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Abstract

We introduce the brain decoding method to the study of herd behavior in laboratory financial markets, enabling us to directly explore the mental states of our subjects. Using a statistical algorithm for decoding and functional near-infrared spectroscopy, our study shows the possibility that different cognitive framings change the characteristics of herd behavior, such as by becoming more rational or more emotional, without making any assumptions in advance about the psychological and behavioral patterns of agents. In this experiment, we examine the effects of two types of cognitive framings. One is a demerit mark method to reject which available type of information, private or public information, is to be used, and the other is a merit mark method to accept which type of the information is to be used.

To obtain more theoretical implications, we also conduct an accelerated game and find that herd behavior is determined less frequently by using the demerit mark method to reject private information and that it is determined more frequently by the merit mark method to accept public information. Our research suggests that in an accelerated booming economy, the characteristics of herd behavior can be more active and emotional than that in a decelerated business depression.

1. Introduction

In this article, we introduce a neuroeconomic method of brain decoding to the study of herd behavior in laboratory financial markets. To examine the possibility of herd behavior, according to Hirshleifer-Teoh (2003), many rational and imperfectly rational approaches have been presented.[1] These studies assume traders' rational and irrational psychological and behavioral patterns in advance and then competitively analyze what explanation power these assumptions have in examining the possibility of herd behavior in our economy. For its part, brain decoding is a type of so-called brain reading, enabling us to directly explore traders' mental states and internal decision-making processes. Without any need for specific assumptions in advance, we can judge what psychological factors have the greatest effects on the phenomenon of herd behavior.

In this study, we discuss the framing effect on the characteristics of herd behavior. The framing effect problem has previously been analyzed by behavioral economics. Using a statistical algorithm for decoding and functional near-infrared spectroscopy (fNIRS), we show the possibility that

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[1] The first theoretical studies on herd behavior are those by Banerjee (1992), Bikhchandani et al. (1992), and Welch (1992). These studies were subsequently extended to include the analysis of an efficient price setting case in the context of a market maker. For example, following Glosten-Milgrom (1985), Avery-Zemsky (1998) examines the possibility of herd behavior in a financial market model in which a market maker sets the market price according to the demand-supply order flow and shows the impossibility of cascade behavior in an efficient financial market. That study suggests that traders determine their optimal non-cascade behavior by considering the difference between their private information and commonly available market information. However, as Cipriani-Guarino (2005) correctly notes, it is difficult to test theoretical results with empirical studies. Because of a lack of data on private information available to traders, it is difficult to determine whether traders will disregard their private information in favor of imitating. The seminal studies by Cipriani-Guarino (2005, 2009) and Drehmann-Oechssler-Rider (2005) have overcome these difficulties by conducting experimental studies.

different cognitive framings change the characteristics of herd behavior, making them more rational and/or more emotional, without making any assumptions in advance about the psychological and behavioral patterns of agents. Furthermore, we investigate what type of cognitive framing is frequently used to determine herd behavior in the laboratory financial market in the change of experimental conditions. The possibility of brain decoding comes from the fact that different usages of cognitive framings produce different neural activities in the brain, and these different neural activities show different mental states in the subject's mind. Therefore, when we use decoding to examine what types of cognitive framings should be used to determine herd behavior, we can theorize about what types of mentality are the internal factors that determine herd behavior. This provides us with two theoretical implications. (1) First, we can examine the realistic effectiveness of a perfectly rational hypothesis. If our decoding of cognitive framings failed perfectly, we would confirm that the subjects participating in the experiment were perfectly rational. As we will explain later, the adoption of cognitive framings is only necessary for subjects to help and support their bounded rationality and limited capacity. Therefore, if perfectly rational subjects existed, they would not need cognitive framings, and there would be no framing effect in their decisions. If this were the case, brain decoding to examine the usage of cognitive framings would fail perfectly. (2) Secondly, the more important implication is that we can confirm that the subjects are bounded rational agents using cognitive framings to support their imperfect rationality and limited cognitive capacity when our decoding is successful, in other words, when there is a framing effect. We are exploring the framing effect on the characteristics of herd behavior and extending earlier analytical frameworks of herd behavior. By conducting devised experiments, we are showing the possibility that different cognitive framings change the characteristics of herd behavior, becoming more rational or more emotional, in economic fluctuations without making any specific assumptions in advance about the psychological and behavioral patterns of our subjects.

First we will discuss bounded rationality and the cognitive framings in the market in detail. We suppose that each agent has private information and public information about profit opportunities in the financial markets. Private information is only available to the agent, but public information is available to all participating agents. Traditional theory assumes that agents judge which information is useful for profit maximization through only the use of reason. However, agents in the real world have only bounded rationality and limited cognitive capacity to understand the world.[2] In this case, it is necessary for agents to have cognitive framings to help and support their limited capacities. The types of cognitive framings to be selected are important. The efficiency of the determination depends upon the choice of cognitive framings, and different cognitive framings will produce different judgments. Thus, we must explore the framing effect on agents making decisions.

Behavioral economics utilizes a famous example in which one of two alternative plans must be chosen. The first has great merits and great demerits, and the other has small merits and small demerits. If the agent has the cognitive framing of "scoring by deducting points" or "the demerit mark method," he will choose the plan with small merits and small demerits. However if he has the framing of "merit mark method," he will choose the plan with great merits and great demerits.[3]

The above example shows that the problem of cognitive framings is the problem of "point of view" that is employed by the agent to evaluate alternative options. Different points of view produces different results. Consider another example of the frame problem whose philosophical

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[2] Since the seminal studies by Simon (1947) , the bounded rationality theory has criticized the fictitious concept of strong rationality with consistent decision makings and an infinite cognitive capacity of information processing to decide optimal behavior. Actual human agents have only limited cognitive capacity, and, while they are not always rational, they may be wise and adaptive in their everyday life. Emotional intelligence, choice of view point, and cognitive frameworks can be used by actual agents to support their bounded rationality and limited capacities. Moreover the emotional and intuitive capacity to understand contextual meanings in the world may provide human agents "other types of rationality" called social wisdom. The existence of "other types of rationality" is strongly suggested by "rational fools" in Sen (1977), who criticized the behavioral foundations of economic theory.

[3] This example is presented by Shafir (1993) and Shafir-Simonson-Tversky (1993). The theoretical implications are explained from the viewpoint of framing effect.

implications are examined by McCarthy-Hayes (1969) and Dennett (1984). Cognitive framings or the limited beliefs held by human beings can avoid a state of frozen action such as that described by Dennett in the context of robots. The selection of the framing and the point of view help our limited capacity to obtain adaptive results in the real world.

It is worth noting that feeling and emotion also play the identical role in supporting the limited capacity of the agents as cognitive framings do. As opposed to their characterization in the traditional consequentialism view that Loewenstein et al. (2001) and Slovic et al. (2004) have criticized, feeling and emotion are not simple noises that disturb the function of reason. Damasio (1994, 1999, 2003) claims that they help the function of reason. Feeling, emotion, and cognitive framings are expected to play the identical roles in a collaborative manner in supporting the limited capacity of agents. We suppose in this study that cognitive framings provide us a realistic framework in which reason and emotion can collaborate. Therefore, a change in cognitive framings is accompanied by a change in the workings of feeling and emotion. We confirm these relations by using the brain decoding in the following experiment.

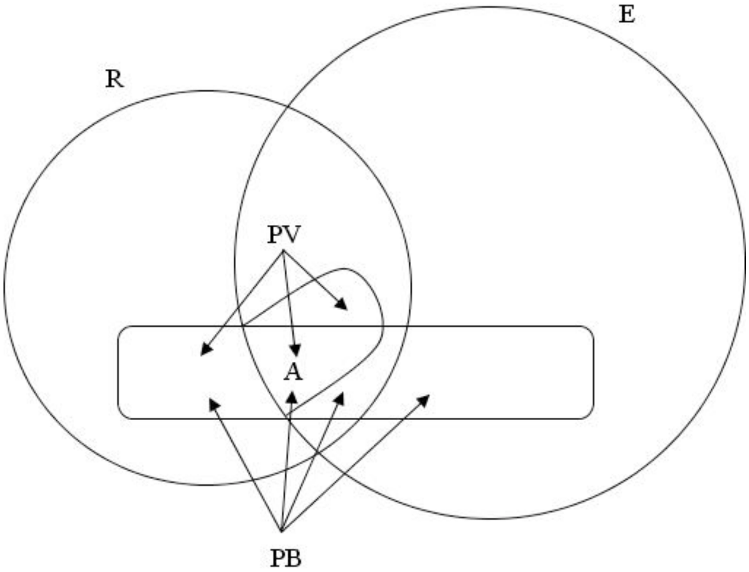
We formulate two cognitive framings to produce herd behavior in a financial market. One is the cognitive framing called the "demerit mark method." When agents choose this framing, they consider which of the two types of information, private information or public information, should be rejected in deciding their behavior. If private information is rejected, i.e., private information is judged to be less valuable than public information, then, public information is indirectly chosen to be used. The other type of framing is called the "merit mark method." When agents choose this framing, they consider which of the two types of information, private information or public information, should be chosen for use in their decision. If public information is accepted, private information is indirectly rejected.

The choice of cognitive framings has fundamental effects on the change in the characteristics of herd behavior. For example, if there is an increasing tendency among agents to choose the merit mark method to directly and actively accept public information, herd behavior may be changed to tend toward strongly emotional herd mentality. When this is the case, the usage of the framing produces strong and robust herd behavior. Agents simultaneously use the identical framing to determine their behavior. As opposed to the traditional definition, the problem of herd behavior is not just the problem of whether agents superficially choose the identical action but also whether agents make their decisions based on the identical cognitive framing. Our brain decoding shows the possibility of changing the emotional characteristics of herd behavior in the adoption of cognitive framings, either merit or demerit mark methods, in the risky financial market of the laboratory..

Using the brain decoding method, we classify the data on neural activities into two groups with different mental states to predict whether subjects use the cognitive framing of the demerit mark method or the merit mark method to determine their behavior. We analyze the change in the characteristics of herd behavior that comes from the change in the cognitive framings held by agents with bounded rationality and limited cognitive capacities, but with the emotional mind to support their limited capacities.

To prepare for the brain decoding analysis, we present an overview of our analysis in a simple figure summarizing the above discussion. Figure 1 illustrates how the adoption of different cognitive framings produces different neural activities when the agent decides herd behavior. The set R represents a possibility set of neural activities when the agent decides his behavior according to reason, whereas the set E is a possibility set of neural activities in which he makes his decision according to emotion. In the intersection of the two sets R and E, the agent decides his behavior according to both reason and emotion. The set PV represents a possibility set of neural activities when the agent determines herd behavior by using the cognitive framing of the demerit mark method to reject private information. The set PB is a possibility set of neural activities when the agent determines herd behavior by using the other framing of merit mark method to accept public information. In the fictitious area $R \setminus (R \cap E)$, as previously explained, the agent is perfectly rational, and he decides his behavior only according to reason. He does not need cognitive framing. Therefore, there is no framing effect in the unrealistically ideal area, i.e., different cognitive framings do not change the subject's neural activities, and the sets PV and PB are perfectly overlapped in the area R╲(R ∩ E).

Figure 1 Relationship among Reason, Emotion, and Cognitive Framings in Herd Behavior



R: a possibility set of neural activities in which the agent decides his behavior according to reason
E: a possibility set of neural activities in which the agent decides his behavior according to emotion
PV: a possiblility set of neural activities in which the agent determines herd behavior by using the cognitive framing of the demerit mark method to reject private information
PB: a possibility set of neural activities in which the agent determines herd behavior by using the cognitive framing of the merit mark method to accept public information

Figure 1 shows, however, that the sets PV and PB are not perfectly overlapped in the area E in which the agent decides his behavior partly or completely according to emotion. It is particularly interesting that the set PB can expand over the area of E╲(R ∩ E) in which the agent is influenced only by emotion. This is the case explained by Lux (1995), Lynch (2000), and Shiller (2000) in which a wave of fads and mob psychology are produced among agents.

Using the brain decoding method and assuming that different neural activities imply different mental states, we show that the sets PV and PB can be distinguished in the mental space with reason and emotion by analyzing the data on the neural activities of our subjects in their herd behavior. This indicates that herd behavior is decided with different mental states in the two alternative cognitive framings and that adopting different cognitive framings produces the possibility of a change in the characteristics of herd behavior, such as becoming more rational or more emotional.

The next interesting problem is determining which economic factors will influence the adoption of the cognitive framings in reality. To explore the problem, we conduct an accelerated experimental game identical to the normal game. We find that, in deciding herd behavior, the accelerated game increases the adoption of the merit mark method to actively accept public information, and that it sharply decreases the adoption of the demerit mark method to reject private information. Recall that a change in cognitive framings is accompanied by a change in feeling and emotion. Therefore, we conclude that the characteristics of herd behavior change with an increase in the speed of playing games. Furthermore, feeling and emotion must help our imperfect reason and limited capacities more strongly to make decisions adaptively in the accelerated game where quick judgments are required. When this is the case, the increased usage of the merit mark method and the decreased usage of the demerit mark method are interpreted to be an actual phenomenon of an increase in the emotion's function to help imperfect reason. The characteristics of herd behavior are expected to be more emotional with an increase in the emotion's function.

The structure of our paper is as follows. Section II describes our experimental methods and design. Section III presents the results of our experiment. Section IV discusses the implications of our results, and Section V provides remarks for future studies.

2. Methods

Brain decoding is a brain-reading method that interprets the data on neural activities. In this manuscript, we use a statistical algorithm for interpretation and fNIRS to classify the data on neural activities into two groups with different mental states to predict which cognitive framings is used to decide behavior in the laboratory market. The introduction of this method extends the analytical possibilities of herd behavior to include the analysis of realistic cases in which agents decide herd behavior according to reason and emotion.

Our experimental method is explained in detail. First, we explain the subjects and the tools to be employed and used for our brain decoding. Next, we illustrate the experimental tasks executed by the subjects.

2.1 Subjects and Tools for Brain Decoding

The experimental games were played by six healthy, right-handed subjects, three were males three were females, and all 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 at hand. Before beginning the experiment, we explained the experimental procedure to the subjects, and we explained the experiment's safety, information security, and how to get their paycheck for their participation. Then we obtain informed consent. Our experiment plans and procedures were endorsed by the Research Ethical Committee of Aoyama-Gakuin University, Tokyo, Japan.

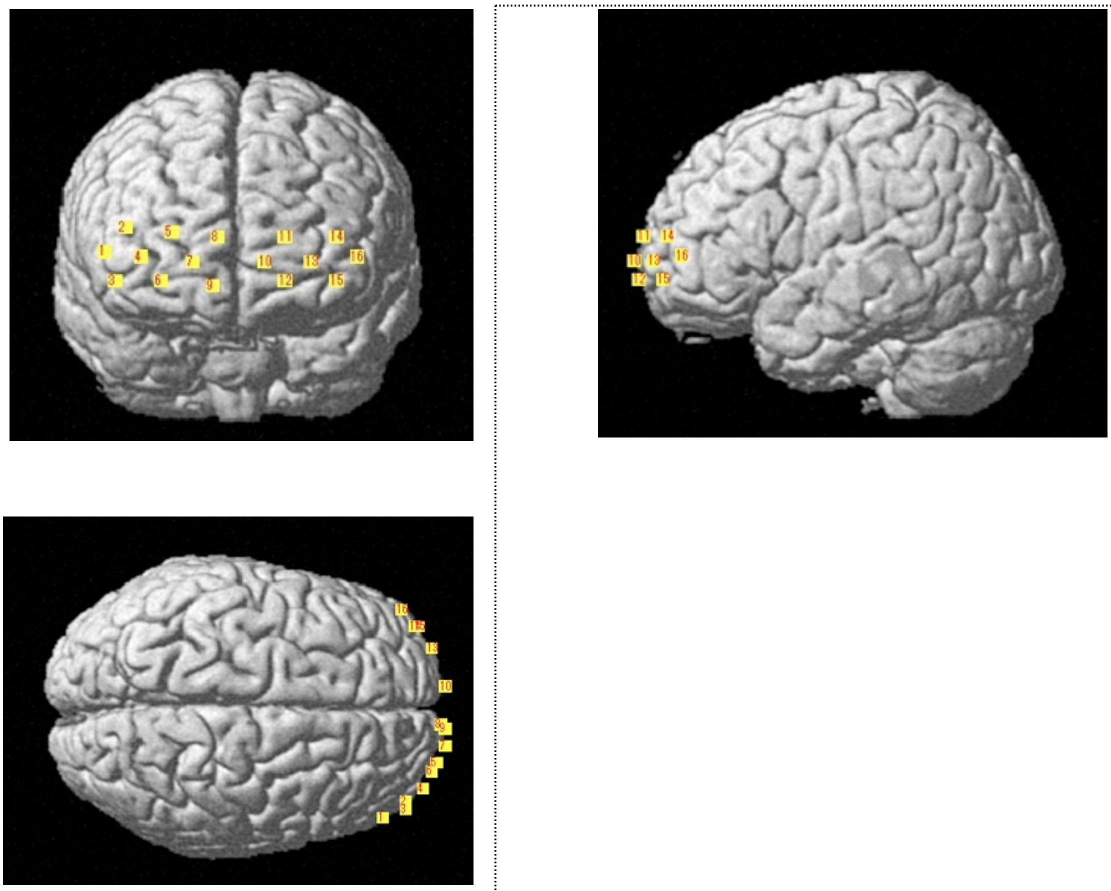
We used the convenient and low-stress fNIRS tool, the Spectratech OEG-SpO2 model (updated from the OEG-16 model, sampling rate 6.10Hz) that is based on the modified Beer-Lambert law, to scan the frontal cortex of the brain primarily.[4] The fNIRS uses small, lightweight, 16-channel digital sensors with a headband to obtain the event-related fNIRS data through a high-sensitivity optical signal that changes dynamically, reflecting how the in vivo hemoglobin combines with oxygen in the blood vessels with high or low cortical activation. Our fNIRS provides two types of event-related neural data, changes in oxyhemoglobin (ΔCoxyHb) and changes in de-oxyhemoglobin (ΔCdeoxyHb). We selected the changes in oxyhemoglobin to use for brain decoding. Strangman et al. (2002) finds a strong correlation between fMRI variables and fNIRS measures, with oxyhemoglobin providing the strongest correlation. Therefore, using the data on oxyhemoglobin, our results on brain decoding may correspond to fMRI studies that will be widely executed in the future.

The locations of the 16-channel digital sensors were fixed by the headband during the experiment. After the completion of each subject's experiment, the locations were measured using a 3D position measuring method with a digital camera (Nikon D5100) and NIRS-SPM software for

4 This model has been previously installed and used for scientific studies, for example, Kita et al. (2011) used the identical tool.

the statistical analysis of the fNIRS signals to confirm that the channels were properly located on the frontal cortex of the brain.[5] For example, Figure 2 illustrates the locations of the 16 channels in the first subject's experiment that are registered onto the compatible canonical brain optimized for NIRS analysis. We obtained the event-related high-sensitivity optical signal from these channels.

Figure 2 Locations of 16 fNIRS Channels in the Case of the First Subject's Experiment Registered onto the Canonical Brain



2.2 Experimental Tasks

We presented the subject the tasks to be executed on a computer monitor. We obtained the neural data when the subject decided his/her herd behavior in the task using cognitive framings. As Figure 3 illustrates, our experiment was composed of three parts, Games, A1, A2 and B. After Game B, each subject was required to play a faster version of Game B, called B+. We planned the first part of Game A1 to obtain data on the subject's typical neural activity pattern when choosing the cognitive framing of the demerit mark system to decide his/her behavior in the laboratory market, i.e., when the subject rejected private information to use to determine herd behavior. Our learning process for the typical neural pattern was executed by using the brain decoding software Neural Network Tool Box on MATLAB. Game A2 was planned to obtain data on the typical neural pattern

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5 There were, of course, slight differences in the channel locations among different subjects' experiments. However, the difference in the locations was 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 subject's experiment suggest that each use of the data in brain decoding can be successfully executed without inconsistency.

of the subject when choosing the cognitive framing of the merit mark system in the laboratory market, i.e., when the subject accepted public information to determine his/her herd behavior. The third game, B, was the essential part 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 mark method or merit mark method as the cognitive framing to decide herd behavior. After obtaining the neural data of the free choices, we use the brain decoding to examine the possibility to distinguish which cognitive framings was chosen by the subject. In the brain decoding, we also used the Neural Network Tool Box. The data obtained from Game B were fitted with the two neural patterns previously identified in Games A1 and A2 to judge which of the cognitive framings was used by the subject. Game B+ was planned to investigate how to change the choice of cognitive framings. We compared the analytical results of the accelerated Game B+ with those of the normal Game B. The change in the cognitive framings teaches us essential information about reason and emotion in the decision-making of our subjects involving herd behavior.

Figure 3 Experimental Games Executed by Each Subject in Our Brain Decoding Experiment

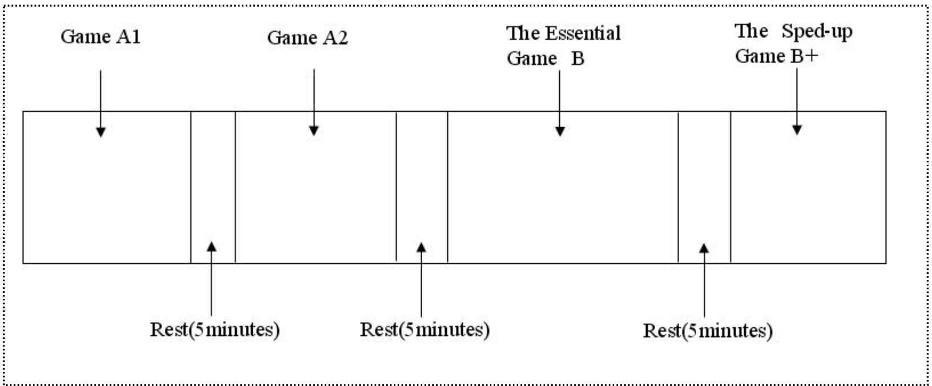


Figure 4(a) Short Task Repeatedly Executed in Games B and B+

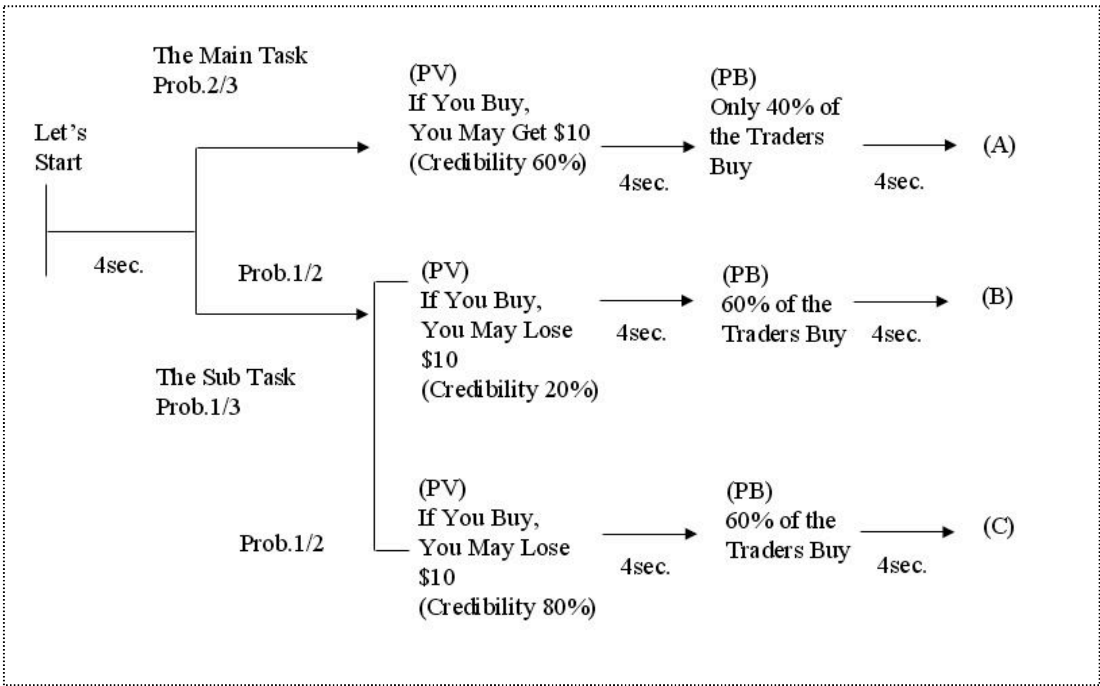
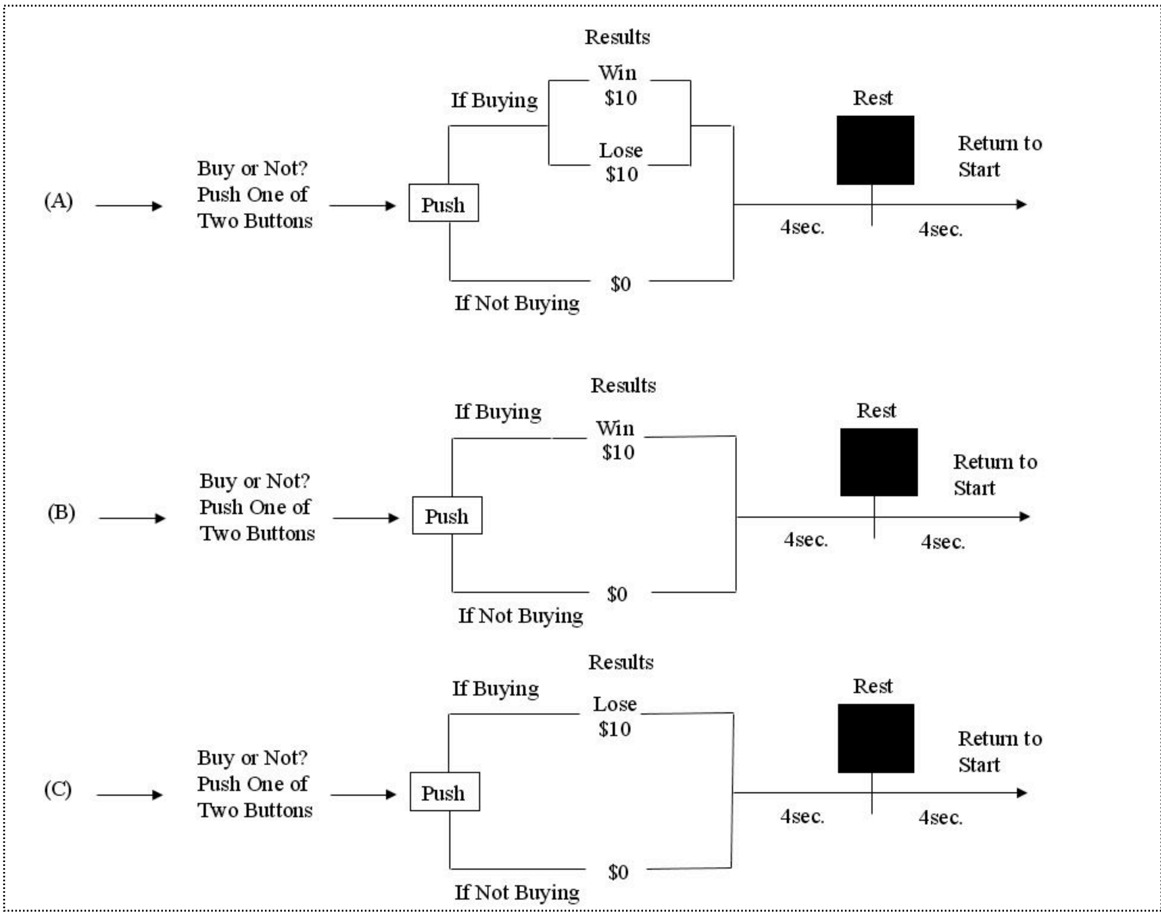


Figure 4(b) Short Task Repeatedly Executed in Games B and B+ (Continued)



Games A1, A2, B and B+ were each composed of short tasks. The short tasks were repeated 30 times in each part of A1, A2, B and B+. Figure 4(a) and Figure 4(b) illustrate a short task repeatedly executed in Games B and B+. In Game B, each screen is switched every 4 seconds, but, in the accelerated Game B+, it is switched every 2.5 seconds. Other short tasks in Games A1 and A2 were simplified versions of this task. Therefore, first, we 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 subject's vigilance to execute the task. The short task, as is illustrated by Figures 4(a) and 4(b), was composed of a main task and a sub-task. The main task and the sub-task 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 of the main task and sub-task were problems of whether the subject would buy or not buy one unit of risky stock. For simplicity, the problems assumed that buying the risky stock would cause the subject to gain \$10 or lose \$10; by not buying the stock, the subject would gain \$ 0.

The first screen of the computer monitor displayed the message "Let's Start." After 4 seconds, either the main task or the 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, the two types of private information were randomly presented at probabilities 1/2 and 1/2 to the subject. Their 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 messages of private information were presented, the third screen appeared after 4 seconds. On the monitor, the subject received public information that was available to all of the agents to determine their behavior. In the main task, the message was "Only 40% of the Traders Buy," whereas in the sub-task, it was "60% of the Traders Buy."

It is worth noting 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 higher expected profit by purchasing the risky stock, whereas the public information suggested that the purchase of the stock could generate poor returns. When he rejected the private information or accepted the public information, he would carry out the identical action as others do who make no trade.

In the sub-task, however, the probability was 1/2 when the private information and the public information suggested adverse opportunities for profits. In process (B) of the sub-task, as illustrated in Figure 4(a), both the private information and the public information suggested that the subject would have higher opportunities for profits by purchasing the stock. In process (C) of the sub-task, however, the private information and the public information suggested the adverse profit opportunities. The asymmetric contents of the main task and the sub-task gave the subject the appropriate psychological stimulus to keep his strong awareness to execute the experimental tasks.

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

When the subject pushed the button, the result was immediately shown. In the main task, as illustrated by Figure 4(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 is the ambiguous state for the subject in which the probability is not known, whereas risk is a different uncertain state in which 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.[6]

In an ambiguous state without information, the subject's decision makings is expected to fluctuate because he may 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 behavior or non-herd behavior with emotional judgment. On the other hand, in the sub-task, the result did not need to be uncertain, because 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.

As previously explained, 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 the brain decoding. In A1, we obtained data on the subject's typical neural activities when he/she chose the cognitive framing of the demerit mark method, and in A2 we obtained the data on the typical neural activities for the choice 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 herd behavior in the non-trade decision-making either by the rejection of private information or by the acceptance of private information. The rejection of private information was expected to be decided by using the cognitive framing of the demerit mark method. The acceptance of public information was expected to be decided by using the merit mark method. Our problem

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6 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 present neurological evidence that the human brain perceives risk and ambiguity differently. The neurological responses to ambiguity, particularly the higher activation of the posterior inferior frontal sulcus (pIFS), come from the anticipation that hidden information under ambiguity is searched for to reduce to risk (uncertainty with known probabilities). We also examine the effects of ambiguity on the brain wave by analyzing the contingent negative variation (CNV). See Nakagome et al. (2011).

was to empirically investigate how herd behavior was actually determined by the subject using the two types of cognitive framings, the merit and demerit mark methods.

For the brain decoding, we randomly sampled the neural data on non-trade decision making from the experimental data obtained by fNIRS. Note that our experimental task was arranged in the reversed oddball pattern to maintain a strong awareness to execute tasks, as illustrated by Figures 4(a) and 4(b). We randomly sampled the neural data only from the main task.

First, to identify the typical neural patterns in the rejection of private information and in the acceptance of public information, 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. We conducted this random sampling for a specific period of time for the experimental data, 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 of time, during which the subjects had previously received available information on the screen (either private information 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 for this period of time were expected to clearly show the characteristics of the neural activity in each subject's consideration of their behavior.

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 period of time 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 buttons to indicate their decision (i.e., the period after the third screen but before the fourth screen in Figures 4(a) and 4(b)).

In Game B, the screens were switched every 4 seconds, but in the sped-up 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 faster 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 Incentives of Subjects to Execute Experimental Games

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

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

3. Results

Figure 5 and Figure 6 illustrate the primary results provided by our 60 times brain decoding of the normal game B and the accelerated game B+, respectively. In the scatter diagrams, each datum of neural activities is interpreted to have the two types of plausibility of the usage of the alternative cognitive framings to determine his/her herd behavior. 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 cognitive framings are represented by the values of the sigmoid function calculated by Neural Network Tool Box on MATLAB. The points located in the lower right of the space have larger value on the horizontal axis than that on the vertical axis, and they can be categorized as those cases in which the subjects use the demerit mark method to reject private information to determine herd behavior. On the other hand, the points located in the upper left of the space can be categorized as those cases in which the subjects use the merit mark method to accept public information.

Figure 5 Scatter Diagram Obtained by Brain Decoding in Game B

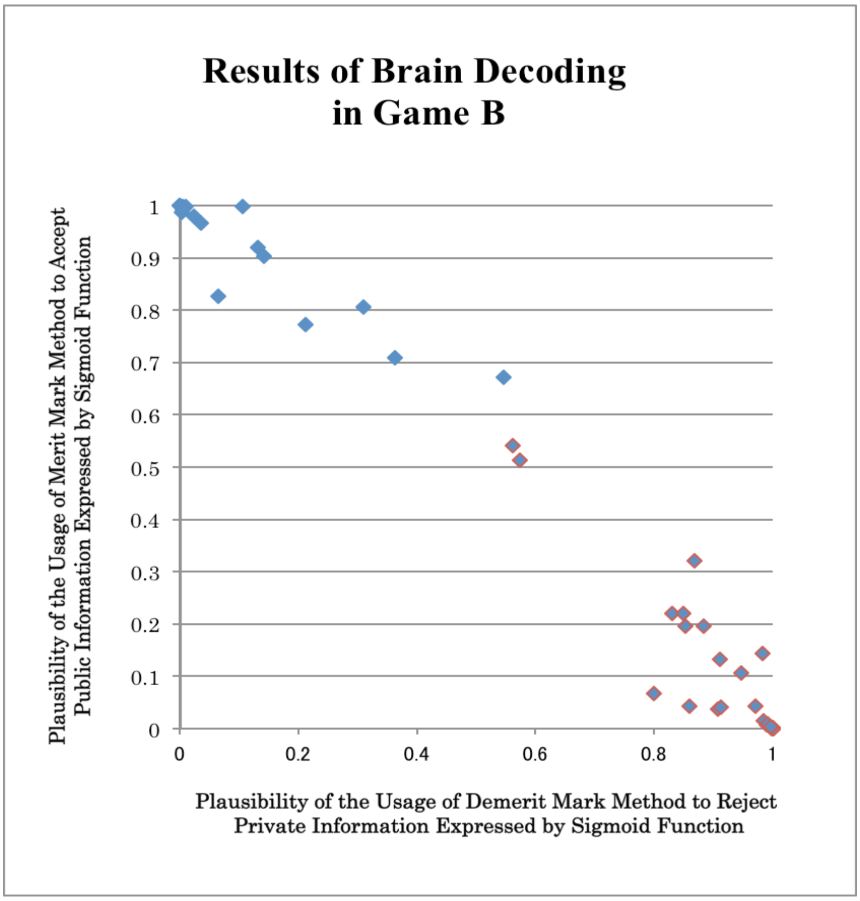
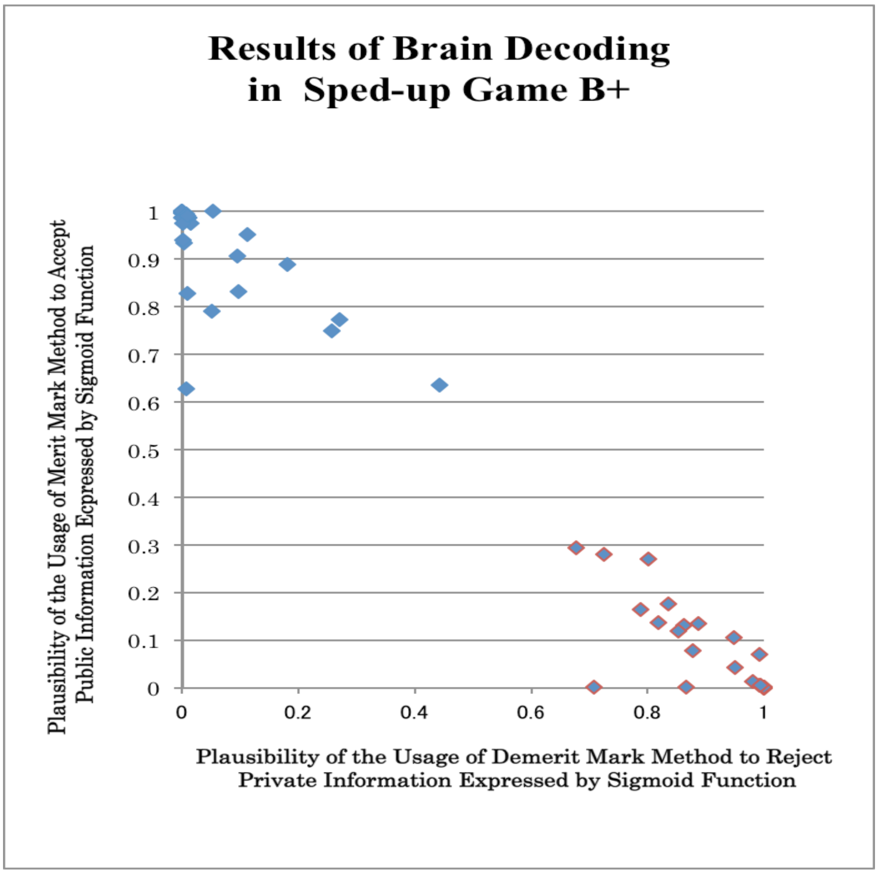


Figure 6 Scatter Diagram Obtained by Brain Decoding in Sped-up Game B+



These scatter diagrams show that there are, however, multiple cases that cannot be clearly categorized. We adopt the following 5% rule to judge whether the decoding is successful enough to categorize each of the neural data into one of the different groups. Denote by x(t) and y(t) respectively the sigmoid values on the horizontal and vertical axes that are obtained by decoding the t'th neural datum, then we define the following rule for judgment.

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

(ii) if $xi(t)< y(t)$ and $x(t)/[x(t)+ y(t)] < 0.05$,
the t'th datum is successfully judged by the decoding to be the case in which the merit mark method is 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 is not successfully judged by the decoding

Using these judgment rules, Figure 7 shows the areas of successful and unsuccessful decoding in the x-y plane. In Figure 7, the lines $y = 19x$ and $y = (1/19)x$ are respectively calculated by $x/(x + y) = 0.05$ and $y/(x + y) = 0.05$. Examining Figures 5,6, and 7, we can count the cases of the successful and unsuccessful decodings of our neural experiment. Table 1 shows that, when we adopt the 5% rule for judgment, 36.6% and 31.6% of decoding cases are interpreted to be unsuccessful to clearly distribute the neural data into the two groups in which the two different types of cognitive framings are used. It is worth noting that there is the overlap area A between sets PV and PB in Figure 1. In the area A, neural activities are identical for the two cases, even with different framings. Therefore, all of the unsuccessful cases are not the result of our experiment's shortcomings. The essential difficulty of decoding comes from the original characteristics of neural activities that are identical in the overlap area A. However, when we develop more efficient decoding methods in future, we will accurately calculate the original difficulty of decoding emanating from the characteristics of neural activities but not from our experiment's technological limitations.

Figure 7 Successful and Unsuccessful Decoding Areas

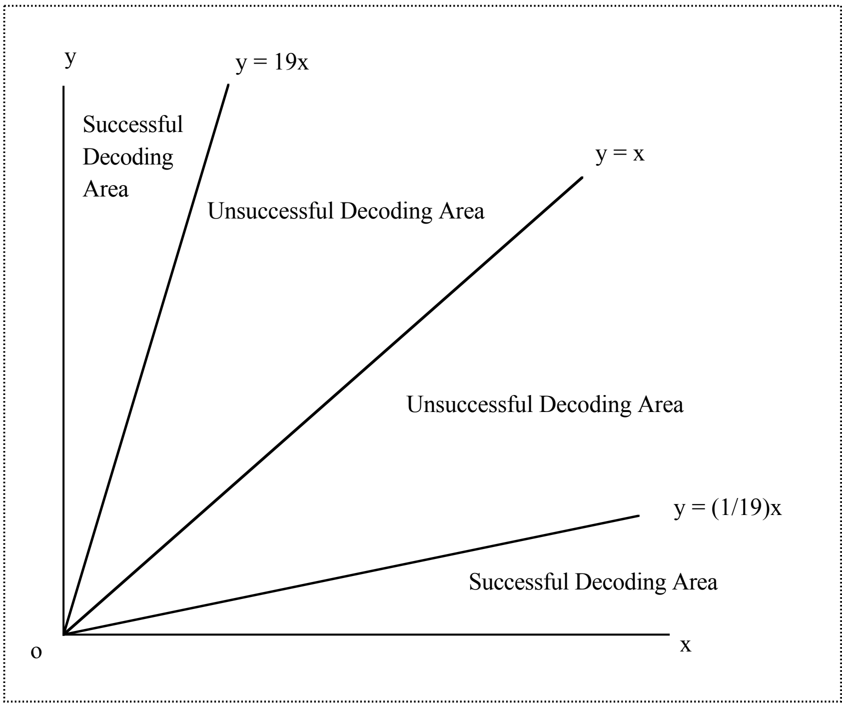


Table 1 The Number of Successful and Unsuccessful Brain Decodings in Game B and Sped-up Game B+

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

Table 1 (Continued)

In Sped-up Game B+ (60 Decodings)

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

Table 1 shows other interesting results obtained by the decoding. When we conduct the accelerated Game B+ and compare the results with that of Game B, we find a remarkable increase in the number of successfully decoded cases in which the merit mark method is used for the determination of herd behavior. In the table, these successful cases increase from 11 times to 26 times. On the other hand, we find a sharp decrease in the number of successfully decoded cases in which the demerit mark method is used. In the table, these cases decrease from 27 times to 15 times. In the next section, we will discuss the theoretical implications that come from the experimental results.

4. Discussions

Going back to our starting point in Figure 1 and joining it with the results shown in Figures 5 and 6 and Table 1, we discuss the theoretical implications of our study.

When we extend the traditional studies of rational herd behavior to include the analysis of decisions with reason and emotion, interesting new problems appear. One of these problems is the effect of framing. Human agents use both reason and emotion to decide our behavior, because we have bounded rationality with limited cognitive capacity. The use of cognitive framings to understand the world provides us a realistic framework for the joint use of reason and emotion. For example, if we change our point of view in seeing the world, new feelings and emotions will arise in our mind that begin constructing new understandings of the world with the collaboration of reason. The point of view implies the cognitive framing. Feeling, emotion, and reason can actively collaborate in the cognitive framings that are appropriately structured.

Before the start of our experiment, we expected that there would be framing effects on the characteristics of herd behavior. We considered that some types of cognitive framings were apt to be selected by many agents as suitable to understand the world with contextual meanings. They may be called ”meme” and are explained by Dawkins (1976) and Blackmore (1999). Dynamic environments continuously change the most popular cognitive framing selected by the agents. We supposed that herd behavior would occur based on the major cognitive framings adopted by agents, and that the characteristics of herd behavior, whether becoming more rational or more emotional, would be influenced by the pattern of reason and emotion collaboratively working in the cognitive framework.

When our expectations are realistic in financial markets, the economic, rational and emotional characteristics of herd behavior can essentially change in the market with the different cognitive framings adopted by traders. Their cognitive framings to understand the economy are realistic frameworks for their joint use of reason and emotion, and the characteristics of herd behavior in the market are influenced by feeling and emotion collaboratively working in the cognitive framework.

Figure 1 shows a possibility in which different cognitive framings produce different neural activities when agents decide herd behavior, which is shown in the area with emotional judgment E, except for the overlap area A between sets PV and PB. From the figure, we expect that our brain decoding can successfully distinguish neural activity data in cases with different uses of cognitive framings to determine herd behavior.

The results of brain decoding are illustrated by Figures 5 and 6 and Table 1. They demonstrate empirically that the possibility suggested by Figure 1 is justified. Our brain decoding method shows that the experimental data on neural activities can be categorized into two groups with the cognitive framing of demerit and merit mark methods. The existence of the overlap area A in Figure 1 shows that there are some cases where we cannot distinguish the data because neural activities are identical even with the different framings. This difficulty in decoding is not the result of our experiment's shortcomings, emanating instead from the original characteristics of neural activities.

According to our experiment results, and after adoption of the 5% judgment rule, unsuccessful decoding cases represent 36.6% or 31.6% of the total, whereas successful decoding cases are 63.4% or 68.4%. When we will develop more efficient decoding methods, we will accurately calculate the original difficulty of decoding that arises from the characteristics of neural activities. In this case, the re-calculated original difficulty of decoding will certainly be less than 36.6% or 31.6%, and the number of successful decodings will increase. We conclude that different cognitive framings can produce different mental states and different neural activities when agents determine their herd behavior.

The other interesting result of our experiment is the effect of introducing the accelerated game on the use of cognitive framings, as illustrated by Table 1. When we conduct the accelerated game, we observe a remarkable increase in successful decoding to judge the cases in which the merit mark method is used, whereas we observe a sharp decrease in the number of successfully decoded cases that judge that the demerit mark method is used. This implies that herd behavior is determined less frequently by using the demerit mark method to reject private information, but that it is determined more frequently by the merit mark method to accept public information. In Figure 1, the latter more frequent cases are illustrated by the expansion of the set PB, and the former less frequent cases are illustrated by the contraction of the set PV. As previously explained, the set PB can be expanded over the area $E \setminus (R \cap E)$ in which the decision is only influenced by feeling and emotion, and emotional judgment can be actively used in the merit mark method to accept public information. Therefore, in an accelerated and sped-up booming economy, the decision of herd behavior may be more emotional than in a decelerated business depression. Different usage of cognitive framings changes the characteristics of herd behavior in accelerated and decelerated business cycles.

Finally we will discuss realistic policy implications of our study. We note a possibility that the change in the characteristics of herd behavior may have an unexpectedly strong effect on the effectiveness of economic policy. For example, the use of monetary policy would have difficulty in slowing down a booming economy, if herd behavior is strongly emotional in financial markets. However, if herd behavior is as rational as the traditional studies have considered, monetary policy should be successful to control the booming economy. The study of economics has investigated only how to plan and design economic policy, but the effectiveness and success of the identical policy to accomplish the goal are influenced by the mentality and emotions of traders that are usually formed in the social and interpersonal relationships. The target of our economic study should be re-examined. The change in the characteristics of herd behavior, more rational or more emotional, has not yet been investigated scientifically, and traditional studies have focused on the cases in which the traders are always rational. Frontiers remain whose development will increase the effectiveness of the herd behavior's analysis to provide new implications for economic policy.

5. Concluding Remarks

We introduce the brain decoding method to the study of herd behavior. In this study, we claim the extension of the theoretical framework of herd behavior to include the analysis of bounded rational agents operating with reason, emotion, and cognitive framings. Cognitive framings provide these agents realistic frameworks for the joint use of reason and emotion. Therefore different frameworks produce different mental states, more rational or more emotional. Herd behavior is based on the cognitive framings those are apt to be selected by the agents, implying that the problem of herd behavior is not only the problem of superficially identical action but also the problem of basic cognitive framings. Our brain decoding study demonstrates that herd behavior is decided in the two alternative cognitive framings with different mental states, and that the adoption of different cognitive framings produces the possibility of a change in the characteristics of herd behavior.

As for policy implications, we expect that different characteristics of herd behavior may have different effects on the effectiveness of economic policies. Some types of herd behavior can be managed but others may not be. Our discussion on the usage of cognitive framings and the characteristics of herd behavior offer the first step in exploring new types of policy implications that are affected by the changeable characteristics of herd behavior.

Problems remain that should be addressed in the future. First, our brain decoding uses the software Neural Network Tool Box on MATLAB, but this is only one method of brain decoding. Future studies will further develop this experimental approach. If more efficient methods are developed, the number of successful decodings will increase.

Second, the topics of framing effects have been analyzed in behavioral economics developed by Kahneman, Tversky, and Thaler etc. We expect that our brain decoding method will be combined with the accumulated knowledge of behavioral and psychological economics for the further development of the neuroeconomic study of herd behavior. However, the study of herd behavior can contribute to the development of behavioral economics. Behavioral economics has focused on anomalies that come from individual decision-making affected by feelings and emotions, but the study of herd behavior considers interpersonal relationships among agents to be essential factors for decision-making. Their cooperation will develop into promising new studies in economics as neuroscience studies do in other scientific fields.

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.

Blackmore, Susan (1999), *The Meme Machine,* New York: Oxford University Press.

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: Boby and Emotion in the Making of Consciousness,* New York: Harcourt.
Damasio, Antonio R. (2003), *Looking for Spinoza,* New York: Harcourt.
Dawkins, Richard (1976), *The Selfish Gene,* New York: Oxford University Press.
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.
Hirshleifer, David and Siew H.Teoh (2003), “Herd Behaviour and Cascading in Capital Markets: a Review and Synthesis,” *European Financial Management,* vol.9, no.1, pp.25-66.
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.
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.
Lux, T. 1995, “Herd Behavior, Bubbles and Crashes,” *Economic Journal*, vol.105, pp.881-896.
Lynch, Aaron (2000), “Thought Contagions in the Stock Market,” *Journal of Psychology and Financial Markets,* vol.1, pp.10-23.
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.
Sen, Amartya, (1977), “Rational Fools: A critique of the behavioral foundations of economic theory", *Philosophy and Public Affairs,* vol.6, no.4, pp.317-344.
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.
Shiller, Robert J.(2000), *Irrational Exuberance,* Princeton: Princeton University Press.
Simon, Herbert A.(1947), *Administrative Behavior,* New York: Free Press.
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.

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