Usage of the Demerit Mark Method to Reject Private Information	Plausibility of the Usage of the Merit Mark Method to Accept Public Information
The Number of Cases	41	41
Average (Variance)	0.943073 (0.010810)	0.069792 (0.017261)

Figure 8 A Scatter Diagram of the Type 2 Herding Cases Obtained by Brain Decoding in Game B



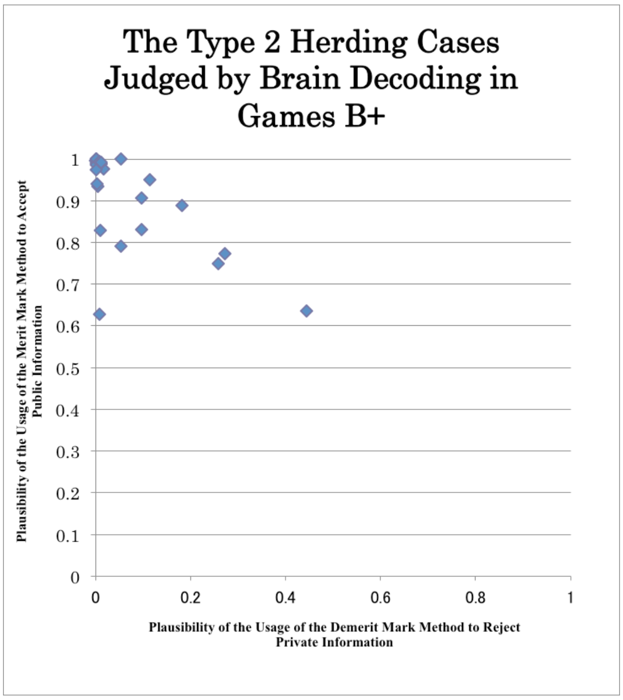
	Plausibility of the Usage of the Demerit Mark Method to Reject Private Information	Plausibility of the Usage of the Merit Mark Method to Accept Public Information
The Number of Cases	19	19
Average (Variance)	0.104026 (0.023468)	0.921778 (0.011892)

Figure 9 A Scatter Diagram of the Type 1 Herding Cases Obtained by Brain Decoding in Accelerated Game B+



	Plausibility of the Usage of the Demerit Mark Method to Reject Private Information	Plausibility of the Usage of the Merit Mark Method to Accept Public Information
The Number of Cases	26	26
Average (Variance)	0.905930 (0.010850)	0.077969 (0.009166)

Figure 10 A Scatter Diagram of the Type 2 Herding Cases Obtained by Brain Decoding in Accelerated Game B+



	Plausibility of the Usage of the Demerit Mark Method to Reject Private Information	Plausibility of the Usage of the Merit Mark Method to Accept Public Information
The Number of Cases	34	34
Average (Variance)	0.049826 (0.009805)	0.930850 (0.010940)

Table 1 The Number of Successful and Unsuccessful Brain Decodings in Game B and Accelerated Game B+

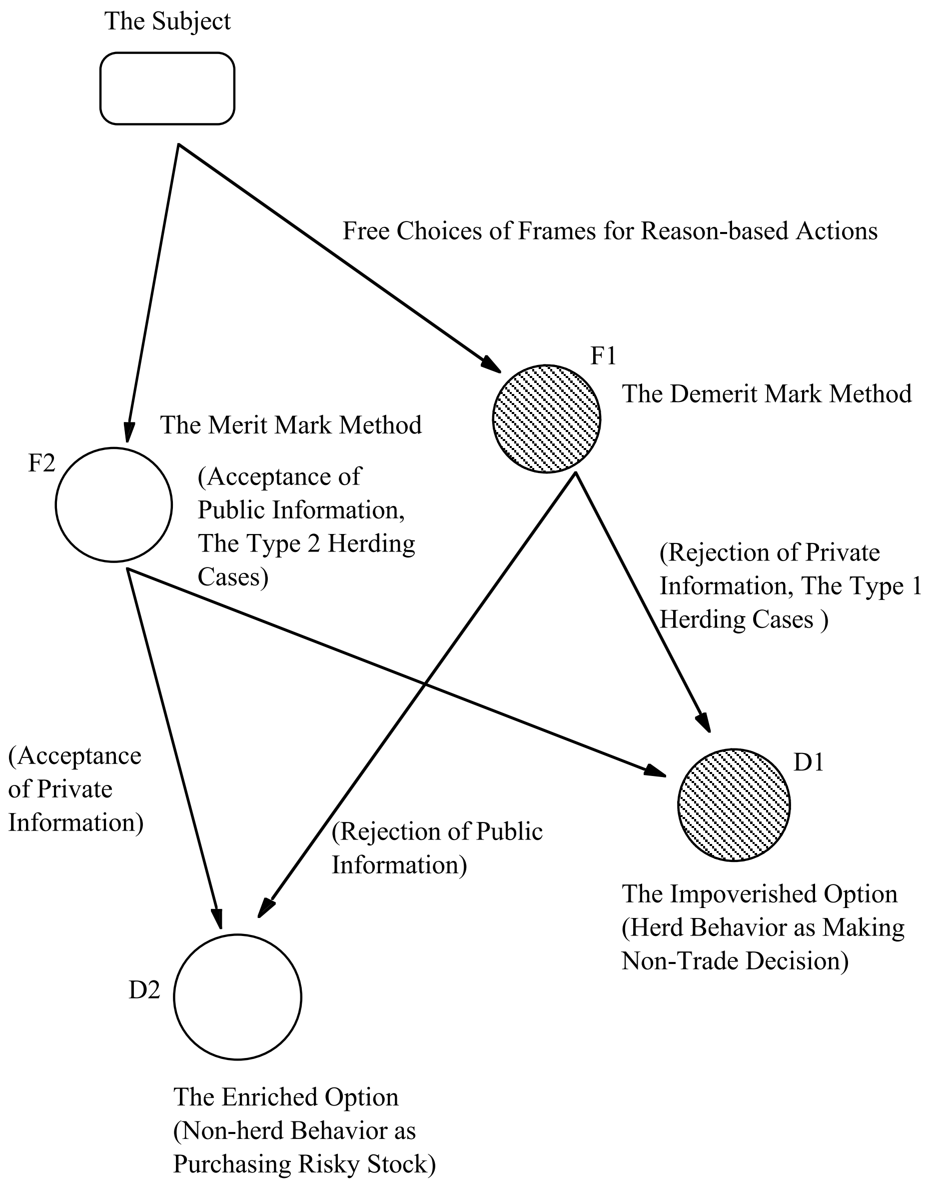
In Game B (60 Decodings)

	The Number of Cases
The Number of Unsuccessful Decodings	22
The Number of Successful Decodings to Judge the Cases of the Demerit Mark Method to Reject Private Information	27
The Number of Successful Decodings to Judge the Cases of the Merit Mark Method to Accept Public Information	11

In Accelerated Game B+ (60 Decodings)

	The Number of Cases
The Number of Unsuccessful Decodings	19
The Number of Successful Decodings to Judge the Cases of the Demerit Mark Method to Reject Private Information	15
The Number of Successful Decodings to Judge the Cases of the Merit Mark Method to Accept Public Information	26

Figure 11 An Explanation for the Extended Reason-based Model with the Free Choice of Frames for Reason-based Actions



F1 and F2… Frames for Reason-based Actions
D1 and D2… Determination of Options

References

Avery, Chirstopher and Peter Zemsky (1998), “Multidimensional Uncertainty and Herd Behavior in Financial Markets,” *American Economic Review,* vol.88, no.4, pp.724-748.

Bach, Dominik R., Ben Seymour and Ray, J. Dolan (2009),”Neural Activity Associated with the Passive Prediction of Ambiguity and Risk for Aversive Events,” *Journal of Neuroscience,* vol.29, no.6, pp.1648-1656.

Banerjee, Abhijit V. (1992), “A Simple Model of Herd Behavior,” *Quarterly Journal of Economics,* vol.107, no.3, pp.797-817.

Bikhchandani, Sushil, David Hirshleifer and Ivo Welch (1992), “A Theory of Fads, Fashion, Custom, and Cultural Change in Informational Cascades,” *Journal of Political Economy,* vol.100, no.5, pp.992-1026.

Cipriani, Marco and Antonio Guarino (2005), “Herd Behavior in a Laboratory Financial Market,” *American Economic Review,* vol.95, pp.1427-1443.

Cipriani, Marco and Antonio Guarino (2009), “Herd Behavior in Financial Markets: An Experiment with Financial Market Professionals,” *Journal of European Economic Association,* vol.7, no.1, pp.206-233.

Damasio, Antonio R. (1994), *Descartes' Error: Emotion, Reason, and the Human Brain,* New York: Putnam.

Damasio, Antonio R. (1999), *The Feeling of What Happens: Body and Emotion in the Making of Consciousness,* New York: Harcourt.

Damasio, Antonio R. (2003), *Looking for Spinoza,* New York: Harcourt.

Dennett, Daniel (1984), “Cognitive Wheels: The Frame Problem of AI,” in *The Philosophy of Artificial Intelligence,* M.A.Boden ed., Oxford: Oxford University Press.

Glosten, Lawence, R. and Paul R. Milgrom (1985), “Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders,” *Journal of Financial Economics,* vol.14, no.1, pp.71-100.

Drehmann, Mathias, Joerg Oechssler and Andreas Rider (2005),”Herding and Contrarian Behavior in Financial Markets; An Internet Experiment,” *American Economic Review*, vol.95, no.5, pp.1403-1426.

Hsu, Ming, Meghana Bhatt, Ralph Adolphs, Daniel Tranel and Colin F. Camerer (2005),”Neural Systems Responding to Degrees of Uncertainty in Human Decision-Making,” *Science,* vol.310, pp.1680-1683.

Huettel, Scott A., C. Jill Stowe, Evan M.Gordon, Brent T.Warner and Michael L.Platt (2006), “Neural Signature of Economic Preferences for Risk and Ambiguity, *Neuron*, vol.49, pp.765-775.

Kahneman, Daniel and Amos Tversky (1984), "Choice, values, and Frames," *American Psychologist,* vol.39, pp.341-350.

Kita,Yousuke, Atsuko Gunji, Yuki Inoue, Takaaki Goto, Kotoe Sakihara, Makiko Kaga, Masumi Inagaki and Toru Hosokawa (2011), “Self-Face Recognition in Children with Autism Spectrum Disorders: A Near-Infrared Spectroscopy Study,” *Brain and Development,* vol.33, pp.494-503.

Knight, Frank H. (1921), *Risk, Uncertainty, and Profit,* Boston: Hart, Schaffner & Marx.

Loewenstein, George F., Elke U.Weber, Christopher K.Hsee and George N.Welch (2001), “Risk as Feelings,” *Psychological Bulletin,* vol.127, no.2, pp.267-286.

McCarthy, John and Patrick Hayes (1969), “Some Philosophical Problems from the Standpoint of Artificial Intelligence,” *Machine Intelligence,* vol.4, pp.463-502.

Nakagome, Masaki, Kazuo Maki, Hiromi Fujimori, Yukiko Uekusa, Keiji Isa, Hirotoshi Asano, Yumiko Baba, HisayaTanaka and Hideto Ide (2011), “The Generation of Perception Gap and Ambiguity Aversion Under Uncertainty:　An EEG Experimental Study of Contingent Negative Variation (CNV),” Working Paper Series, Institute of Economic Research at Aoyama-Gakuin University, no.1, March 2011, pp.1-21.

Nakagome, Masaki, Kazuo Maki, Hiromi Fujimori and Hideto Ide (2012), "Our Choice of Cognitive Frames is Affected by the Frames of Others in Financial Economy: A Neuroeconomic Study Using Brain Decoding Methods," Working Paper Series, Institute of Economic Research, Aoyama-Gakuin University, no.3, December 2012, pp.1-28.

Shafir, Elder (1993), "Choosing Versus Rejecting: Why Some Options Are Both Better and Worse Than Others," *Memory and Cognition,* vol.21, pp.546-556.

Shafir. Elder, Itamar Simonson and Amos Tversky (1993), "Reason-Based Choice," *Cognition,* vol.49, pp.11-36.

Slovic, Paul, Melissa Finucane, Ellen Peters and Donald G.MacGregor (2004), “Risk as Analysis and Risk as Feelings: Some Thoughts about Affect, Reason, Risk, and Rationality,” *Risk Analysis,* vol.24, no.2, pp.1-12.

Strangman, Gary, Joseph P.Culver, John H.Thompson and David A.Boas (2002), “A Quantitive Comparison of Simultaneous BOLD fMRI and NIRS Recordings During Functional Brain Activation,” *Neuro Image,* vol.17, pp.719-731.

Tversky, Amos and Daniel Kahneman (1981),"The Framing of Decisions and the Psychology of Choice," *Science,* vol.211, pp.453-458.

Tversky, Amos and Daniel Kahneman (1986), "Rational Choice and the Framing of Decisions," *Journal of Business,* vol.59, pp251-278.

Welch, Ivo (1992), “Sequential States, Learning, and Cascades,” *Journal of Finance,* vol.47, no.2, pp.695-732.