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A Neuroeconomic Study of Herd Behavior in Financial Laboratory Markets Using the Brain Decoding Experiment Method

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Abstract

Frontiers remain whose development will increase the effectiveness of experimental studies on herd behavior in financial laboratory markets. Our presentation of a new brain decoding method enables us to directly explore traders' mental states and internal decision rules. Brain decoding is a type of so-called brain reading. Using a statistical algorithm for decoding and functional near-infrared spectroscopy (fNIRS), we classify data on neural activity into two groups with different mental states to predict whether subjects will use available information for profit maximization behavior or disregard the information to imitate others' behavior. To confirm our methodological effectiveness, we examine whether a more rapid execution of experimental games increases herd behavior in the laboratory market. If our decoding is conducted effectively, our classified data must show an increase of herd behavior in the sped-up games, because herd behavior is a shortcut and a type of heuristic decision making in situations where the subjects have less time for detailed deliberation on their profit-maximizing behavior. Subjects are expected to make decisions on herding and imitating behavior to overcome their time-delayed reactions to the rapid tasks of the experiment. Our confirmation study successfully shows an increase in herd behavior. Our decoding method extends the analytical possibility of economic investigations of herd behavior.

I. Introduction

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 where 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 the difficulties by conducting experimental studies. In these experimental studies, private information is observable, and herd behavior can be detected by examining whether private information is effectively used by subjects. This examination, however, requires assumptions to specify subjects' utility functions to judge whether private information is effectively used for maximizing behavior. These assumptions represent a methodological restriction. If brain reading (or mind reading) is possible using neuroeconomic methods, this methodological restriction will be removed. There are exciting frontiers that can potentially increase the effectiveness of experimental studies. Our brain decoding does not require assumptions about utility functions. Decoding enables us to directly explore traders' mental states and internal decision rules. It extends the analytical possibilities of experimental studies on herd behavior in laboratory financial markets.

Brain decoding is a brain-reading neuroscience method that interprets the data on neural activity measured with functional magnetic resonance imaging (fMRI) or functional near-infrared spectroscopy (fNIRS). Using a statistical algorithm for interpretation and fNIRS, we classify the data on neural activity into two groups with different mental states to predict whether subjects will use their available information for profit maximization behavior or whether they will disregard it in favor of imitating others' behavior. The introduction of this new method extends analytical possibilities. Specifically, brain decoding overcomes some difficult cases in which earlier studies were unable to judge whether herding occurred in the laboratory market.

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 provides remarks for future studies.

II. Methods

The experimental games are played by six healthy, right-handed subjects, three males and three females, aged 20-23 years. During each subject's games, we obtain the necessary data for 20 times of brain decoding. In total, we obtain data to execute brain decoding 120 times. The subjects are prohibited from eating two hours before playing the games to provide clear neural reactions to the experimental tasks in the games.

We use the convenient and low-stress fNIRS tool, based on the modified Beer-Lambert law, to scan primarily the frontal cortex of the brain. 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 is combined with oxygen in the blood vessels with high or low cortical activation. *1 Our fNIRS provides two kinds of event-related neural data, changes in oxyhemoglobin (ΔCoxyHb) and changes in de-oxyhemoglobin (ΔCdeoxyHb). We select 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 can correspond to fMRI studies that will be widely executed in the future.

The locations of the 16-channel digital sensors are fixed by the headband during each subject's experiment. After the completion of each subject's experiment, the locations are measured using a 3D position measuring method with a digital camera (Nikon D5100) and NIRS-SPM software for the statistical analysis of fNIRS signals to confirm that the channels are properly located on the frontal cortex of the brain. *2 For example, Figure I illustrates the locations of 16 channels in the case of the first subject's experiment that are registered onto the compatible canonical brain optimized for NIRS analysis. We obtain the event-related high-sensitivity optical signal from these channels.

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

As Figure II illustrates, our experiment is composed of three parts, games, A1, A2 and B. After part B, each subject is required to play a faster version of game B, called B+. We plan the first part of game A1 to obtain data on the typical pattern of neural activity of the subject who chooses non-herd optimization behavior using the available information in the laboratory market. The learning process for the typical neural pattern is executed by using the brain decoding software Neural Network Tool Box on MATLAB. The second part A2 is planned to obtain data on the typical neural pattern of the subject who chooses herding and imitating behavior without a detailed examination of private information. The third part B is the essential part of the experiment in which we obtain neural data to execute our brain decoding. By using the brain decoding software Neural Network Tool Box, the data obtained are fitted with the two typical neural patterns already identified in parts A1 and A2 to judge whether the subject chooses herd behavior in the laboratory market. The additional part B+ is planned to confirm the effectiveness of our brain decoding. We compare the analytical results of the sped-up game B+ with those of the normal game B. If we correctively classify the herding cases and the non-herding cases using our brain decoding, the number of classified herding cases must increase in experiment B+, because herding behavior is a shortcut and conventional heuristic behavior, which is determined without deliberation on all available information. The subjects are expected to more frequently choose herd behavior in the sped-up game B+ than in the normal game B. We examine whether our confirmation work is successful.

(Figure II) Experimental Games Executed by Each Subject in Our Brain Decoding Experiment

Parts A1, A2, B and B+ are each composed of short tasks. The short tasks are repeated more than 20 times in each part of A1, A2, B and B+. After 20 times, the experiment is stopped before a tie is reached. Figure III illustrates a typical short task executed in parts B and B+. Other short tasks in A1 and A2 are simplified versions of this task.

To increase the effectiveness of our experiment, we present an incentive system to the subjects. The subjects' pay from participating in the experiment changes with the results of his decisions while playing the games. After completing the games, we randomly select one of the subject's results to determine his final pay.

(Figure III) Typical Short Task Repeatedly Executed in Parts B and B+

As previously mentioned, the tasks in parts A1 and A2 are simplified versions of the typical task executed in parts B and B+. In the task for part A1, the subject receives privately available information on obtaining profits. In the task for part A2, the subject only receives commonly available market news and information about others' behavior. The simplified task in part A1 does not include the fourth screen illustrated in Figure III, and the simplified task in part A2 does not include the third screen.

We focus on the non-trade decision making as an example of difficult cases that cannot be easily determined to be herd behavior. Non-trade decision making comes from either individual profit maximization or herd behavior that imitate others' behavior. For the brain decoding, we randomly sample the neural data on non-trade decision making from the experimental data obtained by fNIRS. First, to identify the typical neural patterns in the non-herd and herd cases, we randomly sample neural data for 40 non-trade cases from parts A1 and A2 of the games played by each subject. We conduct this random sampling for a specific period of time for the the experimental data, 4 seconds $< t <$ 12 seconds from the beginning of each game. Thus, all of the neural data to identify the typical neural patterns are obtained from this specific period of time, during which the subjects have already received available information on the screen (either private information to obtain profits or commonly available market information about others' behavior) but while they are 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 are expected to clearly show the characteristics of neural activity in each subject's consideration of their behavior.

The second random sampling is conducted to obtain necessary neural data for brain decoding from parts B and B+. We select the non-trade cases from the experimental data in parts B and B+. Then, we randomly sample 20 pieces of data from each subject's non-trade cases. The period of time for random sampling is also the time after the subjects have already obtained all of the available information but before they are allowed to push one of the buttons to indicate their decision making (i.e., the period after the third screen but before the forth screen in Figure III). In game B, the screens are switched every 4 seconds, but in the sped-up version of game B+, the screens are switched every 2.5 seconds. Therefore, the period for random sampling is 8 seconds < t < 12 seconds in game B and 5 seconds < t < 7.5 seconds in the faster game B+. Six subjects participate in the experiment. In total, the necessary neural data for 120 times of brain decoding are obtained in the normal speed game B and in the sped-up game B+.

III. The Results of Our Experiment

Figure IV illustrates the main result provided by our brain decoding. The scatter diagram demonstrates the effectiveness of our decoding to determine whether the subjects adopt herd behavior in the laboratory market. The horizontal axis measures the plausibility of non-herd behavior by examining private information for profit maximization. The vertical axis measures the plausibility of herd behavior that disregards private information and imitates others' behavior, as suggested by commonly available market news and information. The two kinds of plausibility for herd and non-herd behavior are represented by the values of the sigmoid function calculated by Neural Network Tool Box on MATLAB. Our 120 times of brain decoding is able to categorize the different mental states and behavioral rules of the subjects into herding and non-herding cases. There are only several exceptional cases that are not clearly categorized. We can calculate the plausibility of herd and non-herd behavior without adopting special or conventional assumptions about the utility functions of the subjects. The effectiveness of the brain decoding is statistically demonstrated by the average values of the sigmoid function that are higher than 0.9 in cases of herding and non-herding and by p-values that are lower than 0.001, refuting the null hypothesis to claim the identity of these average values of the sigmoid function. Our use of brain decoding to examine herd behavior is effective and credible for analysis.

(Figure IV) The Scatter Diagram and Statistically Analyzed Data on Herd and Non-Herd Behavior in the Laboratory Market: Total Results

Our next task is to confirm the classified cases as herd behavior to identify the economic characteristics of the shortcut and heuristic decision making. For this confirmation, we compare the analytical results of the sped-up game B+ with the results of game B. Figure V shows the comparison of these results using two scatter diagrams and their statistically analyzed data. Figure V(A) shows the results of the normal game B, and Figure V(B) shows the results of B+. The scatter diagrams and the statistically analyzed data for the sigmoid function and p-values show the effectiveness of our brain decoding. The number of herd behavior cases in game B is 19, and the number in B+ is 34. The p-values are lower than 0.0001. Herd behavior increases by 1.789 times (34/19 times) when the sped-up experiment is executed. This implies, as expected, that the neural data classified as herd behavior by brain decoding have the characteristics of shortcuts and heuristic decision making. Our confirmation work successfully demonstrates the effectiveness of our analysis.

(Figure V) The Increase in Herd Behavior Illustrated by Scatter Diagrams and Statistically Analyzed Data Obtained From Experimental Games B and B+

IV. Implications and Concluding Remarks

This brain decoding method extends the analytical possibilities of herd behavior by removing the difficulties faced by previous studies.

Problems remain that should be addressed in the future. First, brain decoding using the software Neural Network Tool Box on MATLAB is one of methods of brain decoding. Our study is an initial neuroeconomic study of herd behavior using the brain decoding method. We hope that future studies will further develop this experimental approach and that more efficient experimental methods will be developed. Second, we expect that this innovative brain decoding method will be combined with the accumulated knowledge of economic studies. In particular, we hope that this technology can be combined with insights and results from behavioral economics and psychological economics. This combination can develop promising new research in economics as neuroscience studies do in other scientific fields.

Notes

*1 Our fNIRS is the Spectratech OEG-16 model. This model has previously been installed and used for scientific research, such as the research by Kita et al. (2011).

*2 There are, of course, slight differences in the channels' locations among different subjects' experiments. However, the difference in the locations is not large, and we ensure that the channels are properly located on the frontal cortex using the 3D position measuring method. The neural data obtained from the fixed channels' locations in each subject's experiment suggest that each brain decoding using the data can be successfully executed without any inconsistencies.

Acknowledgements

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

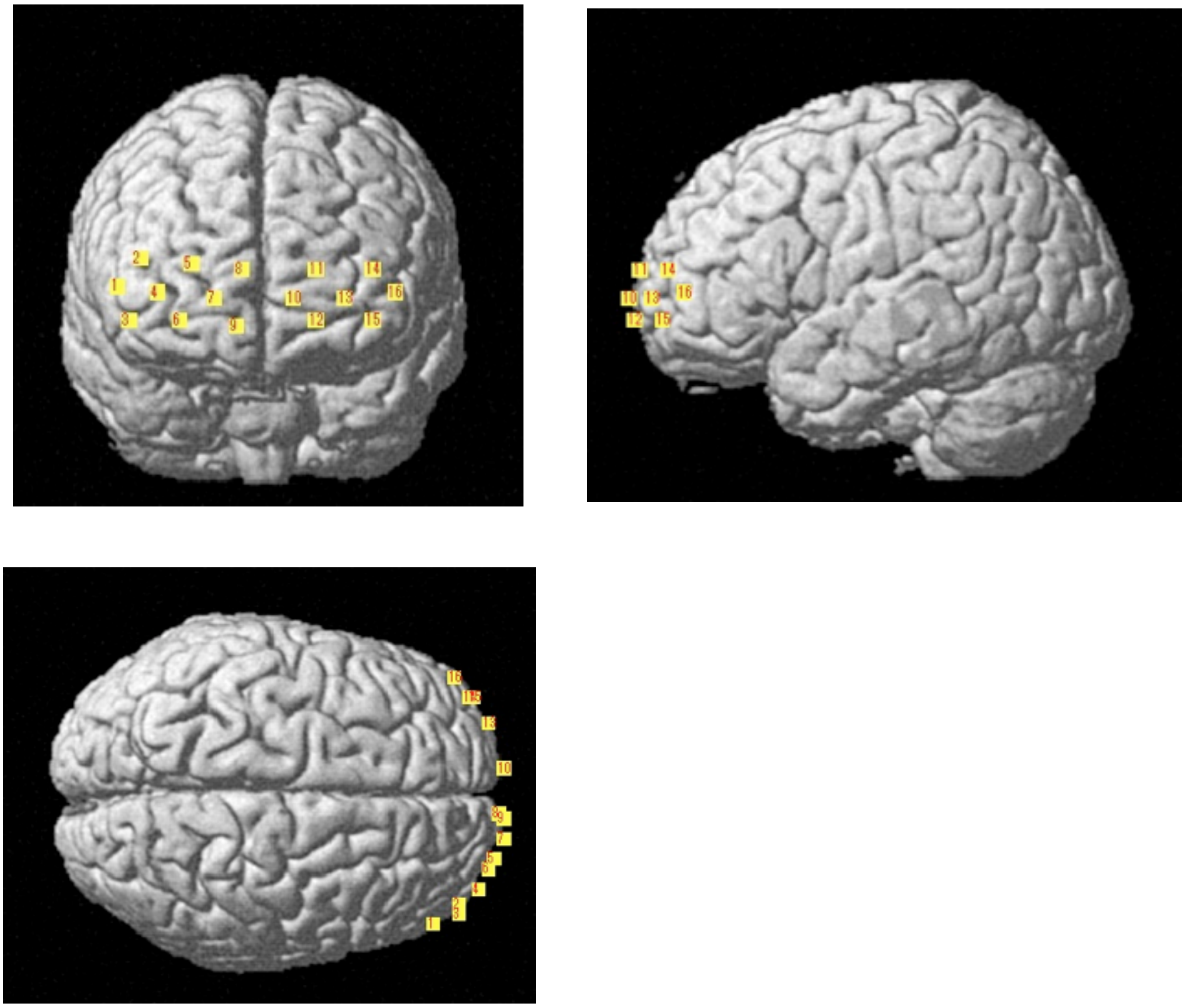
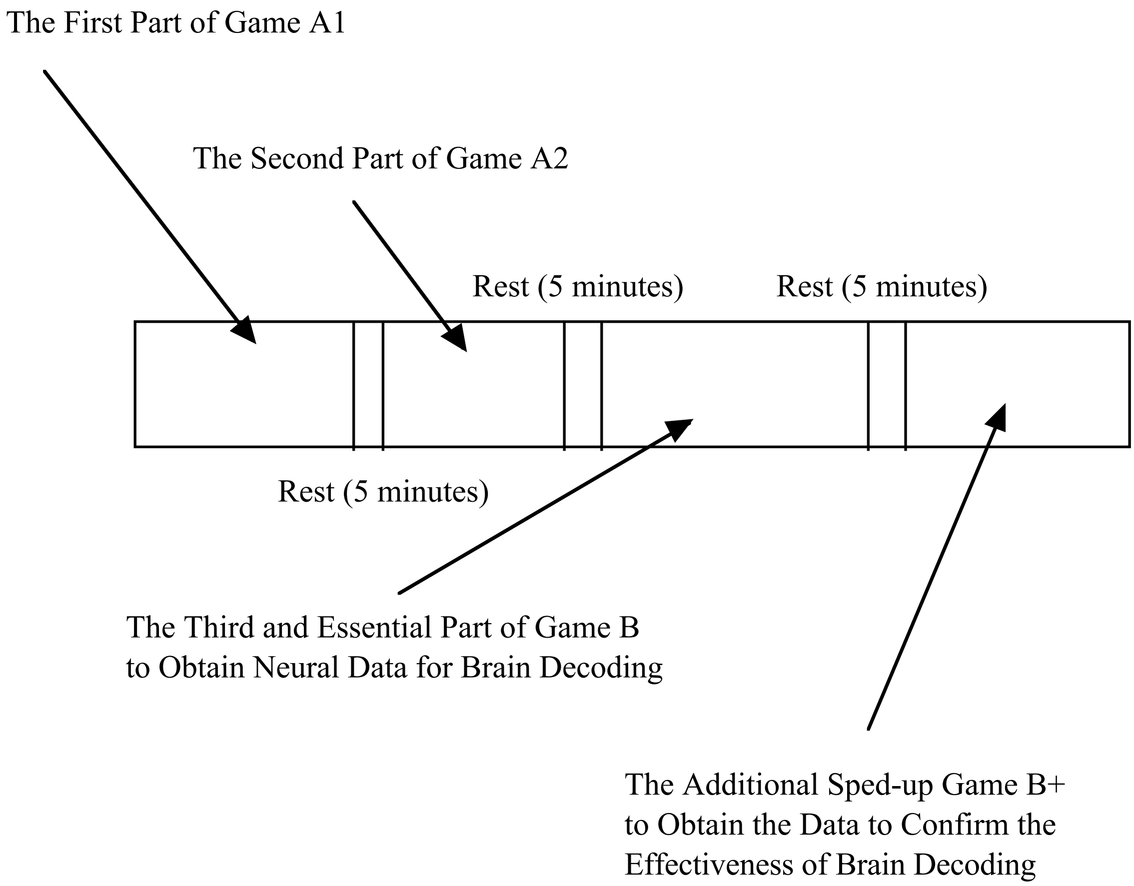
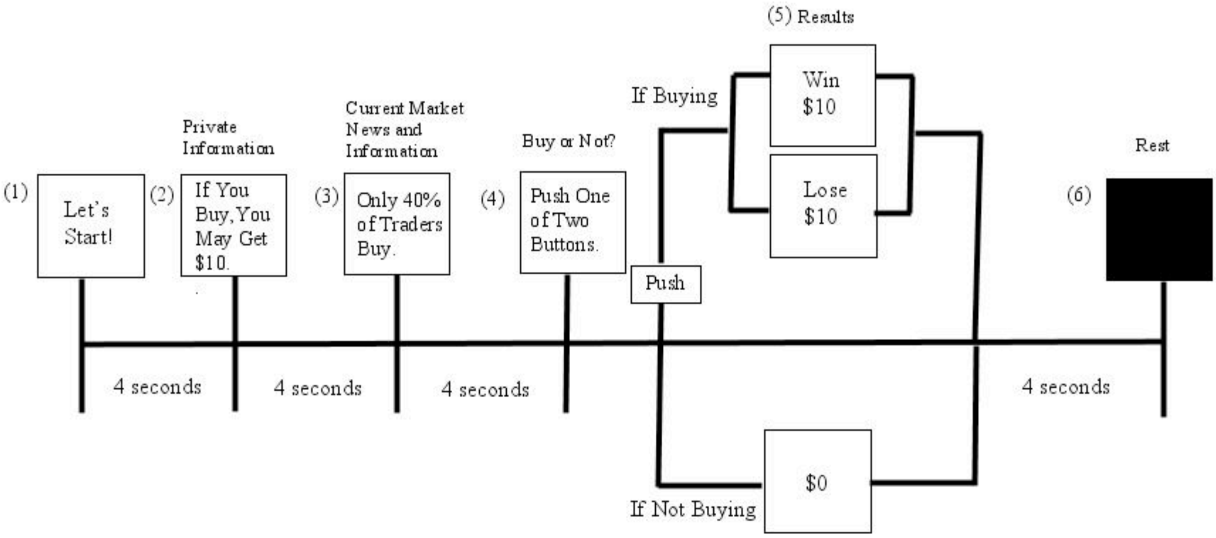


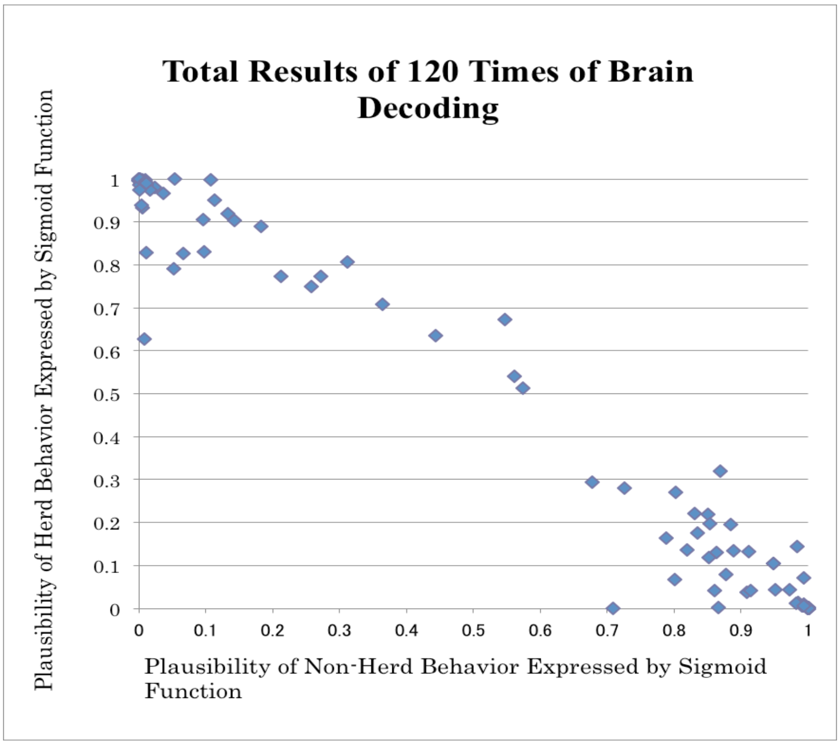
Figure II. Experimental Games Executed by Each Subject
in Our Brain Decoding Experiment



(Figure III) Typical Short Task Repeatedly Executed in Parts B and B+



(Figure IV) The Scatter Diagram on Herd and Non-Herd Behavior in the Laboratory Market: Total Results*



* The plausibility of herd and non-herd behavior is expressed by the values of sigmoid function calculated by Neural Network Tool Box. In the scatter diagram, 67 decoding cases are interpreted as non-herd cases. In these cases, the mean value of plausibility of non-herd behavior (sigmoid function's value) is 0.928659701, and the mean value of plausibility of herd behavior (sigmoid function's value) is 0.072965672. The p-value is 2.31E-80 that refutes the null hypothesis to claim the identity of these average values of the sigmoid function. The scatter diagram also illustrates that 53 decoding cases are judged as herd casses. In the cases, the mean value of plausibility of non-herd behavior is 0.069256604, and the mean value of plausibility of herd behavior is 0.927598113. The p-value is 9.48E-63 that refutes the null hypothesis to claim the identity of these average values.

(Figure V) The Increase in Herd Behavior Illustrated by Scatter Diagrams on Games B and B+*

Figure V(A)

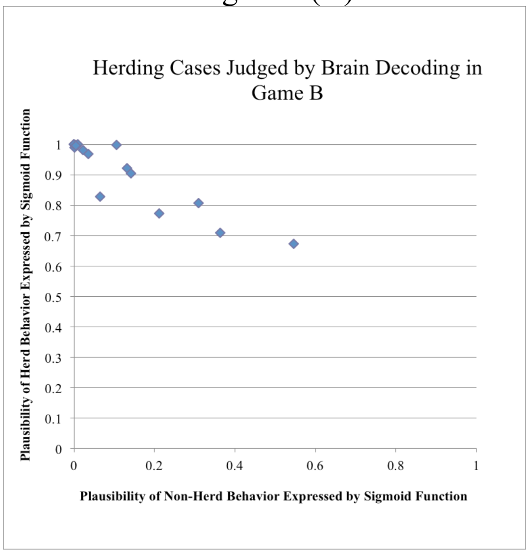
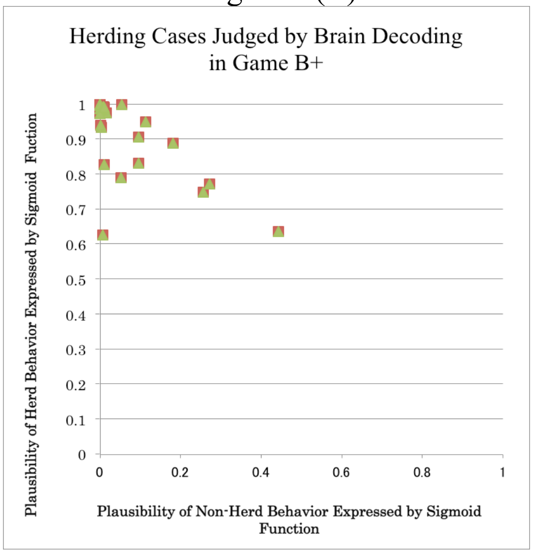


Figure V(B)



* The scatter diagram of Figure V(A) illustrates 19 decoding cases that are interpreted as herd cases in Game B. In these cases, the mean value of plausibility of herd behavior (sigmoid function's value) is 0.921778947, and the mean value of plausibility of non-herd behavior (sigmoid function's value) is 0.104026316. The p-value is 2.62E-19 that refutes the null hypothesis to claim the identity of these average values of the sigmoid function. The scatter diagram of Figure V(B) illustrates 34 decoding cases that are judged as herd casses in Game B+. In the cases, the mean value of plausibility of herd behavior is 0.93085, and the mean value of plausibility of non-herd behavior is 0.049826471. The p-value is 7.45E-45 that refutes the null hypothesis to claim the identity of these average values. From these results, we conclude that herd behavior increases in the sped-up game B+.