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Framing Effects Are Too Weak To Affect Herd Mentality In Financial Decisions: A Neuroeconomic Study Using Brain Decoding

By Masaki Nakagome, Kazuo Maki and Hideto Ide

Abstract

Earlier studies considered the effects of framing on individual decision-making; however, the framing effects on herd behavior have not been studied. We conducted a neuroeconomic experiment to examine the strength of framing effects on herd mentality, the psychological basis of herd behavior in financial decisions. We focused on attribute framing and considered a case in which the identical financial problem was expressed differently by a gain or loss frame. Our experimental results implied that framing effects could not effectively change herd mentality to influence subjects to rely primarily on common information for decision-making. We suggest that framing effects are sufficiently strong to change individual decision-making; however, they are too weak to affect herd mentality. We used a powerful brain reading method of brain decoding to examine directly which of the two types of information, private or common information, was used by the minds of the subjects. This experimental method is useful for broadening the research horizon of neuroeconomic studies.

1. Introduction

Framing effects on decision-making have been studied in behavioral economics since the publication of such seminal manuscripts as those of Kahneman-Tversky (1979), Kahneman-Slovic-Tversky (1982), and Tversky -Kahneman (1981, 1986). Agents are likely to change their decision-making affected by different usage of frames that are the expressive styles of decision problems. Earlier studies have only considered framing effects on individual decision-making. The nature of the relation between framing effects and psychologically based herd behavior is unknown. We conducted a neuroeconomic experiment to examine the strength of framing effects on herd mentality in financial decisions.

Levin-Schneider-Gaeth (1998) claimed, "all frames are not created equal." They classified frames into the following types that have different cognitive properties: risky-choice framing, attribute framing, and goal framing. Attribute framing is simple and strong framing. Levin-Gaeth (1988), Marteau (1989), and Krishnamurthya-Carterb-Blair (2001) provided typical examples for attribute framing to be observable everyday life. We focused on attribute framing and examined the relationship between framing and herd mentality in financial decisions.

The problem of attribute framing presents a case in which the identical problem is differently expressed by, for example, a gain or loss frame. If agents were perfectly rational, they would react identically to a problem regardless of it being expressed by different frames. Boundedly rational agents, however, show cognitive bias produced by the frames of their decision-making.

The study of herd behavior has a long history. According to the survey article by Hirshleifer-Teoh (2003), rational and imperfectly rational approaches have been presented. Recent development in studies of herd behavior is remarkable.[1] The recent studies use the methods of experimental economics and interpret their results by using the neoclassical assumptions of individual profit-maximization behavior. The use of the neoclassical assumption provides clear

[1] The theoretical studies on herd behavior are those by authors including Banerjee (1992), Bikhchandani et al. (1992), and Welch (1992). However, as Cipriani-Guarino (2005) correctly notes, it is difficult to test the theoretical results with empirical studies. Because of the lack of data on private information available to traders, it is difficult to determine whether traders would disregard their private information in favor of common information. The seminal studies by Cipriani-Guarino (2005, 2009) have overcome the research difficulty by conducting experimental studies.

interpretations and understanding of the experimental results; hoever, it restricts our research interest to a narrow field. The neoclassical assumption only allows us to consider the perfectly rational agents who show neither an anomalous framing effect nor herd mentality in decision-making. The use of the neoclassical assumption might produce an underestimation of the actual possibility of herd behavior. To evade the underestimation, we should leave the neoclassical assumption and adopt the concept of boundedly rational agents to allow new interpretations of the experimental results. We executed brain decoding and examined the motivations in the subjects' mind to facilitate the concept of the boundedly rational agents.

To accomplish the purpose of this study, we discuss our strategy for the analysis. We must consider new economic cases that have not been analyzed in earlier behavioral economics. The necessity for the new study derives from the information structure of private and common information. The study on herd behavior considers the cases in which each agent faces two kinds of information, private information and common information, for gaining profits in the market. Private information is individually obtained by the agent, whereas common information is publicly obtained to be known by everyone in the market. Herd behavior is determined by ignoring private information and only accepting common information to induce the agents to choose the identical action as others. We analyzed the complex cases in which private and common information is simultaneously expressed by different types of frames. This situation reflects "a two-dimensions problem of framing effects."

In the two-dimensional problem, private and common information is simultaneously expressed by a gain frame or a loss frame. Table 1 illustrates four cases (2 x 2 cases) with two-dimensional framing effects. Cases 1 and 4 are expressed only by a single frame, whereas Cases 2 and 3 are expressed by mixed frames. Earlier behavioral economics analyzed the single framed cases and did not consider the cases with mixed frames. We consider the new cases with the mixed frames and examine what results would be produced in the Case 2 and 3 experiments. In the later section, we demonstrate that our focusing on Cases 2 and 3 would be more productive than studying other cases for obtaining significant insights.

We used a powerful brain reading method of brain decoding that overcomes the limits of questionnaires. Whereas questionnaires could investigate the characteristics of self-conscious decision making, brain decoding could directly analyze the neural activity of subjects to interpret conscious and unconscious movements in their minds. Brain reading enabled us to examine directly which of the two types of information, private or common information, was used by the subjects in their mind for decision-making. We classified the neural activity data into two groups that represented different mental states in which the subjects used private or common information expressed by a gain frame or a loss frame.

Table1 Four Cases with Private and Common Information Expressed by a Gain or Loss Frame

2. Methods

2.1 Subjects and Tools for Brain Decoding

Eighteen healthy right-handed subjects (nine males; nine females) aged 20 -23 years played the experimental games. All the subjects were students at Aoyama Gakuin University. While each subject played the games, we obtained the necessary brain decoding data. The subjects were not allowed to eat for two hours before the experiment to ensure clear neural reactions to the experimental tasks. Before beginning the experiment, the experimental procedures, safety, security information, and procedure for obtaining payment for participation were explained to the subjects, and informed consent was obtained from the subjects. Our experimental plans and procedures were approved by the Research Ethics Committee of Aoyama Gakuin University, Tokyo, Japan.

As illustrated in Figure 1, we used functional near-infrared spectroscopy (fNIRS), a simpler and more convenient tool for examining brain activation than the more widely used functional magnetic resonance imaging (fMRI). The use of fNIRS results in minimal stress to the subjects. For the fNIRS, we used the Spectratech OEG-SpO2 model (updated from the OEG-16 model, with a sampling rate of 6.10Hz, manufactured by Spectratech, Inc., Tokyo and Yokohama, Japan), which is based on the modified Beer-Lambert law, to scan the frontal cortex of the brain. This fNIRS equipment uses small, lightweight, 16-channel digital sensors on a headband to obtain the event data through a dynamic high-sensitivity optical signal that reflects how in vivo hemoglobin combines with oxygen in blood vessels with high or low cortical activation. fNIRS provides 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 used the changes in oxyhemoglobin for brain decoding. Strangman et al. (2002) found a strong correlation between the fMRI variables and the fNIRS measures, and the oxyhemoglobin data provided the strongest correlation. Therefore, using the oxyhemoglobin data will produce results for fNIRS brain decoding that correspond to those of fMRI studies. We claim that this method enables us to perform efficient and low-stress experiments in brain decoding.

Figure 1 fNIRS Multi-channel Digital Sensors on a Headband

The 16-channel digital sensors were fixed on the frontal cortex by the headband during the experiment. After each subject completed the experiment, the location of each sensor was measured using 3D positioning with a digital camera (Nikon D5100) and NIRS-SPM software to allow statistical analysis of the fNIRS signals and to confirm that the channels were properly located on the frontal cortex of the brain. Figure 2 illustrates the locations of the sensors for the first subject mapped onto a canonical brain optimized for NIRS analysis. We obtained event-related, high-sensitivity optical signals from these channels.

Figure 2 The Locations of the 16 fNIRS Channels in the First Subject, Mapped onto a Canonical Brain

2.2 Experimental Tasks

We examined the framing effect on herd behavior in Cases 2 and 3, which were complex cases in which private and common information was expressed differently by the gain frame and the loss frame.

The basic structure of the experimental task in Case 2 was identical with that in Case 3. Figure 3 illustrates that the tasks were composed of three parts, Games A, B, and C. We presented the subjects with the tasks to execute via a computer monitor and obtained neural data while the subjects were executing the tasks.

Figure 3 Experiment Tasks were Composed of Three Games, A, B, and C

Games A and B were preliminary games that produced neural data to be used in learning and training the neural network architecture to accurately recognize the typical pattern of neural activity in Games A and B. Figure 4 illustrates the concept of learning the neural network architecture. Using the “nntraintool” in the Neural Network Tool Box, we defined a hidden layer 10 and an output layer 2. The input was the neural data obtained in Games A and B. The output was the vector (1,0) when the input was the data from Game A and the vector (0,1) when the input was the data from Game B. The neural network architecture was obtained by training with the input data to recognize the typical patterns of neural activity for either vector (1,0) or (0,1). This approach is a so-called “supervised learning method.”

Figure 4 Learning and Training the Neural Network Architecture Using the Neural Activity Data Obtained in Games A and B

In Game A, the subjects were asked to consider the problem of whether to buy or not to buy the financial stock after viewing private information via a computer monitor. As Table 1 illustrated, the private information was expressed by the gain frame in Case 2 and by the loss frame in Case 3. We expected the subjects to make their decisions in light of the private information. Common information was not displayed on the computer monitor. We expected that the subjects in Game B would consider the identical problem affected by common information. The common information was expressed by the loss frame in Case 2 and by the gain frame in Case 3.

Game C was the core game in which we obtained the neural data that were compared with the typical patterns of Games A and B using a pattern recognition method. In the game, the subjects could freely consider the stock problem after viewing both the private and common information that were expressed by either the gain frame or the loss frame. We expected the subjects to freely choose whether they would or would not ignore the private information to accept only the common information. In brain decoding, each data obtained in Games C was compared with the two typical neural patterns previously identified in Games A and B to obtain a rate of matching. If the rate of matching for the neural pattern of Game B was larger than that of Game A, the subject mainly used common information for financial decision-making in the stock market.

Figure 5 illustrates the monitor screens presented in the short tasks of Games A, B, and C in Cases 2 and 3. First, we explain the short task in Case 2. Before playing the game, we explained that there was a financial stock that provided a chance for either getting or losing $10 and asked the subjects to buy or not buy the stock. Then the game began. The first screen of the computer monitor displayed a white cross on a black ground to indicate that the subjects should begin the game in a state of relaxation. After 10 seconds, Game A began. Game A presented the subjects with the private information for 3 seconds for them to consider the stock problem. The private information was expressed by the gain frame, and the message on the monitor was " This is your private information. If you buy the stock, you will get $10 with a 60% probability. Do you buy the stock?"[2] Neural data were obtained by fNIRS during this consideration period. Figure 5 illustrates by the gray areas the period for obtaining neural data. After the presentation, the subjects were asked to press the key Y for yes or N for no within 2 seconds. To evade emotional upsets of the subjects, the results of their decisions were informed after they finished all of the games. Game A was repeated 4 times.

Game B presented the subjects with the common information for 3 seconds for them to consider the problem. The common information was expressed by the loss frame, and the message on the monitor was " This is the common information to be known by everyone. If you buy the financial stock, you will lose $10 with a 40% probability. Do you buy the stock?" After the presentation, the subjects were asked to press Y or N within 2 seconds. Game B was repeated 4 times.

Game C simultaneously presented the subjects with the private and common information in the same screen for 3 seconds. The private information was expressed by the gain frame, and the common information was expressed by the loss frame. The subject could freely select either the private information or the common information to consider the problem. Neural data were obtained during the consideration period. After the simultaneous presentation of the two types of information, the subjects were asked to press Y or N within 2 seconds. Game C was repeated 4 times.

The structure of the short task in Case 3 was basically the same as that in Case2. Case 3 was only different from Case 2 in the frames that expressed the private and common information. The private

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[2] 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.

information was expressed by the loss frame in Case 3 and by the gain frame in Case 2. The common information was expressed by the gain frame in Case 3 and by the loss frame in Case 2.

Figure 5 The Monitor Screens in the Short Tasks of Games A, B, and C in Cases 2 and 3.

2.3 Random Selection of Neural Data for Brain Decoding

For the brain decoding, as Figure 6 illustrates, we randomly selected the data obtained by the fNIRS during the experiment in two steps. First, we randomly selected a sample of 40 neural data points per subject from Games A and B in Cases 2 and 3 to determine the neural network architecture and establish the typical neural patterns. Next, we randomly selected a sample of 10 data points per subject from Game C in Cases 2 and 3. Each of the 10 data points was matched by pattern recognition with the two typical neural patterns from the preliminary games to obtain the rates of matching. If the rate of matching with Game B was larger than the rate of matching with Game A, the subject mainly used the common information for financial decision-making. The random selection was conducted for all 18 subjects. The data existed for 180 cases of brain decoding with pattern recognition.

Figure 6 Random Selection of Neural Data for Brain Decoding in Two Steps for Each Subject (in Cases 2 and 3)

3. Results

We obtained the following two results in this experiment.

Result (1): We illustrate the result of Case 2 in the bubble chart in Figure 7. Large bubbles represent large cumulative frequency in the frequency distribution chart. The horizontal axis of the diagram measures the rate of matching with the typical neural pattern of Game A that corresponds to the probability of utilizing the private information for the financial decision-making. The vertical axis measures the rate of matching with Game B that implies the probability of utilizing the common information. The average matching rate with the typical pattern of Game B was 0.552532, whereas the average matching rate with the typical pattern of Game A was 0.448374. This result implies that when the subjects freely executed Game C in Case 2, the common information expressed by the loss frame was more primarily used for their decision-making than the private information expressed by the gain frame. The common information had larger effects than the private information on their decision-making.

Result (2): We illustrate the result of Case 3 in the bubble chart in Figure 8. The average matching rate with the typical pattern of Game B was 0.502719, whereas the average matching rate with the typical pattern of Game A was 0.466542. When the subjects freely executed Game C in Case 3, the common information expressed by the gain frame had larger effects on their decision-making than the private information expressed by the loss frame.

Figure 7 The Bubble Chart Obtained by Brain Decoding of Neural Data in Case 2

Figure 8 The Bubble Chart Obtained by Brain Decoding of Neural Data in Case 3

Explanations of the Results

We trained the neural network architecture to recognize each subject's typical neural patterns in Games A and B, using the algorithms and the progress stop conditions of the Neural Network Tool Box listed in Table 2(a). Table 2(b) lists the seed numbers that were used to generate a random number sequence for the neural network weights initialization and to partition the initial data into a

training set for learning and a validation set. The seed numbers were determined to maximize the performance in determining the neural network architecture. The numbers enable reproduction of our analytical results when the same numbers are used with the same experimental data.

Table 2(a) The Algorithms and Progress Stop Conditions for Determining the Neural Network Architecture Using the Neural Network Tool Box (nntraintool)

Table 2(b) The Seed Numbers Used to Begin the Sequence of Random Numbers for Learning with the Neural Network Tool Box for Each Subject

We executed the brain decoding by matching the neural data obtained from Game C with the typical neural patterns obtained from Games A and B. For each subject, 10 neural data points from Game C were matched with his/her typical neural patterns using pattern recognition to obtain a rate of matching. Figures 7 and 8 illustrate the results of Cases 2 and 3 in the bubble charts obtained from our 180 (= 10 x 18) brain decoding values.

The points in the lower right section of the bubble charts have larger values along the horizontal axis than along the vertical axis; these points could be considered cases in which the subjects relied on the private information for their decision-making. Conversely, the points located in the upper left section of the charts could be considered cases in which the subjects relied on the common information for their decision-making. In cases in which the matching rates were located in the lower right section or the upper left section, brain decoding was able to clearly classify the neural activity data into the two groups. Figures 7 and 8 illustrate, however, that some cases could not be clearly sorted into these two groups. These observations were not produced by a technological failure of brain decoding; they reflected the subjects' use of other cognitive capacities, such as physiological reasons.

We calculated the average value of the matching rates in Cases 2 and 3. In case 2, the average matching rate with the typical pattern of Game A was 0.448374 and that of Game B was 0.552532. In Case 3, the average matching rate of Game A was 0.466542 and that of Game B was 0.502719. The changes in the average matching rates were produced by the different combination of gain and loss frames that respectively expressed private and common information. In Case 2, the private information was expressed by the gain frame, and the common information was expressed by the loss frame. In Case 3, the private information was expressed by the loss frame, and the common information was expressed by the gain frame. The change in the average matching rates represented the magnitude of the framing effects on the use of private and common information for financial decision-making.

Figure 9 illustrates the difference of the average matching rates in Cases 2 and 3. Point X represents the average matching rate in Case 2. Point Y represents the average matching rate in Case 3. The magnitude of the framing effect produced by the mixed frames is obtained by the difference between X and Y. Our problem is whether the framing effect measured by the difference between X and Y was large enough to be worth noting that the framing effect remarkably changed the use of private and common information in financial decision-making. Could the framing effect effectively weaken herd mentality by changing the use of the two types of information? We executed a t-test to examine the statistical effectiveness of the difference between Points X (0.448374, 0.552532) and Y (0.466542, 0.502719). The p values of the differences in the average matching rates between 0.448374 and 0.466542 and between 0.552532 and 0.502719 were, respectively, $p = 0.721236$ and $p = 0.290755$, and they were not statistically effective ($p > 0.05$). The difference between Points X and Y was too small to be statistically effective. We could not claim that the framing effect effectively affected the use of private and common information for financial decision-making.

The average matching rates with the typical pattern of Game B (i.e., 0.552532 and 0.502719) continued to be higher than the average matching rates with that of Game A (i.e., 0.448374 and 0.466542) in Cases2 and 3. The continuous higher values of the matching rates with Game B imply

that the subjects continued to rely more strongly on common information than private information for their decision-making. The strong reliance on common information was herd mentality to induce the agents to choose the identical action as others. The framing effect produced by the different use of gain and loss frames could not effectively weaken herd mentality in financial decision-making.

Figure 9 The Magnitude of Framing Effects on Herd Mentality Measured by the Difference Between the Rates of Matching

4. Discussions

We focus on Cases 2 and 3 with mixed frames ignoring Cases 1 and 4 with a single frame. In this section, we additionally consider the reason for focusing on Cases 2 and 3. The problem is whether our focusing on Cases 2 and 3 can be justified when we examine the magnitude of framing effects on herd mentality.

We consider the following alternative cases (A) and (B) in which framing effects theoretically change the use of private and common information for decision-making.

(A) We consider the case in which agents prefer gain frame to loss frame. Agents increase the use of information with gain frame and decrease the use of information with loss frame. In Case 3, common information is expressed by gain frame, and private information is expressed by loss frame. The possibility of using common information is maximized in Case 3. Conversely, in Case 2, common information is expressed by loss frame, and private information is expressed by gain frame. The possibility of using common information is minimized in Case 2. The change of the possibility of using common information implies the change of the strength of herd mentality that is a framing effect produced by the preference for gain frame to loss frame. To examine whether the framing effect on herd mentality is strong or weak, we should compare the maximized and minimized possibilities of using common information in Cases 2 and 3. If the difference between the maximized and minimized possibilities of using common information is too small to be statistically effective, we conclude that framing effects cannot effectively affect herd mentality in the financial decision-making. Conversely, if the difference is sufficiently large, we conclude that framing effects remarkably affect herd mentality.

(B) We consider the other case in which agents pay attention more carefully to loss frame than gain frame for decision-making. This case is dealt with in the same manner as discussed above. The possibility of using common information is maximized in Case 2 and minimized in Case 3. To examine whether the framing effect on herd mentality is strong or weak, we should compare the maximized and minimized possibilities of using common information in Cases 2 and 3.

The above discussions of (A) and (B) justify that we focus on Cases 2 and 3 with mixed frames ignoring Cases 1 and 4 with a single frame. We can obtain sufficient results by analyzing Cases 2 and 3 to examine the strength of framing effects on herd mentality for financial decision-making.

5. Concluding Remarks

Whereas earlier studies have considered the framing effect on individual decision-making, the effect of frames on herd mentality and herd behavior has not been studied. We conducted a neuroeconomic experiment to challenge the new unsolved problem. We focused on the concept of attribute framing, the robust and strong framing, to consider the case in which the identical financial problem was differently expressed by the gain or loss frame. Our problem was to examine whether attribute framing would have substantial effects on herd mentality, as well as on individual decision-making. Our results implied that the framing effect could not effectively affect the herd mentality to primarily rely on common information to induce agents to choose the same action as

others. We claim that the framing effect is sufficiently strong to change individual decision-making; however, it is too weak to affect herd mentality.

Our conclusion suggests that herd behavior produced by herd mentality has a long duration in the market once the herd mentality exists in the minds of many people. This strong psychological property of herd behavior suggests a new explanation for the long waves of business cycles.

In this experiment, we executed a powerful brain reading method of brain decoding. Whereas questionnaires could investigate the characteristics of self-conscious decision making, brain decoding could directly analyze the neural activity of subjects to interpret conscious and unconscious movements in their mind. By brain decoding, we could examine which of the two types of information, private or common information, was used by the subjects for their financial decision-making. This experimental method is useful for broadening the research horizon of neuroeconomic studies.

Table1 Four Cases with Private and Common Information Expressed by a Gain or Loss Frame

	common information expressed by a gain frame	common information expressed by a loss frame
private information expressed by a gain frame	Case 1	Case 2
private information expressed by a loss frame	Case 3	Case 4

Table 2

Table 2(a) The Algorithms and Progress Stop Conditions for Determining the Neural Network Architecture Using the Neural Network Tool Box (nntraintool)

Algorithms

Data division function: random data division function
Training function: scaled conjugate gradient training function
Performance function: mean squared error performance function
Derivative function: default derivative function

The Progress Stop Conditions for Learning

Epoch: 1000
Performance: 0.00
Gradient: 1.00 e-10
Validation Checks: 6

Table 2(b) The Seed Numbers Used to Begin the Sequence of Random Numbers for Learning with the Neural Network Tool Box for Each Subject

subject	1	2	3	4	5	6	7	8	9
seed	13	-18	24	29	19	-1	4	-13	-15

subject	10	11	12	13	14	15	16	17	18
seed	21	-20	23	2	-19	-4	-27	-19	-9

Figure 1 fNIRS Multi-channel Digital Sensors on a Headband

Figure 2 The Locations of the 16 fNIRS Channels in the First Subject, Mapped onto a Canonical Brain

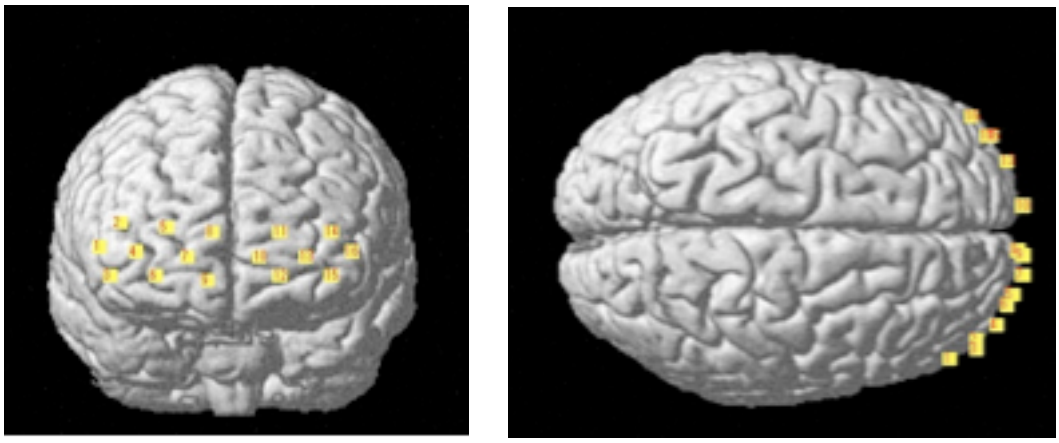


Figure 3 The Experimental Tasks were Composed of Three Games, A, B, and C

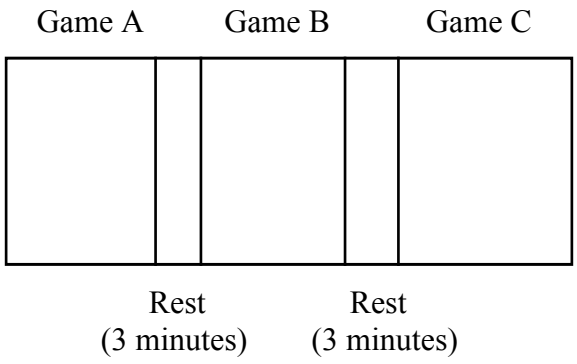


Figure 4 Learning and Training the Neural Network Architecture Using the Neural Activity Data Obtained in Games A and B

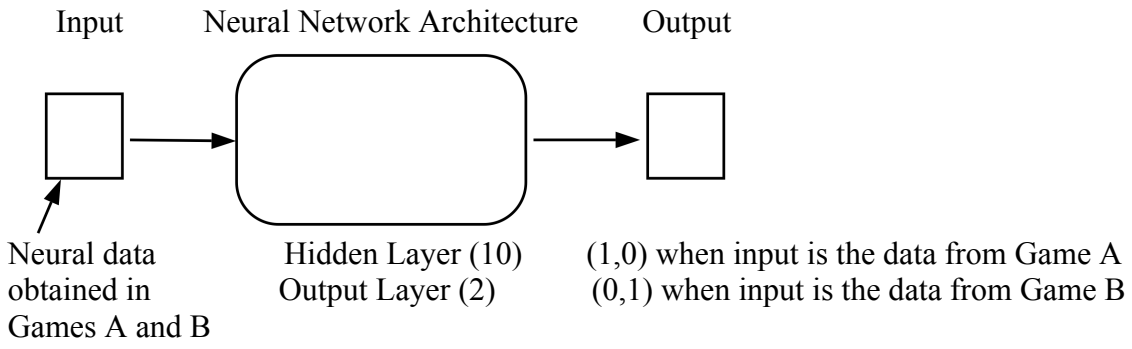


Figure 5 The Monitor Screens in Short Tasks of Games A, B, and C in Cases 2 and 3

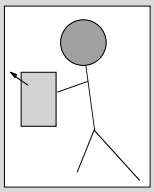
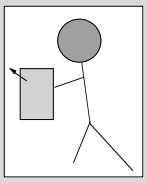
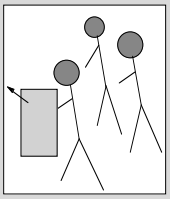
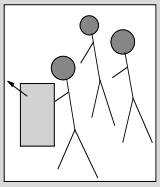
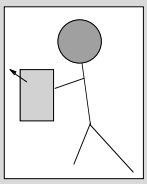
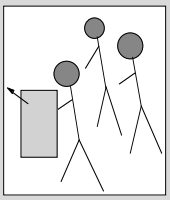
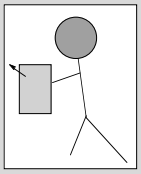
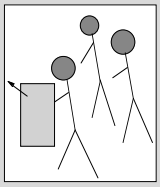
	Case 2	Case 3
Start (10 seconds)	+	+
Game A (3+2 seconds, repeated 4 times)	If you buy the stock, you will get $10 with a 60% probability.  This is your private information. Do you buy the stock? (3 seconds)	If you buy the stock, you will lose $10 with a 40% probability.  This is your private information. Do you buy the stock? (3 seconds)
	Press Y or N. (2 seconds)	Press Y or N. (2 seconds)
Game B (3+2 seconds, repeated 4 times)	If you buy the stock, you will lose $10 with a 40% probability.  This is the common information to be known by everyone. Do you buy the stock? (3 seconds)	If you buy the stock, you will get $10 with a 60% probability.  This is the common information to be known by everyone. Do you buy the stock? (3 seconds)
	Press Y or N. (2 seconds)	Press Y or N. (2 seconds)
Game C (3+2 seconds, repeated 4 times)	If you buy the stock, you will get $10 with a 60% probability.  This is your private information. Do you buy the stock? (3 seconds) If you buy the stock, you will lose $10 with a 40% probability.  This is the common information to be known by everyone. Do you buy the stock? (3 seconds)	If you buy the stock, you will lose $10 with a 40% probability.  This is your private information. Do you buy the stock? (3 seconds) If you buy the stock, you will get $10 with a 60% probability.  This is the common information to be known by everyone. Do you buy the stock? (3 seconds)
	Press Y or N. (2 seconds)	Press Y or N. (2 seconds)

Figure 6 Random Selection of Neural Data for Brain Decoding in Two Steps for Each Subject (in Cases 2 and 3)

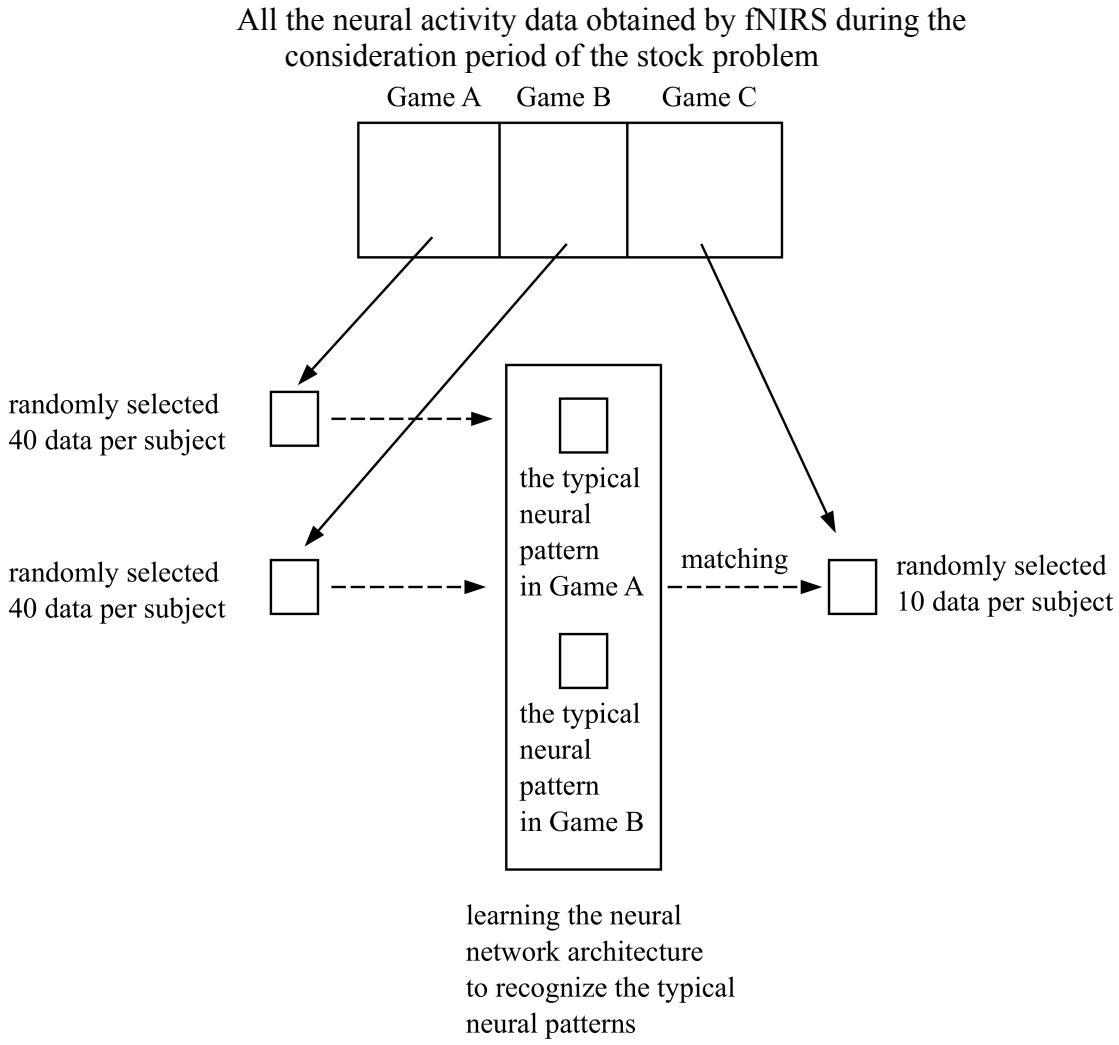


Figure 7 The Bubble Chart Obtained by Brain Decoding of Neural Data in Case 2

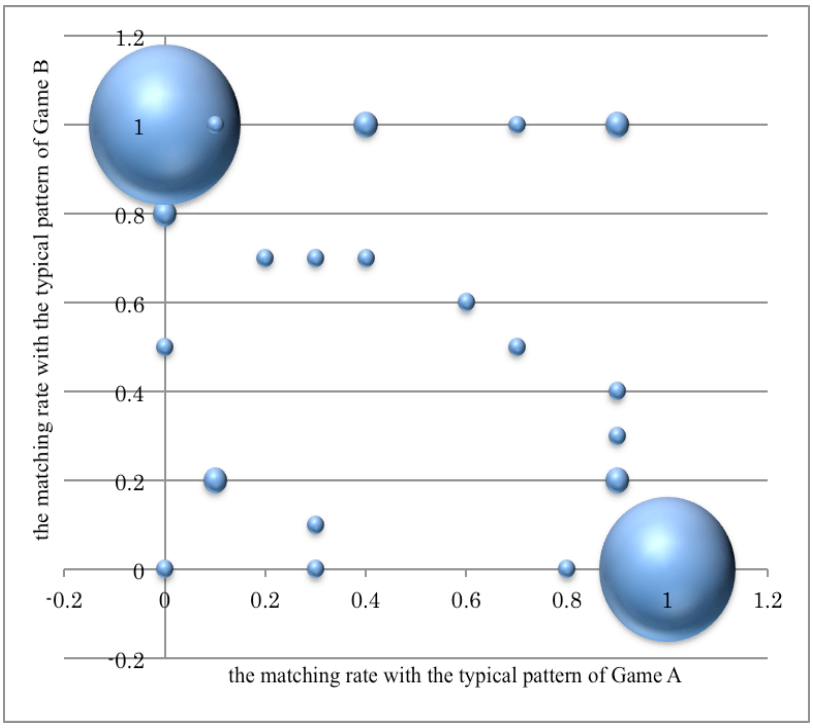


Figure 8 The Bubble Chart Obtained by Brain Decoding of Neural Data in Case 3

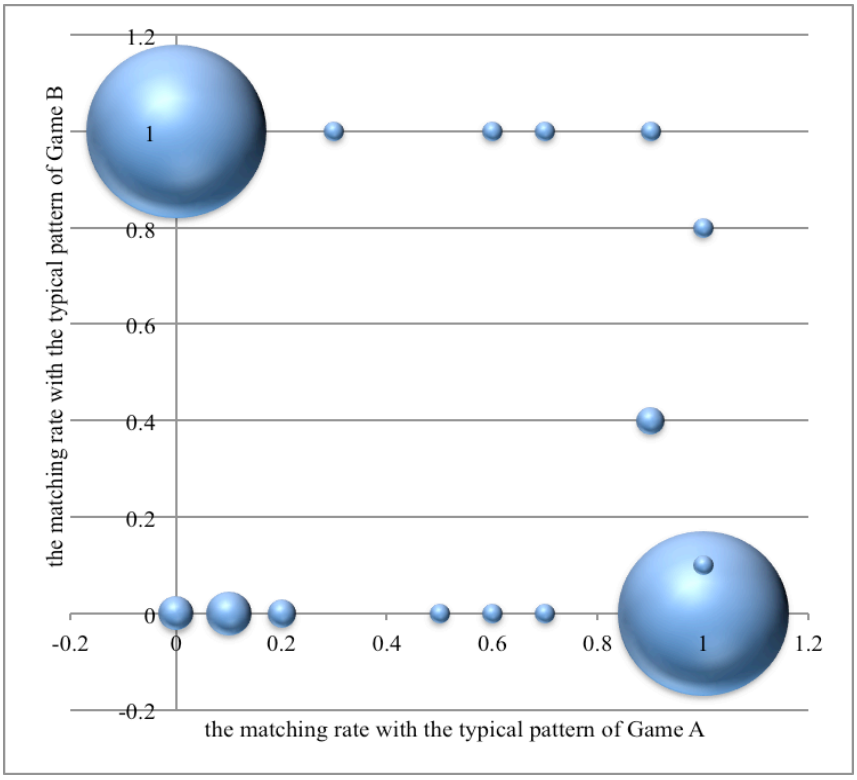
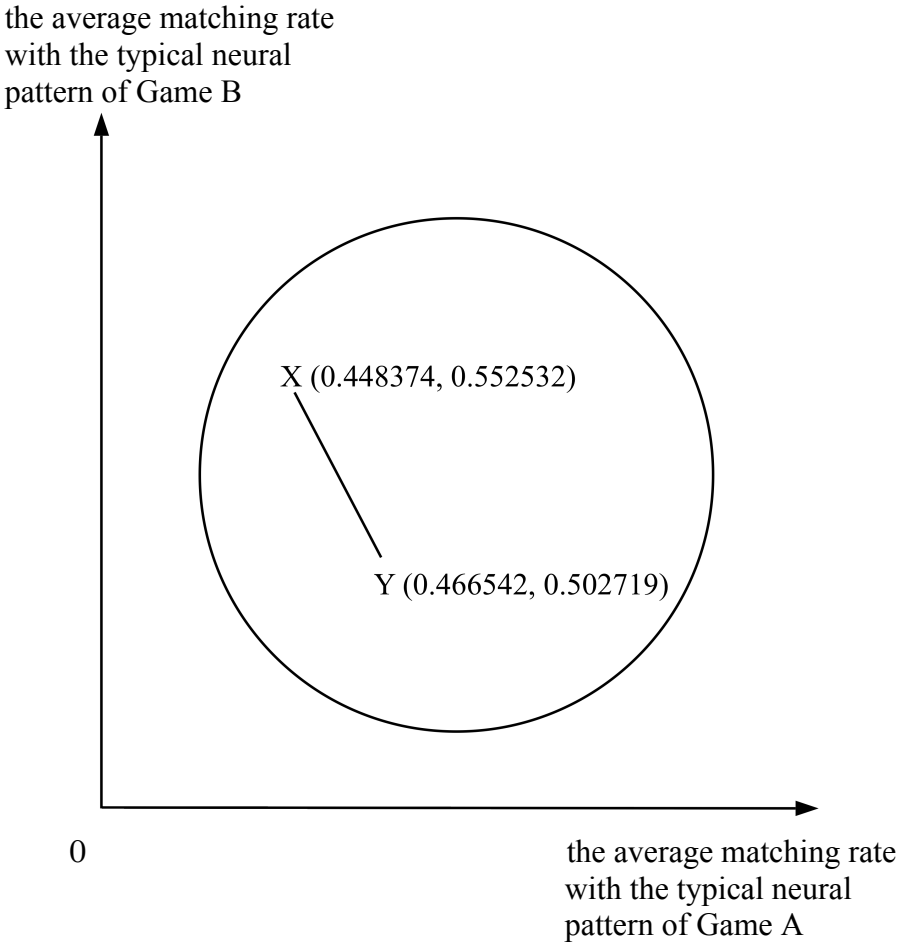


Figure 9 The Magnitude of Framing Effects on Herd Mentality Measured by the Difference Between the Rates of Matching



X: a point representing the average matching rate in Case 2 where private information was expressed by the gain frame and common information was expressed by the loss frame
Y: a point representing the average matching rate in Case 3 where private information was expressed by the loss frame and common information was expressed by the gain frame

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