Direct Tests on Individual Behaviour in Small Decision-Making Problems

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ABSTRACT

This paper provides an empirical and experimental analysis of individual decision making in small decision-making problems with a series of laboratory experiments. Two experimental treatments with binary small decision-making problems are implemented: (1) the search treatment with the unknown payoff distribution to the decision makers and (2) the choice treatment with the known payoff distribution. A first observation is that in the search treatment the tendency to select best reply to the past performances, and misestimation of the payoff distribution can lead to robust deviations from expected value maximisation. A second observation is concerned with choice problems with two options with the same expected value: one option is more risky with larger payoff variability; the other option is moderate with less payoff variability. Experimental results show that it is likely that the more the decision makers choose a risky option, the higher they can achieve high points, *ex post*. Finally, I investigate the exploration tendency. Comparison of results between the search treatment and the choice treatment reveals that the additional information to the decision makers enhances expected value maximisation.

Key words: experiments; exploration; search; small decision; the certainty effect

1. INTRODUCTION

It is imperative to note that the relevant economic theory and recent developments in experimental economics have been developed in the context of decision making in *big decision-making* (BDM) problems conducted by a number of researchers [e.g., 1; 2; 9; 14; 15; 16; 17; 19; 21; 22; 23; 24]. In BDM problems, an economic actor takes a decision that is known to have a significant bearing on her/his welfare via the well-defined return and cost functions. On the contrary, my focus of research in this paper is solely upon what economists call decision making in *small decision-making* (SDM) problems that have received little attention from researchers.

This paper addresses important issues of SDM problems and reports experiments of those problems. One subset of SDM problems includes "small explicit-feedback-based decision (SEFB) making problems" which are defined in the following three features. First, SEFB problems include repeated tasks; the decision makers face the same choice problem many times in similar situations. Second, each single choice is not *very* essential; the alternatives tend to have similar expected value that may be fairly small. Finally, the decision makers *do* have (i.e., they are disclosed) objective prior information as to the payoff distribution.

There have been a few studies of SDM problems. Barron and Erev [4] conducted experimental research and introduced some properties in small feedback-based decision (SFB) problems, such as deviations from expected value maximisation, which are the reverse phenomena observed in BDM problems. Their results revealed that each decision maker's experience led the *reversed certainty effect*, contrary to the certainty effect, a key finding of BDM problems in Kahneman and Tversky [17]. Barron and Erev showed that the decision makers were likely to be sensitive to payoff variability and payoff ranks in making decisions in SFB problems. Erev and Barron [11] analysed the payoff variability effect and the payoff rank effect in SFB problems, applying to reinforcement learning among cognitive strategies. Fujikawa [12] discussed a problem of petty corrupt behaviour by some officials or officers in the context of SEFB problems with a structured economic experiment.

One presumes that the analysis of decision making in SDM problems should be divided into two treatments: the *search treatment* and the *choice treatment*. I perform the former treatment in Experiment 1, where the subjects are not disclosed probability of each possible outcome. The latter treatment is performed in Experiment 2, where the subjects are disclosed probability of each possible outcome prior to the experiment. Experiment 1 refers to SFB problems, whereas Experiment 2 refers to SEFB problems.

One set of hypotheses in this paper is that in the search treatment (i.e., SFB problems) the tendency to select best reply to the past outcomes/performances, and misestimation of the payoff distribution can lead to robust deviations from expected value maximisation. I set up simple regression models to test the hypothesis above. As the rest of this paper will show, the tendency to play best reply to the past outcomes/performances is more plausible in the search treatment than in the choice treatment. It is shown that the alternative with higher expected value is likely to be chosen many times by the decision makers who have achieved higher outcomes, *ex post*.

Another set of hypotheses is concerned with the behavioural tendency in a binary choice problem, where two options with the same expected value are available: one option is more risky with larger payoff variability; the other option is moderate with less payoff variability. I will show that it is likely that the more the decision makers choose the risky option, the higher they can achieve high points, *ex post*. This involves the assertion that the decision makers seem to follow the belief in playing best reply to the past performances more frequently in the search treatment than in the choice treatment.

The nature of the exploration tendency in SDM problems is investigated. Comparison of results between the search treatment and the choice treatment reveals that the exploration tendency observed in the search treatment cannot be explained as rational exploration (i.e., expected value maximisation). Similar exploration is observed even in the choice treatment, that is, even when the payoff distribution is known. It suggests that the additional information to the decision makers (i.e., making the payoff distribution available to the decision makers) leads them toward expected value maximisation. On the other hand, the exploration tendency can be explained by tenets of the adjustment process in the ambiguity model axiomatised by Einhorn and Hogarth [10].

The remainder of this paper contains the following. Section 2 reviews early literature on SDM problems. Section 3 presents the design of the current SDM problems experiments. Section 4 includes results of the current experiments and its discussion. The final section contains conclusions of this paper.

2. EARLY LITERATURE

Barron and Erev [4] and Erev and Barron [11] focused upon SFB problems, which are important subsets of SDM problems. Both of the papers conducted experiments by employing Problem 1 and 2, both of which are replica of the choice problems in Kahneman and Tversky [4], as well as Problem 3:

Problem 1. Choose between:

H:	4 with probability 0.8	;	0 otherwise
L:	3 with certainty		

Problem 2. Choose between:

H:	4 with probability 0.2	;	0 otherwise
L:	3 with probability 0.25	;	0 otherwise

Problem 3. Choose between:

H:	32 with probability 0.1	;	0 otherwise
L:	3 with certainty		

Forty-eight undergraduates served as paid participants in each problem. Each subject faced the computer screen in which she/he was instructed to choose one of two unmarked buttons which corresponded to H and L for 400 times in each of the three problems. That is, the subjects' task was to choose either H or L in each trial t (t=1, 2, … , 400) in each problem. For example, one selection of H in Problem 1 made the subjects earn four points with probability of 0.8 and zero point with probability of 0.2; one selection of L in Problem 1 made them earn three points for sure. The information available to the subjects was limited to feedback concerning the outcomes of their previous decisions. Note that the payoff structure of each problem is not disclosed to the subjects. Amongst both experiments, the computer provided the subjects with binary types of feedback immediately following each choice: (1) the payoff for the choice that appeared on the screen for the duration of one second and (2) an update of an accumulating payoff counter, which was constantly displayed.

The experimental result of Problem 3 revealed that the mean proportions of H choices were 0.28. Erev and Barron [11] raised an issue as to Problem 3 in which the alternative that yielded the best outcome most of the time had lower expected value. In Problem 3, the alternative H yielded the worst outcome (i.e., 0 point) for the decision makers for 90% of trials, whereas the alternative L yielded the best outcome (i.e., 3 points) for whole trials. Note that in Problem 3, H had higher expected value (3.2 vs. 3) but in most (90%) of the trials, L yielded better payoff (0 vs. 3). Erev and Barron's hypothesis was that in this situation, the reasonable tendency to rely on the typical outcomes should imply underweighting of rare outcomes. The hypothesis was confirmed with the experiment with Problem 3, the result of which revealed that the mean proportions of H choices were 0.28.

Barron and Erev [4] claimed that the *reversed certainty effect* was observed in their SFB problems experiments, whereas the certainty effect was observed in Kahneman and Tversky's [17] BDM problems experiments. While the mean proportions of H choices over the subjects were 0.63 for Problem 1, it decreased significantly to 0.51 for Problem 2 in Barron and Erev's experiments. However, we must be careful in accepting Barron and Erev's interpretation of the observation of the reversed certainty effect. Barron and Erev compared their results with those of Kahneman and Tversky to check whether the certainty effect should hold even in decision making in SFB problems. Yet, Barron and Erev's results are not directly comparable with Kahneman and Tversky's results, due to the following three perspectives.

Addressed is a first distinction in interpreting experimental results of Barron and Erev [4] and Erev and Barron [11]. On the one hand, in Kahneman and Tversky's [17] experiments, the subjects in Problem 1 and 2 were performed only one round in each problem with hypothetical payoffs, that is, they were asked to make only one selection in Problem 1 and 2. On the other hand, the experiments in Barron and Erev [4] and Erev and Barron [11] included the treatments, where the subjects were asked to choose either H or L 400 times and paid real money according to their performance at a conversion rate of one point to 0.01 Israeli Shekel (about 0.25 US cent).

The second distinction is that Barron and Erev's [4] and Erev and Barron's [11] subjects were asked to make their selections for a number of times in each problem. For example, one implies that the optimal behaviour for Problem 1 under a repeated-play condition is not necessarily to repeat the optimal choice for Problem 1 under a one-shot condition. Suppose that the decision maker is willing to choose H once in Problem 1 as her/his optimal choice when she/he is asked to make one selection between H and L. This does not necessarily imply that the decision maker is willing to choose H 400 times in Problem 1 when she/he is asked to perform the problem 400 times. I should like to highlight that multi-decision making is not mere repetition of single-decision making.

The third distinction is to be noted. In the experiments of Barron and Erev [4] and Erev and Barron [11], the subjects were *not* disclosed complete, prior information on the payoff structure of Problem 1, 2 and 3. Notice that in Kahneman and Tversky's [17] experiments, the subjects were disclosed complete information on the payoff structure prior to the experiment. It has not been examined whether or not the subjects in Barron and Erev [4] and Erev and Barron [11] could correctly estimate each alternative only with hundreds of trials. As they were not disclosed objective information as to the payoff structure, the subjects would have to refer to feedback of their past outcome in every round to estimate the payoff distribution in each problem. In the process of trying alternatives repeatedly, the subjects would gradually form their subjective payoff distribution of the problem, which was or was not the same as the objective payoff distribution. Having finished searching for the payoff distribution of both alternatives (H and L) with only 400 trials, some subjects would regard H (L) as the alternative with higher (lower) expected value, that is, they had estimated the alternative correctly. Others, however, would regard H (L) as the alternative with lower (higher) expected value, that is, they had misestimated the alternative.

A straightforward example of the decision maker's misestimation mentioned above is interpreted by exemplifying the decision maker who has misestimated the payoff structure. Let us consider the decision maker who chose H and L ten times in each for the first 20 trials to search and estimate the payoff structure in Problem 1. Suppose a situation in which the decision maker has received 28 points after ten selections of H, and of course 30 points after ten selections of L in Problem 1. In this situation, the decision maker's posterior average points of H were 2.8 (=28/10) after ten selections of H; those points of L were 3 (=30/10) after ten selection of L. Hence, the decision maker is likely to subjectively estimate that the expected value of H and that of L should be 2.8 and 3, respectively. It follows that the decision maker might have judged that the expected value of L was greater than that of H, *ex post*. That is, the decision maker might have misestimated the payoff structure of Problem 1.

Therefore, it is quite ambiguous whether or not the subjects in Barron and Erev [4] and Erev and Barron [11] chose H (L) with supposing that H (L) has higher (lower) expected value in Problem 1, 2 and 3. Indeed, the mathematical model in Fujikawa [13] asserts that the probability that the decision maker misestimates the probability of uncertain outcomes in Problem 3 is fairly large in just hundreds of trials. It is also asserted that such misestimation may lead the decision maker to deviations from expected value maximisation.

3. EXPERIMENTAL DESIGN

I implemented two laboratory settings of SDM problems: Experiment 1 (the search treatment) and Experiment 2 (the choice treatment). Experiment 1 was conducted to examine SFB problems without providing the subjects with any prior information as to the payoff structure and the exact length of the experiment. The subjects in Experiment 1 were, however, aware of the expected length of the experiments when being recruited, so they knew that it should include many rounds. Yet, they were not disclosed the exact number of rounds to be performed. On the other hand, Experiment 2 was conducted to examine SEFB problems under the condition that the subjects were disclosed the exact payoff structure and number of rounds to be performed.

Experiment 1 and 2, both of which were computerised, were conducted at Kyoto Experimental Economics Laboratory (KEEL). Forty-two subjects participated in Experiment 1 first and did in Experiment 2, subsequently. Participants, undergraduates from different departments at Kyoto Sangyo University, were all volunteers noticed by a mimic board on KEEL portal. The subjects received written instructions which were read aloud and were given an opportunity to ask questions individually before each experiment. These instructions included explanations of computer screens and experimental procedure for consolidation of each experiment. At the conclusion of the experiments, the subjects were paid individually and privately, at a conversion rate of one point to 0.3 Yen (0.25 US cent) and received no initial (showing up) fee.

Experiment 1 and 2 were conducted by replicating the choice problems in Barron and Erev [4]. The subjects in the two experiments were confronted with the three choice problems: Problem 1, 2 and 3, each of which included 400 rounds with an immediate feedback. Among the two experiments, the basic task was a binary choice between H and L at each round t (t=1, 2, …, 400).

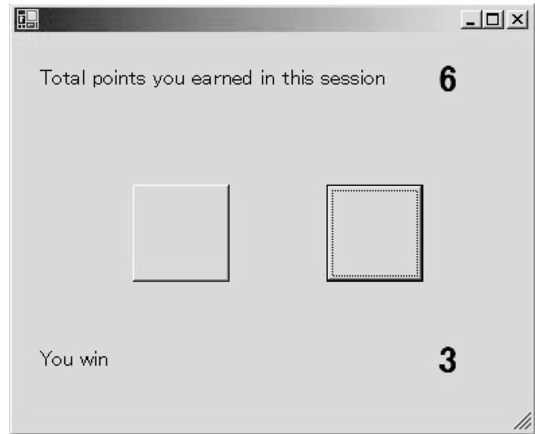

Figure 1 The computerised money machine for Experiment 1

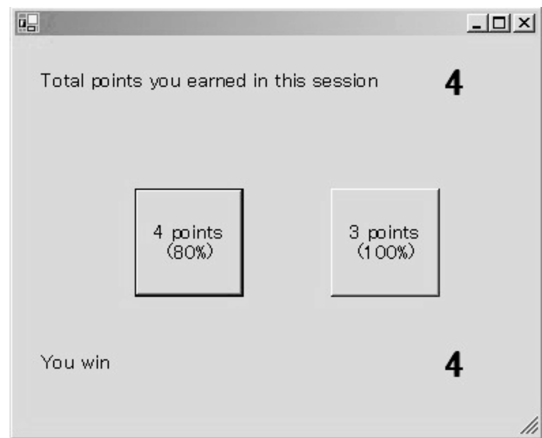

Figure 2 The computerised money machine for Experiment 2

The subjects were instructed to operate a "computerised money machine" both in Experiment 1 and in Experiment 2. The subjects in Experiment 1 were instructed to choose one of two *unmarked* buttons 400 times in the computerised money machine for each of Problem 1, 2 and 3. (See Figure 1 for an experimental screen for Experiment 1.) Each button in the machine corresponded to H and L in each of the three problems; however the subjects were not disclosed that the left button referred to H and therefore the right button referred to L. All of the same types of the procedure explained above were done for Experiment 2 with the exception that the subjects in Experiment 2 were presented with *marked* buttons, as shown in Figure 2, on which corresponding payoff and its probabilities were appeared. Amongst both experiments, the money machine provided the subjects with binary types of feedback immediately following each choice: (1) the payoff for the choice that appeared on the screen for the duration of one second and (2) an update of an accumulating payoff counter, which was constantly displayed.

4. RESULTS AND DISCUSSION

The mean proportions of H choices, denoted by N_H, throughout 400 rounds are 0.48, 0.55 and 0.22 for Problem 1, 2 and 3 in Experiment 1 respectively; whereas N_Hs are 0.63, 0.69 and 0.40 for Problem 1, 2 and 3 in Experiment 2 respectively. We here define the posterior average points of H choices, denoted by *posterior-H*, as the points the decision maker has earned from H after it was chosen *m* times. For example, if the decision maker in Problem 1 has acquired 12 points from H after she/he chose it five times, then *posterior-H* is 12/5=2.4.

The Tendency to Play Best Reply to the Past

One hypothesis is concerned with the tendency to play best reply to the past. To put the hypothesis to test, we will analyse the interdependence between *posterior-H* and N_H in Problem 1, 2 and 3 for each of Experiment 1 and 2. For Problem 2 in which both H and L include uncertain outcomes, we will also analyse the interdependence between the posterior average points of L (*posterior-L*) and the mean proportions of L choices (N_L). For a convenient way, let $posteriorH_{rv}$ denote *posterior-H* in Problem r (r=1, 2, 3) in Experiment v (v=1, 2) and $posteriorL_{2v}$ denote *posterior-L* in Problem 2 in Experiment v.

The regression analysis was conducted to account for the interdependence between *posterior-H* and N_H for Problem 1, 2 and 3, and the interdependence between *posterior-L* and N_L for Problem 2 in each of Experiment 1 and 2. We considered the following two regression models in which ε_H and ε_L were standard normal error terms:

$$posteriorH_{rv} = \alpha_{rv} + \beta_{rv} N_H + \varepsilon_H \qquad (1)$$

$$posteriorL_{2v} = \gamma_v + \theta_v N_L + \varepsilon_L . \qquad (2)$$

Table 1 Transformed regression coefficients

	p-value	*TRCH*	*TRCL*
Problem 1			
Experiment 1	0.000	0.453	
Experiment 2	0.694	0.008	
Problem 2			
Experiment 1	0.004	0.420	
	0.839		0.028
Experiment 2	0.580	-0.041	
	0.006		0.621
Problem 3			
Experiment 1	0.000	1.523	
Experiment 2	0.100	0.300	

Here, we defined $TRCH_{rv}$ as the transformed regression coefficient for H in Problem r in Experiment v; we defined $TRCL_{2v}$ the transformed regression coefficient for L in Problem 2 in Experiment v. Table 1 shows $TRCH_{rv}$ and $TRCL_{2v}$, which were computed by the following rules:

$$TRCH_{1v} = \beta_{1v} \times \frac{400}{3.2} \qquad (3)$$

$$TRCH_{2v} = \beta_{2v} \times \frac{400}{0.8} \qquad (4)$$

$$TRCL_{2v} = \theta_v \times \frac{400}{0.75} \qquad (5)$$

$$TRCH_{3v} = \beta_{3v} \times \frac{400}{3.2} . \qquad (6)$$

We now adduce the following three arguments on *TRCH*. First, it is found from Table 1 that $TRCH_{r1}$ is greater than $TRCH_{r2}$ (r=1, 2, 3). That is, *TRCH*s for Experiment 1 (the search treatment for SFB problems) are greater than *TRCH*s for Experiment 2 (the choice treatment for SEFB problems). The result reveals that the more the subjects chose H, the higher *posterior-H* they achieved in Experiment 1 than in Experiment 2. It follows that N_H more highly depends upon *posterior-H* in Experiment 1 than in Experiment 2. One implies that the tendency to play best reply to the past outcomes/performances is more plausible in the search tasks than in the choice tasks. It is from the point of view above that we find that H was likely to be chosen many times by the decision makers who had achieved higher *posterior-H*, *ex post*.

Second, as seen in Table 1, $TRCH_{12}$ is approximately zero, whereas $TRCH_{11}$ is 0.453. That is, as for Problem 1, *TRCH* is approximately zero in Experiment 2, whereas it is 0.453 in Experiment 1. It implies that N_H depends very little upon *posterior-H* in Problem 1 in Experiment 2. It is legitimate to say that the decision makers in Problem 1 hardly made their decisions depending upon *posterior-H*. One implies that in choice tasks (in which the payoff distribution is known), risk attitude may be the most important factor for the decision makers rather than playing best reply to the past performances in making decisions. Finally, the decision makers in Problem 2 in Experiment 2 do not often tend to search L, the expected value of which is smaller than that of H. It implies that given binary SDM problems, the decision makers hold little appeal with the alternative that yields the best outcome more frequently but has lower expected value than the other alternative. For example, the best outcome (i.e., 3 points) should be theoretically realised 50 (=200*0.25) times after 200 selections of L in Problem 2; whereas the best outcome (i.e., 4 points) should be theoretically realised only 40 (=200*0.2) times after 200 selections of H in Problem 2.

The Payoff Variability Effect

We here will attempt a comparison between Problem 1 and 3 in which each alternative has the same expected value but has larger payoff variability in Problem 3 than in Problem 1. Note that we have observed that N_Hs throughout 400 rounds are 0.48 and 0.22 for Problem 1 and 3 in Experiment 1 respectively; whereas N_Hs are 0.63 and 0.40 for Problem 1 and 3 in Experiment 2 respectively. This observation follows by the assertion that the payoff variability effect impairs expected value maximisation.

On the other hand, the current calibration reveals that $TRCH_{3v}$ is higher than $TRCH_{1v}$ (v=1, 2). It will hold that in Problem 3, where the payoff variability is large, it is probable that the more the subjects chose H, the higher they could achieve *posterior-H*, *ex post*. It follows that the payoff variability effect enhances the decision makers' belief in playing best reply to the past performances.

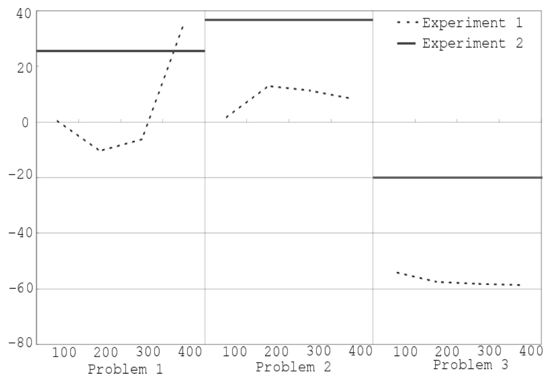

Figure 3 The difference between N_H and N_L

The Adjustment Process

Figure 3 shows that the difference between N_H and N_L in blocks of 100 rounds in Problem 1, 2 and 3 in each experiment. We note that the greater values on *y*-axis are, the more frequently H is chosen. For example, the difference is zero in case that the decision makers choose H and L 50 times each in 100 rounds. On the one hand, as we see from Figure 3, the more rounds the decision makers perform, the greater N_H is achieved in Problem 1 in Experiment 1. Among three problems, N_Hs in Experiment 2 are significantly greater than N_Hs in Experiment 1. The corresponding *p*-values are 0.000, 0.000 and 0.000 for Problem 1, 2 and 3 respectively. One implies that the decision makers would like to try out both alternatives frequently to update their judged subjective probability with a mental simulation process at the beginning of each problem in Experiment 1, where no prior information as to the payoff structure is available.

As for Problem 1 and 2, Figure 3 tells us that the decision makers in Experiment 1 searched the payoff structure of two alternatives by trying out both alternatives over and over at the first 100 rounds, then the decision makers often chose H in the last 100 rounds. The decision makers' mental simulation/adjustment process obtained at the first 100 rounds may lead them to judge that H had higher expected value than L. From what has been discussed above, it seems reasonable to conclude that the difference between N_H and N_L in each problem reflects the effect of the adjustment process in ambiguity model proposed by Einhorn and Hogarth [10]. This examination, however, remains as a matter to be investigated further.

Table 2 Correlations between N_Hs in the search treatment and in the choice treatment

	csear1	*csear2*	*csear3*	*cchoi1*	*cchoi2*	*cchoi3*
csear1	1.0000					
csear2	0.0212	1.0000				
csear3	-0.0165	0.0150	1.0000			
cchoi1	0.0063	0.0261	0.1095	1.0000		
cchoi2	-0.0122	0.0413	0.0604	0.0808	1.0000	
cchoi3	-0.0830	-0.0183	0.1384	0.1187	0.1430	1.0000

Exploration Tendency

Comparison of results between Experiment 1 (the search treatment for SFB problems) and Experiment 2 (the choice treatment for SEFB problems) reveals that the exploration tendency observed in the search treatment cannot be explained as rational exploration (i.e., expected value maximisation). Similar exploration is observed even in the choice treatment, that is, even when the payoff distribution is known. One considers Experiment 2 as a distinct treatment from Experiment 1 on more than one dimension (i.e., the information and experience). Hence, the comparison of results between Experiment 1 and 2 is not trivial.

A first assertion that exploration is a robust trait implies positive correlations between N_Hs in the search treatment and N_Hs in the choice treatment. Table 2 indicates correlations of N_H for each problem in which we denote *csear1* and *cchoi1* as N_H of Problem 1 in Experiment 1 and N_H of Problem 1 in Experiment 2, respectively. This transcription follows for the other problems. As we see in Table 2, correlations between N_Hs in Experiment 1 and N_Hs in Experiment 2 are 0.0063, 0.0413 and 0.1384 in Problem 2, 3 and 4 respectively. These positive correlations among three problems suggest that the additional information (i.e., making payoff distribution available to the decision makers) lead the decision makers toward expected value maximisation. This seems to conform with the assertion by Bikhchandani et al. [6] that if new information arrives, suggesting that a different course of action is optimal, the equilibrium may radically shift.

A second assertion is that the decision makers chose H more frequently among three problems in Experiment 2 than in Experiment 1. This seems to be explored within the framework of the ambiguity model. The decision makers often chose H in the latter part of Problem 1 since they judged that H had had higher expected value than L in their mental simulation/adjustment process obtained in the first part of the problem. It seems reasonable to conclude that the difference between *posterior-H* and N_H reflects the effect of the adjustment process in the ambiguity model.

5. CONCLUSION

This paper has addressed issues on SDM problems with a series of structured experiments. I implemented two binary choice experiments: Experiment 1 (the search treatment) and Experiment 2 (the choice treatment). Experiment 1 was conducted without providing the subjects with any prior information as to the payoff structure. Experiment 2 was conducted under the condition that the subjects were disclosed the exact payoff structure and number of rounds to be performed.

We have tested the hypothesis that there exists a remarkable tendency to play best reply to the past in the search treatment. It reveals that the more the subjects choose H, the higher they achieve *posterior-H* in Experiment 1 than in Experiment 2. This follows that N_H more highly depends upon *posterior-H* in Experiment 1 than in Experiment 2. On the other hand, it implies that N_H depends very little upon *posterior-H* in Problem 1 in Experiment 2. The implication is that the decision makers hardly made their decisions depending upon *posterior-H*. It is likely that in the choice treatment, risk attitude may be the most important factor for the decision makers rather than playing best reply to the past performances in making decisions.

The assertion has been tested that the decision makers are more likely to follow the belief in playing best reply to the past performances in the search treatment than in the choice treatment when the decision makers face two options: one option has high payoff variability and the other option has less payoff variability.

The exploration tendency has been investigated by comparison of the search treatment and the choice treatment. We observed positive correlations between the N_Hs in the search treatment and N_Hs in the choice treatment. These positive correlations suggest that the additional information to the decision makers lead them toward expected value maximisation in the experiment. On the other hand, the exploration tendency can be explained by tenets of the adjustment process in the ambiguity model axiomatised by Einhorn and Hogarth [10].

This paper has experimentally analysed individual responses in one-person games in sequential SDM problems. My experiments were conducted with a repetition of many rounds (i.e., the subjects faced 2,400 rounds in two experiments). It is followed by a consensus among a great number of experimental economists that there is a strong and seemingly growing belief in the important repetition. (See Lowenstein [20] for a detailed discussion.) The results from my experiments have important implications on some individual tendencies, such as *posterior-H* and N_H in the context of SDM problems. It is hoped that future studies on SDM problems can open a door for applying principles or ideas of those problems to investigate behaviour in multi-person games, such as cheap-talk environments. (For a discussion on cheap-talk games, see Charness [7] and Charness and Grosskopf [8].)

Previous experimental studies of individual decision making have been proposed in the context of some traditional decision heuristics, such as Bayesian analysis [e.g., 5] and two-armed bandit problems [e.g., 3; 18]. However, I did not conduct an analysis with these traditional heuristics in this paper. A further direction of the current study is to provide evidence from the perspectives of previous studies above and to develop a quantitative model that accounts for much existing data as well as experimental findings proposed by the author.

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