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An Experimental Study of Behavior and Cognition

from the Perspective of Inductive Game Theory

by

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An Experimental Study of Behavior and Cognition from the Perspective of Inductive Game Theory[*]

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Abstract

We conduct an experimental study on behavior and cognition in prisoner's dilemmas with and without role-switching from the perspective of inductive game theory (IGT). It is basic for our study that subjects have no prior knowledge about any payoffs, even their own; they may learn them by repeated play. Without role-switching, many subjects learned relevant payoffs successfully and played a dominant strategy consistently with predictions of IGT. With role-switching, IGT makes two behavioral predictions: one is a Nash equilibrium, and the other is maximization of the sum of payoffs. These two alternatives were observed for many matched pairs of subjects. We study subjects' understandings of payoffs by analyzing their answers to a questionnaire given after the experiment, and look into the relations to behaviors; we find that behavior is often determined by the learned payoffs. We present a model of individual behavior based on the basic postulates of IGT, which allows us to conduct various statistical hypothesis tests for the behavior data. One test shows some statistical (history-) independence of subjects' behavior. Our study not only supports but also sharpens the basic postulates of IGT.

JEL Classification Numbers: C72, C79, C91

Key words: Inductive Game Theory, Knowledge of Payoffs, Hypothesis Test, History-Independence, Dominant Strategy, Intrapersonal Coordination Equilibrium

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1. Introduction

We present an experimental study on cognitive/behavioral issues in game theory from the perspective of inductive game theory (IGT), developed in Kaneko-Matsui [14], Kaneko-Kline [10]-[13]. Our study has three new features relative to the experimental economics tradition. The first is the introduction of the *no-knowledge assumption* from IGT that a subject has no prior knowledge on payoffs even for himself. This leads to a dynamics of interactions of cognition and behavior. The second is the introduction of *role-switching*, i.e., a subject plays the roles of row and column players alternately. In IGT, this has a possibility to lead to an emergence of cooperation as discussed in [13]. The third feature is a theoretical framework for our experiment, which sharpens IGT and is used to inform our statistical analysis. Here, focusing on these features, we explain the backgrounds of IGT and our results.

We choose Prisoner's dilemmas in order to provide some clear-cut contexts for our experimental study. For each behavioral prediction from IGT, we may find some standard theory making the same or similar predictions. We are not particularly interested in these behavioral comparisons. We study behavioral, cognitive and epistemic bases for IGT. Consequently, we will show a lot of different underlying structures for cognition/behavior, and will obtain also confirm some new predictions from IGT.

1.1. Theoretical Backgrounds and New Aspects of our Experiment

Since our study is based on the basic idea of IGT, we first explain it and its differences from the standard game theory. The basic idea is that experiences are the source for a player's knowledge on the structure of the game. In this paper, we restrict our attention to payoffs of a player.

In classical game theory since Nash [18], which we call also the *ex ante* game theory, each player is presumed to be fully cognizant of the game structure. Partial knowledge is typically expressed as uncertainty about some parameters, but this is under the presumption of full cognizance of the entire game structure for each player. Evolutionary game theory/learning theory avoids this presumption by assuming that each behaves mechanically without conscious decision making.

The standard experimental game theory has been, by and large, based on the *ex ante* game theory, though the literature covers a range of approaches (cf. Camerer [4]); some follow the *ex ante* approach and others are more critical of it. The no-knowledge assumption and cognitive limitations are not issues in the literature, except for a few studies to be mentioned below; if an experimental subject is given a well specified instruction of the game structure including payoffs, neither is an issue, though inferential/computational ability may still be a problem. The main focus has been on actual behavior versus theoretical prediction. The entanglement of behavior and

cognition has remained outside the scope of the experimental literature.

Due to the no-knowledge assumption, it is relevant to discuss a subject's learning of his payoffs in our approach. This "learning" has a different meaning from the learning literature where "learning" is typically meant to be behavioral adjustments and convergences to some equilibrium (cf. Camerer [4], Chap.6). In our approach, we use the same term "learning" to mean that a subject has acquired "subjective payoff values" from his experiences, i.e., he constructs his subjective payoff matrix.

Under the no-knowledge assumption, interactions between behavior and cognition (learning) are central. Also, role-switching is one source to learn the entire game. Thus, we focus on those interactions both in the cases with/without role-switching. Before going deeper to the scope of IGT, we should mention experimental studies related to ours, which will help us to see our study relative to the literature.

In our experimental design, we avoid the possibility of the subjects knowing which rounds they are playing and when the experiment actually stops (see Section 2.1). With this, our results are behaviorally very different from some known results on prisoner's dilemmas (cf., Selten-Stoecker [23], Andreoni-Miller [1]); in those, a strong tendency of cooperative behavior was supported by trigger-strategies. Under the no-knowledge assumption, we have quite opposite results: We observe dominant strategy behavior in the case without role-switching, and some cooperative behavior with role-switching, which is supported in a different way from trigger-strategies.

In the case without role-switching, some behavioral tendency similar to ours has been observed by several authors. For example, Shubik [24], McCabe-Rassenti-Smith [16], Oechssler-Schipper [19] reported some experimental studies dealing with the case where each subject knows only his own payoffs but not the other's payoffs. These correspond to the behavior of subjects in late periods of our experiment. Apesteguia [2] and Erev-Greiner [5] studied some experiment under the no-knowledge assumption for each player's payoffs and without role-switching, in which sense their study is closest to ours. They obtained experimental results, behaviorally quite consistent with ours in that noncooperative outcomes were observed.

Now, let us turn to the perspective of IGT[1]. First, two aspects of learning are: generation of experiences, and cognitive limitations. Two informal postulates on each aspect were given in Kaneko-Kline [10]. Since these are central in our study, we list them here:

Postulate BH1 (Regular behavior): Each subject typically behaves following his regular behavior pattern.

Postulate BH2 (Occasional deviations): Once in a while (more frequently in the

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[1]The terms, *exploration* and *exploitation*, in cognitive science help to understand the roles of the following six postulates. Postulates BH1, BH2 constitute exploration, and ID1, ID2 do exploitation. EP1 and EP2 form bases for both.

beginning), each person unilaterally and independently makes a trial deviation from his regular behavior and then returns to his regular behavior.

We will formulate a model of individual behavior representing these postulates in Section 3, based on which we will conduct statistical tests on our experimental results.

The other two postulates are about cognitive limitations: *Long-term memories* are the source for knowledge, and *short-term memories* are temporal and may disappear from the mind of a person:

Postulate EP1 (Forgetfulness): If experiences are not frequent enough, they would not be transformed into a long-term memory and disappear from a subject's mind.

Postulate EP2 (Habituation): A local (short-term) memory becomes lasting as a long-term memory in the mind of a subject by habituation, i.e., if he experiences something frequently enough, it remains in his memory as a long-term memory.

These postulates have an implication on a subject's learning: By BP1 and BP2, to have new experiences would take some time, but by EP1 and EP2, they may evaporate from his mind. Thus, it takes some or many repetitions of the game to revise his thinking as well as his behavior; cognitive/behavioral updating is not an immediate process after a subject's receipt of new information.

Under the above informal postulates, Kaneko-Kline [10]-[12] made their theoretical development of IGT. Since it is also relevant to our experimental study, we mention this part as postulates, too. The first one is the inductive derivation of a subject's view, and the second states occasional revisions of his view and behavior.

Postulate ID1 (Inductive Derivation): After a subject accumulates enough long-term experiences, he constructs his view on the game; in our experiment, he constructs his subjective payoff matrix (matrices).

Postulate ID2 (Revising Behavior): As a subject accumulates new experiences, he may revise his view and behavior only occasionally.

These postulates together with BH1 and BH2 imply that each subject behaves following the same behavior pattern (including some trials/errors) for some successive rounds, and then he may revise it as well as his view. We will introduce a concept of temporal phase consisting of several successive rounds for which a subject keeps the same behavior, and between two phases, he may revise his view and behavior. The revision may not be statistically visible between close phases, but we may detect differences if we take two remote phases.

In order to study the appropriateness of the above postulates, we adopt a specific behavioral model and apply various statistical methods. We can use the experimental observations to study behavioral issues. To study cognitive issues, we will focus on the subjects' recollections about payoffs solicited by a questionnaire given after the experiment. We find good supports for the above postulates by studying the behavioral

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and cognitive data in various manners. Thus, with our statistical analyses, we are able to discuss the experiential foundations of IGT.

1.2. Experimental Design and Data

We use the three variants of the Prisoner's Dilemma (PD): quasi-symmetric QS1, QS2, and twisted T, which are described in Table 1.1. Games QS1 and QS2 become symmetric by adding 1 to each payoff for the column player. Game T is obtained from QS1 by adding 5 to the column player's payoff from (c, d). Each of QS1, QS2 and T has the same dominant strategies (ds) as the standard PD's, and is equivalent up to individual payoff orderings. Asymmetry and twist are introduced to avoid the possibility of subjects to infer payoffs from symmetry.

The experimental design starts with the following specifications, which will be described in a more precise manner in Section 2:

(1^*): Two matched subjects play one of QS1, QS2, and T for 50 rounds; and each subject knows he plays a 2×2 game but is given no information about the payoffs. He receives a payoff value after each round.

(2^*): A role-switching mechanism is specified before each experiment, and in each round, it assigns each subject to the role of *blue* (row) player or that of *green* (column) player. A subject knows this fact but has no more specification about it before each round. We consider two types of mechanisms: No role-switching (NRS); each has a fixed role, and Alternating role-switching (ARS); the two subjects alternate roles each round[2].

Table 1.1: Quasi-Symmetric and Twisted PD's

	c	d
c	$(5,4)^{ICE}$	$(2,5)$
d	$(6,1)$	$(3,2)^{ds}$

Game QS1

	c	d
c	$(8,7)^{ICE}$	$(2,8)$
d	$(9,1)$	$(3,2)^{ds}$

Game QS2

	c	d
c	$(5,4)$	$(2,10)^{ICE}$
d	$(6,1)$	$(3,2)^{ds}$

Game T

In the end of each round, a subject receives the feedback information consisting of his role, actions taken by the subjects, and his own payoff value, summarized as a quadruple such as:

$$[g, (c, d), 10] \text{ in game T.} \tag{1.1}$$

That is, he was assigned to role "green", actions (c, d) were chosen, and his payoff is 10.

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[2]We find some literature dealing with role-switching (cf., Weg-Smith [25], Burks-Carpenter-Verhoogen [3], and also see Camerer [4]). In this literature, role-switching was introduced in the ultimatum game, trust games and other variants. Role-switching is introduced to study its effects on equity/reciprocity in the one-shot situation with the assumption that the payoff structures are given to the subjects. Our aim is to give an opportunity for a subject to understand the both payoffs by playing both roles (player positions) repeatedly.
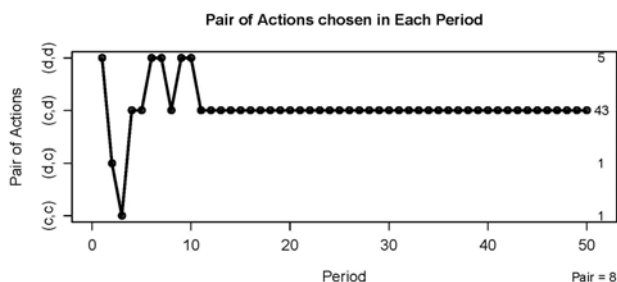
Figure 1.1: Game T with Role-Switching

Here, we give brief explanations of behavioral and cognitive data to show some characteristics of our experimental study.

Behavioral Data: The behavioral data consist of trajectories of action pairs with length 50 for matched subject pairs. We have the $6 = 3$(games) $\times$ 2(patterns of role-switching) treatments, and 14 subject pairs for each treatment.

Fig.1.1 describes the trajectory of action pairs for 50 rounds taken by subject pair #8 of the treatment of game T with ARS. The action pair converges to (c, d) after round 10, which is an *intrapersonal coordination equilibrium* (ICE) given in Kaneko-Kline [13] and will be explained in Section 3. This kind of clear-cut convergence is found only for a few pairs in our data.

Cognitive Data: After 50 rounds, each subject is given a questionnaire soliciting answers about his understanding of payoffs. For a NRS-treatment, each subject answers 4 payoff values, and for ARS, each gives 8 values. The payoff answers of pair #8 for game T with ARS are given as Table 1.2, where $[\cdot]$ indicates "incorrectness". Subject 1 gave all correct payoffs except for two unexperienced ones, but subject 2 gave quite simplified but incorrect payoffs. In fact, we will find in Section 5.3 that subject 2's incorrectness may be interpreted as forgetting unnecessary details and their simplified payoffs may still capture some behavioral criteria.

Table 1.2: Examples of Payoff Answers: $[\cdot]$ incorrect payoffs

b\g	c	d
c	5, [5]	2, 10 ^{ICE}
d	[3] , 1	3, 2

1's answers

b\g	c	d
c	[1] , [1]	2, 10 ^{ICE}
d	[1] , [1]	[1] , [1]

2's answers

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1.3. Salient Points

A small summary of salient points of our study may help the reader understand the paper. The first is based on the introduction of role-switching. The second is the study of interactions between cognition and behavior. The last one is ambitious in that we facilitate foundations for statistical analyses of our experimental data by providing a model of individual behavior.

ICE in the ARS Cases: ARS has a significant difference from NRS. By role-switching, we anticipate some subjects could play the ICE, predicted in [13]. It suggests equilibrium behavior maximizing the joint-payoff sum of the two subjects, which is explained in Section 3. The ICE is (c, c) in QS1, QS2, and it is (c, d) in T, indicated in Tables 1.1. Indeed, some subjects pairs showed this ICE-behavior in the experimental data of ARS. In [13], the authors allow other possibilities of having the Nash equilibrium (d, d). If these possibilities are allowed, then almost all data are in the scope of the theory (a few outliers remain).

Interactions between Behavior and Cognition: We anticipate cognitive and behavioral differences between NRS and ARS. Our results show that the subjects in NRS had a very high accuracy of recollection of the 4 payoffs. On the other hand, subjects in ARS showed much worse numerical recollection results on the entire 8 payoffs, as indicated in Section 1.2. We will go much further than this simple analysis, and can discuss postulates EP1, EP2 in a meaningful manner.

Behavioral Model and Various Hypothesis Tests: We provide a model of individual behavior based on postulates BH1, BH2, which is formulated as a stochastic process, describing a subject's (deterministic) behavior with stochastic disturbances (trials/errors). Accumulations of experiences are depending upon the cognitive ability of a subject by EP1, EP2. By postulates ID1, ID2, a subject revises (constructs) his subjective understanding of payoffs only from time to time, and then revises his behavior pattern. This part can be regarded as a development of IGT itself as well as its application.

This model enables us to conduct various hypothesis tests over a subject's behavior. Although we assume all the postulates for each agent, there is still a room for differences of subjects in their degrees of doing trials/errors, recalling experiences, and revising a view and behavior. Hence, it would be natural to focus on individual behavior of each subject rather than the aggregated one, which will be tested. We emphasize the result of an independence test that a subject's behavior is typically *statistically independent* (in the Markov scope) of his and the other subject's past behavior, which has the implication that subjects' behaviors are history-independent, unlike trigger strategies considered in Selten-Stoecker [23] and Andreoni-Miller [1].

These three salient points indicate that our study is not only a support for IGT but

also an advancement of it.

The paper is organized as follows: Section 2 summarizes the experimental design, and gives rough evaluations of experimental data. Section 3 gives a probabilistic model of individual behavior based on IGT, and a brief summary of behavioral criteria. Sections 4 and 5 analyze the experimental and cognitive data for NRS and ARS, respectively. In Section 6, we present hypothesis tests of stochastic independence in subjects' behaviors. Section 7 gives a summary, future problems, and concluding remarks.

2. Experimental Design and the Resulting Data

Our experiment, conducted in 2009, is designed to fit the no-knowledge assumption. We describe the experimental design in Section 2.1, and provide glimpses of the data[3] in Section 2.2.

2.1. Experimental Design

Treatments: As stated in Section 1.2, we use three variants, QS1, QS2 and T, of the PD game, and two types of role-switching, NRS and ARS. A treatment τ is expressed by a vector in the set $\{QS1,QS2,T\} \times \{NRS,ARS\}$. The experiment was conducted in the "between-subject design", i.e., any experimental subject participated only in one experimental run. Each treatment was divided into two sessions.

Subjects: Each treatment has 14 pairs of subjects; the total number of subjects is 6 (treatments) $\times 14$ (pairs) $\times 2$ (subjects) $= 168$. We chose 168 subjects from the undergraduate students of Waseda University, a comprehensive private university having $44,212$ undergraduates ($01/05/'08$). They were chosen from all majors, except economics to avoid subjects familiar with economics and game theory.

Laboratory Setting: The laboratory was set to prohibit direct interactions between the subjects: The two subjects of a pair had interactions only through the computer system to keep anonymity.

Experimental Procedure: The subjects were assembled and given a computer based instructional tutorial. The tutorial took 30 minutes, including an understanding test and a small rehearsal[4], where all payoffs were specified to be 1.

The instructions included a statement that the experiment would stop at some round between 40 to 60. Actually, we stopped all experimental runs at the end of round 50. This method was chosen to avoid the end-game effect. After the experiment, each subject was given a questionnaire, which took about 10 minutes to complete, and the
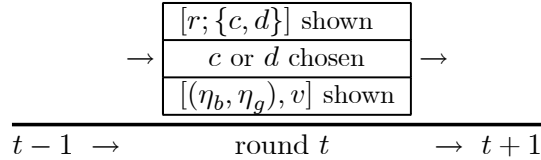
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[3]Experimental materials and analyzed data are available at:
http://aitakeuchi.web.fc2.com/materials/igt_experiment.html
[4]We use the Z-tree program by Fischbacher [7] for our experiment.

rewards to the subjects were paid at completion. The duration of each session was about 70 minutes.

Basic Information: In the tutorial, each subject was told that he would play a 2-person game with a fixed opponent and had 2 available actions for his choice in each round. Also, he was told that role-switching might happen and his role would be specified in the beginning of each round. He would notice the pattern of role-switching only during the experimental run. His own payoff values, but not those for the other subject, were experienced in the experimental run, and they could be memorized only in his mind (no devices for taking notes are allowed). Subjects were informed that the payoff structure would be constant over all rounds.

The information flow to each subject in each round is as follows:

$$
\begin{array}{c}
\rightarrow \boxed{\begin{array}{c} \boxed{[r; \{c, d\}] \text{ shown}} \\ \boxed{c \text{ or } d \text{ chosen}} \\ \boxed{[(\eta_b, \eta_g), v] \text{ shown}} \end{array}} \rightarrow \\
\hline
t - 1 \;\rightarrow \qquad \text{round } t \qquad \rightarrow \; t + 1
\end{array}
$$

In the beginning of round t, two pieces of information $[r; \{c, d\}]$ appear on the monitor screen: role r (row or column player) and available actions c, d. Then, a subject chooses c or d within 10 seconds[5]. After their choices, his screen shows the feedback information, $[r; (\eta_b, \eta_g), v]$, including his role r, b's and g's choices, η_b, η_g, and his own payoff value v. This screen lasts for 10 seconds, and the experiment goes to the next round.

For the NRS treatments, a subject is identified with the assigned role, but, for the ARS treatments, a subject differs from a role, and the one having role b at round 1 is called subject 1.

During the experimental run, subjects were not told which round they were in.

Payoffs (Rewards) to Subjects: It is also stated before the experiment that the total reward to each subject will be paid in cash. It is calculated as: (the sum of payoffs from the 50 rounds) $\times$ 5yen $+$ 500yen (participation fee). Hence, in QS1, if (c, c) is played for 50 rounds, the total payment for subject 1 becomes 1,750yen. (The average payment over all the subjects was 1,484yen.)

Questionnaire: Three types questions were given to each subject: (1) payoff structure; (2) behavioral criteria (in ordinary language); and (3) free writing comments about his and the opponent' behavior. For (1), we asked each subject about the 8 payoffs. Each answer should be given as a nonnegative integer, or a "?" in the case he cannot recall. Before the experiment, those questions were not explained to the subjects; simply each

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[5]In the instruction, each subject was informed that if he fails to make a choice in a round, his payoff for that round would be 0. In this case, the payoff to the other player is 5, but the subjects were not informed of this fact. The number of failues to make choices was 23 out of $8,400 = 50 \times 28 \times 6$ moves.
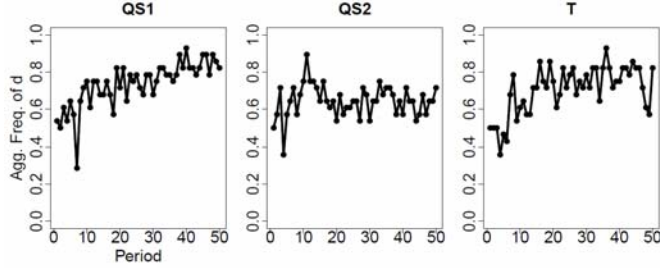
Figure 2.1: Aggregated Frequencies of Action d for NRS

subject was asked to answer the questionnaire after the experiment.[6].

Language Neutrality: We use the roles as the row and column players, and available actions c and d in writing up the experimental results. In the actual laboratory setting, we used "blue" and "green" for the two roles, and "E" and "W" ("N" and "S") for c and d. Also, the 14 pairs of subjects for each treatment τ were divided into two sessions where the labels "E" and "W" are switched. These methods were adopted to avoid framing effects and to keep neutrality. Our experimental results do not indicate much difference in the behaviors of subjects between those two different sessions.

2.2. Observed Behavioral and Cognitive Data

Behavioral Data: The behavioral data for treatment $\tau \in \{\text{QS1,QS2,T}\} \times \{\text{NRS,ARS}\}$ are:

$$\langle (\widehat{\eta}_{1,1}^{\tau,\pi}, \widehat{\eta}_{1,2}^{\tau,\pi}), \cdots, (\widehat{\eta}_{50,1}^{\tau,\pi}, \widehat{\eta}_{50,2}^{\tau,\pi}) \rangle, \text{ pairs } \pi = 1, ..., 14. \tag{2.1}$$

That is, $(\widehat{\eta}_{t,1}^{\tau,\pi}, \widehat{\eta}_{t,2}^{\tau,\pi})$ means the action pair taken by subjects 1 and 2 of pair π in round t in treatment τ. We stipulate that the subjects taking roles b and g at the first round are called, respectively, 1 and 2. So, $\langle \widehat{\eta}_{1,i}^{\tau,\pi}, \cdots, \widehat{\eta}_{50,i}^{\tau,\pi} \rangle$ means the sequence of actions taken by subject i. In NRS, each takes the same role for the 50 rounds, but in ARS, subject i takes alternating roles in $\langle \widehat{\eta}_{1,i}^{\tau,\pi}, \cdots, \widehat{\eta}_{50,i}^{\tau,\pi} \rangle$.

In Fig.2.1, the average frequencies of choices d over the 28 subjects for each round are depicted for each of the three NRS treatments. Looking at the trajectory of QS1, we find that actions d and c were chosen almost equally in the early rounds, and in later

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[6]If we give some monetary incentives to answer payoffs correctly after the experiment, a subject may not state his subjective view, including make-up payoffs based on his partial memory and some other sources such as an arbitrary guess. To avoid such a bias, we did not include monetary rewards for answers. A possible drawback of this design is that the stated beliefs without monetary incentives have higher error than ones with monetary incentives (cf. Rustrom-Wilcox [21]).

rounds, the frequency of playing d is getting higher to around 0.8. The other figures show some differences, but their frequencies of d are getting larger in later rounds.

At the level of an individual pair, however, we will find considerable difference in behaviors even in later rounds: We will show in Section 4.2 that the above aggregation over subjects is not statistically legitimate based on our model of individual behavior.

Cognitive (Payoff) Data: The payoff question itself is the same for all the treatments, but, in NRS and ARS, a subject received different information. Recall that a subject experienced (at most) 4 payoffs in NRS, but 8 in ARS. Table 2.1 shows the average individual score, stating that in NRS, about 91% of subjects' answers are correct, while Table 2.2 shows that the corresponding number becomes about 45% in ARS.

Table 2.1; NRS: Range from 0 to 4

	QS1	QS2	T
avg	3.69	3.36	3.86

Table 2.2; ARS: Range from 0 to 8

	QS1	QS2	T
avg	4.19	2.89	3.64

It is difficult for a subject to memorize and recall 8 payoffs, but much easier to memorize only 4. This is reminiscent of Miller's [17] "the magic number 7", which is the observation that 7 digits are a typical limit for short-term memorization. This will be discussed more in Section 5.

Table 2.1 states that each subject in NRS is practically aware of his payoff structure in later rounds. Thus, in NRS, we focus our attention on behavioral results. On the other hand, Table 2.2 shows the statistical richness of the cognitive data in ARS and the fact that the memory limitations are having impacts in this setting. In ARS, the focus is concentrated on the analysis of interactions between behavior and cognitive learning.

3. An IGT-Model of Individual Behavior, and Behavioral Criteria

We develop an IGT-model of individual behavior to study the experimental data both statistically and game theoretically. It consists of a deterministic part, expressed as a behavioral criterion, and a stochastic disturbance representing trials/errors. Section 3.1 describes this model, and Section 3.2 describes behavioral criteria.

3.1. Trials/Errors to Deterministic Behavior

A subject may revise his thought and behavior from time to time, though the timing does not follow a clear-cut rule. In Section 2.2, we already mentioned that behavior differs between early and later rounds. To study this difference, we introduce the concept of a *temporal phase,* an example of which is depicted in Fig.3.1: During each phase, a subject is assumed to keep the behavior constant as well as his view while making occasional trials/errors. This "temporal phase" is for an analytic purpose to compare behavioral changes over the course of play. For example, we compare the first and last
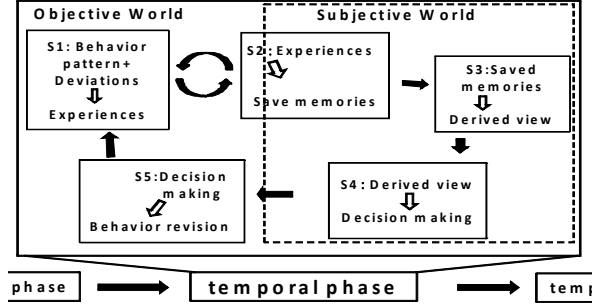
Figure 3.1: Temporal Phases

10 rounds by regarding them as temporal phases. We will show statistically that trials/errors are dominant in the first phase, while deterministic behavior emerges with the temporal phases. The arbitrariness of the choice of 10 rounds will be discussed later.

Stochastic Process for each (τ, π): We regard each trajectory $\langle (\widehat{\eta}_{1,1}^{\tau,\pi}, \widehat{\eta}_{1,2}^{\tau,\pi}), ..., (\widehat{\eta}_{50,1}^{\tau,\pi}, \widehat{\eta}_{50,2}^{\tau,\pi}) \rangle$ in (2.1) as the realization of some stochastic process:

$$\langle (X_{1,1}^{\tau,\pi}, X_{1,2}^{\tau,\pi}), ..., (X_{50,1}^{\tau,\pi}, X_{50,2}^{\tau,\pi}) \rangle. \tag{3.1}$$

Recall that τ is a treatment and π is a pair of subjects. We assume that all stochastic moves are based on the probability space $(\Omega, \mathcal{B}, \mathrm{Pr}^{\tau,\pi})$ for (τ, π). Each $X_{t,i}^{\tau,\pi}$ is a random variable defined over Ω taking value c or d, i.e., $X_{t,i}^{\tau,\pi} : \Omega \to \{c, d\}$, and its realization in the experiment is $\widehat{\eta}_{t,i}^{\tau,\pi}$.

For each (τ, π), we let the sets Ω and $\mathcal{B}$ be given as: $\Omega = ([0,1]^2)^{50}$, and $\mathcal{B}$ is the σ-algebra of Borel subsets of Ω^7. The last component, $\mathrm{Pr}^{\tau,\pi}$, is a probability measure defined over $\mathcal{B}$. Now, our task is to study $\mathrm{Pr}^{\tau,\pi}$ based on our experimental data and IGT. We sometimes abbreviate the superscript of $\mathrm{Pr}^{\tau,\pi}$ by just Pr when we focus on a particular (τ, π).

Objective Representation of Individual Behavior by $X_{t,i}^{\tau,\pi}$: We restrict $X_{t,i}^{\tau,\pi}$ to be a function from $([0,1]^2)^{t-1} \times [0,1]^2 \to \{c, d\}$. For example, when $t = 1$, the probabilistic behavior for period 1 is casued by stochastic elements in the present $[0,1]^2$, and when $t = 2$, it may depend upon both the previous $[0,1]^2$ and present $[0,1]^2$.

This formulation is rich enough to capture stochastic disturbances and players' feedback information. Let us see the latter. Since the feedback information comes as $[r, (\eta_b, \eta_g), v]$, the dependence of variable $X_{t,i}^{\tau,\pi}$ on r and ν requires some explanation.

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[7]We can adopt a finite set for Ω, but it should be large enough to capture our random variables. We thank S. Turnbull for pointing this fact out.

┌───┐
│ **1: <u>Indirect route:</u>** Between temporal phases, │
│   revising subjective payoffs/behavior │
└───┘

                    VS

┌───┐
│ **2: <u>Direct route:</u>** Within a temporal phase: │
│ 2a: Dependence upon previous choices, │
│ 2b: Independence from previous choice │
│   │
│ i.e., whether or not $\sigma_{t,i}^{\tau;\pi}$ is dependent │
│   of feedback information? │
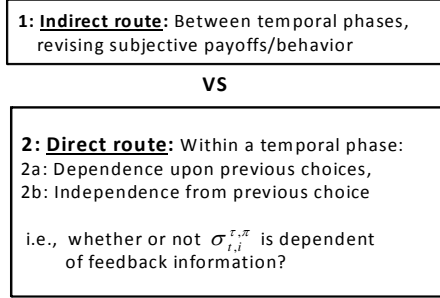└───┘

Figure 3.2: Two Types of History-Dependence

Since we use only deterministic role-switching mechanisms, this dependence on the past r is taken care of by the subscript t of variable $X_{t,i}^{\tau;\pi}$. Since payoff v is determined by (η_b, η_g), the dependence upon v can be regarded as dependence upon the previous actions (η_b, η_g). Hence, it is enough to consider the dependence upon the histories in $(\{c,d\}^2)^{t-1}$.

This direct dependence of $X_{t,i}^{\tau;\pi}$ upon the feedback information is regarded as a *direct route* from the past to the present choice, which is emphasized by the repeated games literature.

There is another route affecting subjects' behavior. As a temporal phase proceeds, a subject may revise his subjective payoff function and change his behavior accordingly. This is the *indirect route* from the accumulated experiences on payoffs to his action choice which is emphasized by IGT in postulates ID1 and ID2.

Decomposition of the Individual Behavior: We work directly on the random variables in (3.1), but the IGT background is needed to interpret our statistical tests. Based on postulates BH1 and BH2, we decompose each random variable $X_{t,i}^{\tau;\pi}$ into a deterministic part and a stochastic (trials/errors) part:

(a): *intentional behavior or trials/errors* $Y_{t,i}^{\tau;\pi} : \Omega \to \{0,1\}$;

(b): *deterministic behavior pattern* $\sigma_{t,i}^{\tau;\pi} : \Omega \to \{c,d\}$;

(c): *stochastic disturbance* $Z_{t,i}^{\tau;\pi} : \Omega \to \{c,d\}$.

The variable $Y_{t,i}^{\tau;\pi}$ dictates whether he follows deterministic $\sigma_{t,i}^{\tau;\pi}$ or trials/errors $Z_{t,i}^{\tau;\pi}$. The behavior pattern $\sigma_{t,i}^{\tau;\pi}$ prescribes an action, c or d, depending only upon his previous information; thus it is effectively written as $\sigma_{t,i}^{\tau;\pi} : (\{c,d\}^2)^{t-1} \to \{c,d\}$. The decomposition of behavior $X_{t,i}^{\tau;\pi}$ is formulated as follows:

$$X_{t,i}^{\tau,\pi}(\omega) = \begin{cases} \sigma_{t,i}^{\tau,\pi}(\omega) & \text{if } Y_{t,i}^{\tau,\pi}(\omega) = 1 \\ \\ Z_{t,i}^{\tau,\pi}(\omega) & \text{if } Y_{t,i}^{\tau,\pi}(\omega) = 0. \end{cases} \tag{3.2}$$

If $Y_{t,i}^{\tau,\pi}(\omega) = 1$, then subject i follows $\sigma_{t,i}^{\tau,\pi}$ and if $Y_{t,i}^{\tau,\pi}(\omega) = 0$, then he follows $Z_{t,i}^{\tau,\pi}$. An example of $Z_{t,i}^{\tau,\pi}$ is the independent variable taking c or d with probability $\frac{1}{2}$.

A possible scenario is as follows: In early phases, $Y_{t,i}(\omega)$ takes value 0 more often than 1. This is justified by the no-knowledge assumption about payoffs. Later, as he learns payoffs, he follows the deterministic part $\sigma_{t,i}^{\tau,\pi}$ more often.

The above model is similar to Selten's [22] "trembling hand" model. One difference is that Selten allows mixed (behavioral) strategy as $\sigma_{t,i}^{\tau,\pi}$, but we do not. Selten's purpose was to describe rationalistic decision making when trials/errors vanish, while we aim to describe a boundedly rational subject who learns his and others' payoffs by trials/errors, and revises his behavior accordingly. We do not consider a limit of this process, but investigate the process itself with experimental data. Even though $X_{t,i}^{\tau,\pi}$'s are random variables, we do not regard them as mixed strategies in the intentional sense[8].

Choices of Temporal Phases: For our statistical study, we divide the entire 50 rounds into 5 temporal phases consisting of 10 rounds each. We will look at the suitability of this division later. For some statistical tests, we will take a longer phase consisting of 20 rounds, because of the data size, but other tests justify this. As mentioned, each subject's behavior is assumed to be constant over a temporal phase. We will return to this issue in Section 4.3.

Stochastic Independence: We refer to stochastic independence quite often: The general form is as follows: $X_{1,i}^{\tau,\pi}, ..., X_{50,i}^{\tau,\pi}$ are *independent* iff for $t = 1, ..., 50$ and $\eta_1, .., \eta_{50} \in \{c,d\}^2$,

$$\begin{aligned} \Pr((X_{1,1}^{\tau,\pi}, X_{1,2}^{\tau,\pi}) &= (\eta_{11}, \eta_{12}), ..., (X_{50,1}^{\tau,\pi}, , X_{50,2}^{\tau,\pi}) = (\eta_{50,1}, \eta_{50,2})) \\ &= \left[\prod_{t=1}^{50} \Pr(X_{t,i}^{\tau,\pi} = \eta_{t,i}) \right] \times \Pr(X_{1,j}^{\tau,\pi} = \eta_{1,j}, ..., X_{50,j}^{\tau,\pi} = \eta_{50,j}). \end{aligned} \tag{3.3}$$

If $X_1^{\tau,\pi}, ..., X_{50}^{\tau,\pi}$ are all independent, the right-hand side of (3.3) is decomposed into $\prod_{i=1}^{2} \prod_{t=1}^{50} \Pr(X_{t,i}^{\tau,\pi} = \eta_{t,i})$. In Section 6, we will conduct some independence tests with our experimental data.

As already stated, there are two possible routes of effects from previous choices to the present one, described in Fig.3.2: The direct route is described by $\sigma_{t,i}^{\tau,\pi}$. The indirect route is through a constructed view and the revision of $\sigma_{t,i}^{\tau,\pi}$, and is truly a focus of IGT. It is an important benchmark to check whether $\sigma_{t,i}^{\tau,\pi}$ is history-independent, except for

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[8]We regard the intentional use of a mixed strategy as incompatible with the basic postulates for IGT, since it requires a player to be very intelligent in that he is consciously capable of choosing and generating a probability.

role-dependence. We will show, using independence tests in Section 6, that the direct route is observed only in a small degree.

3.2. Behavioral Criteria

Another issue is which behavioral criteria are observed or are at least consistent with the data. Here, we provide several criteria for NRS and ARS. We use the cognitive data on answered payoffs to check these criteria in Sections 4.2 and 5.3 respectively.

(1): NRS-Treatments: We consider two history-dependent criteria and two independent criteria.

History-Dependent Criteria: Two typical examples from the folk-theorem literature are the *Tit-for-Tat Strategy* Criterion and the *Trigger-Strategy* Criterion. In the former, a player mimics his opponent's previous choice. In the latter, each sticks to some specified action, provided that the other does too, and any deviation triggers a switch to the other action. As mentioned in Section 1.1, Selten-Stoecker [23] and Andreoni-Miller [1] found a strong tendency of the trigger-strategy in their experiment. Our independence tests in Section 6 deny such history-dependent behavior in our experimental design.

History-Independent Criteria: One candidate for NRS is the *Dominant-Strategy* criterion (Dom), which recommends a subject to choose a dominant strategy. This is applied to a subjective view: No subject can use this criterion in the beginning of the experiment because of the no-knowledge assumption. According to Table 2.1, many subjects constructed the correct payoff matrix in NRS by the end of the experiment. So Dom could recommend each to choose d in later rounds. As far as utility maximization is required and the subjective view has a dominant strategy, Dom is, effectively, the unique history-independent criterion.

The answered payoff matrices by subjects may not allow dominant strategies. Hence, the best response (Br) to the other's choice may be also a relevant criterion. We remark that Br may look to be history dependent if we regard it as the best response to the previous period choice. However, our results of Section 6 suggest that this type of lagged best response is not being used by our subjects, so we can concentrate on the history-independent version.

(2): ARS-Treatments: For these, we have also history-dependent and history-independent behavioral criteria. We will consider the same history-dependent criteria as in NRS, but for these treatments, we have the possibility of role-dependent behavior.

According to the low rates of correct answers in Table 2.2, a subject's understanding of payoffs may differ from the objective ones. Now, let subject i's subjective view be denoted by $G^i = (b, g, S_b, S_g, \widehat{h}_b^i, \widehat{h}_g^i)$. In our experimental context, $\widehat{h}_b^i$ and $\widehat{h}_g^i$ are given as the answered payoff matrices. History-dependent criteria will be considered relative to this subjective game. Here, we consider three history-independent criteria.

The first two are Dom and the *Nash Equilibrium Criterion* (NE). Since we have role-switching, Dom should be considered from each role. NE is regarded as a pair of his decision and his prediction about the other subject's decision, assuming that when the roles are switched, the same decision/prediction pair is made. These criteria are not distinguished at the behavioral level, but may be separated with respect to the subjective payoffs. We study these in Section 5.3.

When criterion Br holds for both answered payoff matrices for the two roles, NE holds, too. In Section 5.3, we refer to the NE criterion as well as Br.

We now give the decision criterion for ARS proposed by Kaneko-Kline [13]. The following was more generally defined in [13], but here, we give a form restricted to the present context.

ICE: A pair (s_b^*, s_g^*) is an *intrapersonal coordination equilibrium* (*ICE*) iff we have the following two inequalities in G^i:

$$\frac{1}{2}\widehat{h}_b^i(s_b^*, s_g^*) + \frac{1}{2}\widehat{h}_g^i(s_b^*, s_g^*) > \frac{1}{2}\widehat{h}_b^i(s_b, s_g^*) + \frac{1}{2}\widehat{h}_g^i(s_b, s_g^*) \qquad (3.4)$$

$$\frac{1}{2}\widehat{h}_b^i(s_b^*, s_g^*) + \frac{1}{2}\widehat{h}_g^i(s_b^*, s_g^*) > \frac{1}{2}\widehat{h}_b^i(s_b^*, s_g) + \frac{1}{2}\widehat{h}_g^i(s_b^*, s_g),$$

where $s_b \neq s_b^*$ and $s_g \neq s_g^*$. Weaker inequalities are adopted in [13], but here we adopt strict inequalities for simplicity. The same action, e.g., s_b, appears twice in the right-hand side of the first formula. The first s_b is under i's own control, but the second is under j's. For QS1,QS2, (c, c) is an ICE, and (c, d) is for T.

The rationale for ICE is as follows: When each subject has had enough experiences of each role from role-switching, subject i projects his view G^i onto the other subject j, and so i's thought about j's understanding of the game is the same as his own. The next step is for a subject to count his payoff stream, which is the average of the payoffs for two roles, $\frac{1}{2}\widehat{h}_b^i(s_b, s_g) + \frac{1}{2}\widehat{h}_g^i(s_b, s_g)$[9]. Then, subject i thinks that if subject j takes the same role as i, he would behave in the same manner as subject i. This may be regarded as the *shoe-switching metaphor*: When he puts his feet into the other's shoes, he behaves as the other, and correspondingly, when he puts the other's feet into his shoes, he expects the other to behave as he does. See [13] for more considerations such as the generality of the above argument.

The ICE can be regarded also as a behavioral criterion. When we consider this in Section 5.3, we denote it as *Utility-sum* (Ut-s).

If each subject i tries to optimize his behavior in both roles b and g without shoe-switching, we may return to Nash equilibrium. For this, shoe-switching is replaced by

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[9]This criterion is based on the emprical frequency (see Hu [9]).

i's prediction of j's choice as fixed leading to:

$$\frac{1}{2}\widehat{h}_b^i(s_b^*, s_g^*) + \frac{1}{2}\widehat{h}_g^i(s_b^*, s_g^*) \;>\; \frac{1}{2}\widehat{h}_b^i(s_b, s_g^*) + \frac{1}{2}\widehat{h}_g^i(s_b^*, s_g^*) \qquad (3.5)$$

$$\frac{1}{2}\widehat{h}_b^i(s_b^*, s_g^*) + \frac{1}{2}\widehat{h}_g^i(s_b^*, s_g^*) \;>\; \frac{1}{2}\widehat{h}_b^i(s_b^*, s_g^*) + \frac{1}{2}\widehat{h}_g^i(s_b^*, s_g).$$

Since (s_b^*, s_g^*) in 3.5 is a Nash equilibrium, we have an alternative rationale for NE.

Remark: An Individual Behavior vs. the Aggregated Behavior: The above description of the model of individual behavior has an implication for the consideration of the behavioral data. For NRS, although we have, more or less, a unique behavioral criterion, the process leading to the criterion may vary with an individual subject with the degrees of trials/errors, abilities of memorization, etc. Hence, it would be natural to focus on individual data, rather than the aggregated behaviors such as Fig.2.1. This is more imperative for ARS, since in addition to those differences, the theory has multiple predictions. We will do some statistical tests for this issue in Sections 4.3 and 5.2.

4. An Analysis of the Experimental Data for NRS

We start our analysis of the behavioral and cognitive data for NRS with summary statistics in Section 4.1. Then, we check the history-independent behavioral criteria of Section 3.2 using the data for answered payoffs. As mentioned there, our results of Section 6 justify ignoring the history-dependent criteria. In Section 4.3 we construct various hypothesis tests to show that aggregation of the behavior across phases and individuals is inappropriate.

4.1. Preliminary Look at the Data

Let us look at the action trajectory $\langle (\widehat{\eta}_{1,1}^{\tau,\pi}, \widehat{\eta}_{1,2}^{\tau,\pi}), ..., (\widehat{\eta}_{50,1}^{\tau,\pi}, \widehat{\eta}_{50,2}^{\tau,\pi}) \rangle$ for subject pair (τ, π) in terms of some summary statistics. Consider the occurrences of d for the temporal phases from rounds 1 to 10 (1\10) and from rounds 41 to 50 (41\50) for each subject. Columns 1) and 3) of Table 4.1 show the numbers of occurrences of d in these phases for treatment (QS1,NRS). For example, $(4, 5)$ for $\pi = 1$ in Column 1) means that subjects 1 and 2 of pair 1 played d for 4 and 5 times, respectively. For 1\10, the number of occurrences of d (f_d^i) greater than or equal to 8 is observed only for 6 subjects out of 28; and this becomes 21 subjects for the latter phase 41\50.

Consider also the standard deviation for those phases. We stipulate that $\widehat{\eta}_{t,i}^{\tau,\pi} = 1$ if it is d, and $\widehat{\eta}_{t,i}^{\tau,\pi} = 0$ if it is c. The standard deviation for subject 1 of pair π for periods 1\10 is given as $s_{1\backslash10}^1 = \sqrt{\sum_{t=1}^{10}(\widehat{\eta}_{t,1}^{\tau,\pi} - \overline{p}_1^{\tau,\pi})^2/9}$ and $\overline{p}_1^{\tau,\pi} = \sum_{t=1}^{10}\widehat{\eta}_{t,1}^{\tau,\pi}/10$. The possible values for $s_{1\backslash10}^1$ are .53, .52, .48, .42, .32, and 0. In the last row, $\overline{\mathrm{sd}}_{1\backslash10}$ ($= \mathrm{avg}(\mathrm{sd}_{1\backslash10}^i)$) is

the average of $\mathrm{sd}^i_{1\backslash10}$ over the 28 subjects. For example, $(.52, .53)$ for $\pi = 1$ in Column 1) are the standard deviations for 1 and 2 of pair 1 for phase $1\backslash10$.

Columns 2) and 4) give the standard deviations for phases $1\backslash10$ and $41\backslash50$ for each subject. Column 5) shows that they decreased from $1\backslash10$ to $41\backslash50$ for 20 subjects and increased only for 3 subjects. We interpret this as meaning that in phase $1\backslash10$, the trial/error, $Z^{\tau,\pi}_{t,i}$, dominates the behavior of subjects, while in phase $41\backslash50$, the deterministic behavior, $\sigma^{\tau,\pi}_{t,i}$, is getting stronger. The last column is about the hypothesis testing of this observation, which will be discussed in Section 4.3.

Table 4.1: QS1 with NRS

	1) $1\backslash10$	2) sd's	3) $41\backslash50$	4) sd's	5) sign:	6) $1\backslash10{:}41\backslash50$
π	f^i_d	$\mathrm{s}^i_{1\backslash10}$	f^i_d	$\mathrm{s}^i_{41\backslash50}$	$\mathrm{s}^i_{41\backslash50} - \mathrm{s}^i_{1\backslash10}$	rej^i
1	(4, 5)	(.52, .53)	(6, 8)	(.52, .42)	(0, -)	[not, not]
2	(5, 5)	(.53, .53)	(9, 8)	(.32, .42)	(-, -)	[not, not]
3	(8, 5)	(.42, .53)	(10, 8)	(0, .42)	(-, -)	[not, not]
4	(7, 7)	(.48, .48)	(10, 9)	(0, .32)	(-, -)	[not, not]
5	(3, 8)	(.48, .42)	(10, 5)	(0, .53)	(-, +)	[rej, not]
6	(3, 4)	(.48, .52)	(7, 9)	(.48, 0)	(0, -)	[not, rej]
7	(9, 5)	(.32, .53)	(10, 8)	(0, .42)	(-, -)	[not, not]
8	(8, 7)	(.42, .48)	(5, 10)	(.53, 0)	(+, -)	[not, not]
9	(7, 8)	(.48, .42)	(10, 10)	(0, 0)	(-, -)	[not, not]
10	(7, 2)	(.48, .42)	(9, 8)	(.32, .42)	(-, 0)	[not, rej]
11	(6, 7)	(.52, .48)	(6, 7)	(.52, .48)	(0, 0)	[not, not]
12	(8, 4)	(.42, .52)	(5, 10)	(.53, 0)	(+, -)	[not, rej]
13	(6, 5)	(.52, .53)	(10, 10)	(0, 0)	(-, -)	[rej, rej]
14	(3, 6)	(.48, .52)	(9, 9)	(.32, .32)	(-, -)	[rej, not]
	$\mathrm{f}^i_d \geq 8$: 6	$\overline{\mathrm{sd}}_{1\backslash10} = .48$	$\mathrm{f}^i_d \geq 8$: 21	$\overline{\mathrm{sd}}_{41\backslash50} = .26$	$\#\{\text{sign -}\} = 20$	rej^i: 7

Table 4.2 gives a summary of those summary statistics for (QS1,NRS), (QS2,NRS), and (T,NRS). It shows a smaller tendency for the convergence to d for QS2 and T than for QS1. Row 1) shows the numbers of subjects with $\mathrm{f}^i_d \geq 8$, but if we take frequency $\mathrm{f}^i_d \geq 7$, they are 23, 16 and and 21 for QS1, QS2 and T; thus large tendencies to play action d in $41\backslash50$ are found for QS1 and T. Row 2) gives the number of pairs having $\mathrm{f}^i_d \geq 8$ for both subjects out of 14 pairs for each treatment. Row 6) shows that the standard deviations decreased from $1\backslash10$ to $41\backslash50$ for 20 and 18 subjects in QS2 and T, respectively. In sum, we find some tendencies of convergence to d as a temporal phase goes to the last, while trials/errors still remain.

Table 4.2; Summary for NRS

	QS1	QS2	T
1): $f_d \geq 8$ ($f_d \geq 7$) : $41\backslash50$	21 (23)	14 (16)	14 (21)
2): $f_d \geq 8$ pairwise: $41\backslash50$	8	7	6
3): $f_c \geq 8$ pairwise: $41\backslash50$	0	2	0
4): $\overline{sd}^i_{1\backslash10}$	.48	.49	.47
5): $\overline{sd}^i_{41\backslash50}$	.26	.26	.35
6): $\#\{sd^i_{41\backslash50}-sd^i_{1\backslash10} < 0\}$	20	20	18

Outliers: Row 3) of Table 4.2 shows convergences to (c,c) for two pairs in QS2. No other individual subjects played c at such a high frequency in any treatment with NRS. In Section 4.3, they cause quite different results in the statistical test between the individualistic vs. aggregated behaviors[10].

4.2. Cognitive Aspects

Now, let us look at the behavioral results discussed in Section 4.1 from the viewpoint of the cognitive data, i.e., *answered payoffs*. Row 1) of Table 4.3 shows the numbers of subjects, out of 28, whose subjective payoff answers had d as the dominant strategy (Dom). The number is high, since understandings of subjective payoffs are quite correct as shown in Table 2.1. Nevertheless, some did not play d; in QS1, 16 subjects played d with frequency $f^i_d \geq 8$, out of the 21 subjects with subjective payoffs having Dom. Table 4.1 shows that 21 subjects played d with $f^i_d \geq 8$ regardless of Dom. Thus, 5 subjects played d without having Dom.

Table 4.3; Cognitive and Behavioral Relations for NRS

	QS1	QS2	T
1): #Dom	21	23	25
1a): $f^i_d \geq 8$ (7) in 1	16 (16)	13 (15)	12 (19)
2): #Br	25	24	26
2a): $f^i_d \geq 8$ (7) in 2	19 (20)	13 (15)	14 (22)

Row 2) shows the number of the subjects whose subjective payoffs had d as the *best response* (Br) to the other's d. In QS1, 4 subjects in addition to 21 with Dom showed Br, but such a difference is observed only in QS1.

To see the difference between subjects with Dom and with Br, we look at pair 8 for QS1: They gave the payoff answers depicted in Table 4.4: They did not play (c,c) at all, and they answered "?" to the payoff to (c,c), so Dom cannot be checked, but their answers satisfy Br. In fact, many other subjects gave numerical answers rather than

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[10]We found some explanations in their answers to the questionnaire; one subject wrote that the game looks like a prisoner's dilemma, and the other subject wrote he followed subject 1's behavior.

"?" to the action pairs they did not experience often. Though they played (c, d) only twice, both answered correct payoffs to (c, d).

Table 4.4: Pair 8 in (QS1,NRS)

1's answers				2's answers				#occurrences		
b\g	c	d		b\g	c	d		b\g	c	d
c	?	2		c	?	5		c	0	2
d	6	3		d	1	2		d	10	38

4.3. Various Hypothesis Tests

Here we assume that the model of individual behavior has 5 temporal phases. We test whether individual behavior for phase 1\10 should be regarded as different from that for phase 41\50. We have three other comparisons; the relationships between them are described in Fig.4.1. They rely upon the independence assumption in the sense of (3.3), which will be tested in Section 6. We will find that behaviors for 1\10 are significantly different, and as the phase goes on, the difference becomes smaller. We also consider whether the aggregation of behaviors over the subjects is appropriate or not.

We explain one statistical test in detail. The first four tests follow the *binomial test* with 2 populations in statistics (cf., Lehmann [15] and Randles-Wolfe [20])[11].

Comparison between phases 1\10 and 41\50: Recall that $\widehat{\eta}_{t,i}^{\tau,\pi}$ is regarded as 1 if $\widehat{\eta}_{t,i}^{\tau,\pi} = d$ and $\widehat{\eta}_{t,i}^{\tau,\pi}$ is 0 if $\widehat{\eta}_{t,i}^{\tau,\pi} = c$. Since τ and π are arbitrarily fixed in the following, we abbreviate the superscripts τ, π; $\langle \widehat{\eta}_{1,i}^{\tau,\pi}, ..., \widehat{\eta}_{10,i}^{\tau,\pi} \rangle$ is expressed as $\langle \widehat{\eta}_{1,i}, ..., \widehat{\eta}_{10,i} \rangle$.

Now, we assume that $X_{1,i}, ..., X_{10,i}$ and $X_{41,i}, ..., X_{50,i}$ are independent and follow, respectively, $\Pr(X_{t,i} = d) = p_i^1$ for $t = 1, ..., 10$ and $\Pr(X_{t,i} = d) = p_i^2$ for $t = 41, ..., 50$. We formulate the null hypothesis as follows:

$$\mathbf{H}_0^I : p_i^1 = p_i^2.$$

This hypothesis is tested with the data $\langle \widehat{\eta}_{1,i}, ..., \widehat{\eta}_{10,i} \rangle$ and $\langle \widehat{\eta}_{41,i}, ..., \widehat{\eta}_{50,i} \rangle$.

Under the independence assumption together with $\mathbf{H}_0^I$ ($p_i^1 = p_i^2 = p_i$), the *likelihood* of the observed sequences $\langle \widehat{\eta}_{1,i}, ..., \widehat{\eta}_{10,i} \rangle$ and $\langle \widehat{\eta}_{41,i}, ..., \widehat{\eta}_{50,i} \rangle$ is calculated as $p_i^{\widehat{k}_i}(1 - p_i)^{20-\widehat{k}_i}$, where $\widehat{k}_i = \sum_{t=1}^{10} \widehat{\eta}_{t,i} + \sum_{t=41}^{50} \widehat{\eta}_{t,i}$. The maximization by controlling p_i is attained at $p_i^* = \widehat{k}_i/20$, which is the *maximum likelihood estimator* of $p_i^1 = p_i^2 = p_i$. In the following, we assume that $X_{1,i}, ..., X_{10,i}$ and $X_{41,i}, ..., X_{50,i}$ follow $p_i^* = \widehat{k}_i/20$.

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[11]The statistical test here, at least its purpose, is similar to the well-known method called Fisher's *exact probability test for two groups* (cf., Gibbons-Chakraborti [8]). If we apply the Fisher test to the comparison between 1\10 and 41\50, then it should be assumed that the total number of choices of d in both phases is fixed. This assumption prohibits the independent behavior of a subject across the two phases.
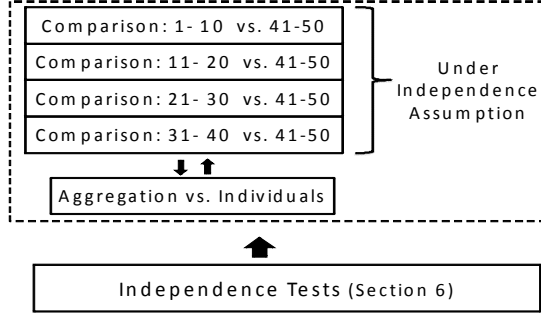
Figure 4.1: Statistical Hypothesis Tests

In order to test the null hypothesis $\mathbf{H}_0^I$, we use the following statistic K_i^0 over Ω :

$$K_i^0(\omega) = \sum_{t=1}^{10} X_{t,i}(\omega) - \sum_{t=41}^{50} X_{t,i}(\omega) \text{ for } \omega \in \Omega. \tag{4.1}$$

This is an unbiased estimator of $10(p_i^1 - p_i^2)$, i.e., $E(K_i^0) = 10(p_i^1 - p_i^2)$. Thus, this statistic detects a difference between p_i^1 and p_i^2. Under $\mathbf{H}_0^I$, this follows the probability distribution defined as the difference between the two identical binomial distributions, and its range is the set $\{-10, ..., 0, ..., 10\}$. Using this probability distribution, we estimate the difference between $\langle \widehat{\eta}_{1,i}, ..., \widehat{\eta}_{10,i} \rangle$ and $\langle \widehat{\eta}_{41,i}, ..., \widehat{\eta}_{50,i} \rangle$ is.

We calculate $\widehat{k}_i^o := \sum_{t=1}^{10} \widehat{\eta}_{t,i} - \sum_{t=41}^{50} \widehat{\eta}_{t,i}$ from $\langle \widehat{\eta}_{1,i}, ..., \widehat{\eta}_{10,i} \rangle$ and $\langle \widehat{\eta}_{41,i}, ..., \widehat{\eta}_{50,i} \rangle$, which can be regarded as a realization of K_i^0. We evaluate whether the event "$K_i^0 = \widehat{k}_i$" $(= \{\omega \in \Omega : K_i^0(\omega) = \widehat{k}_i\})$ is "rare" or not. We collect the possible numbers k_i of occurrences of d that are not more likely than the observed $\widehat{k}_i$. That is,

$$\text{RJ} = \{k_i : -10 \leq k_i \leq 10 \text{ and } \Pr(K_i^0 = k_i) \leq \Pr(K_i^0 = \widehat{k}_i)\}. \tag{4.2}$$

Then, we have the definition of rejection with significance level 0.05 : We *reject* the hypothesis $\mathbf{H}_0^I$ iff $\sum_{k_i \in \text{RJ}} \Pr(K_i = k_i) \leq 0.05$. This means that $\langle \widehat{\eta}_{1,i}, ..., \widehat{\eta}_{10,i} \rangle, \langle \widehat{\eta}_{41,i}, ..., \widehat{\eta}_{50,i} \rangle$ occurred as a "rare" event with the level of significance 0.05, and being "rare" is attributed to the hypothesis $\mathbf{H}_0^I$. We call the total probability $\sum_{k_i \in \text{RJ}} \Pr(K_i = k_i)$ the *p-value* of $\langle \hat{\eta}_{1,i}, ..., \hat{\eta}_{10,i} \rangle$ and $\langle \widehat{\eta}_{41,i}, ..., \widehat{\eta}_{50,i} \rangle$.

The results for the above test for (QS1,NRS) are given in Column 6) of Table 4.1. It gives 7 rej's out of 28 subjects. In the other treatments (QS2,NRS) and (T,NRS), we have 9 and 10 rej's, which are summarized in Row 1) of Table 4.5. Since the level of significance is 0.05, the rejection of $\mathbf{H}_0^I$ is made on a conservative base. Thus, the rejection has a strong implication: for many subjects, the individual behavior is significantly different between the first phase and the last phase. These are consistent with the previous comparisons between $s_{1\backslash 10}^i$ and $s_{41\backslash 50}^i$.

Table 4.5; Behavioral Comparisons for NRS

Four Comparisons	QS1	QS2	T
1): #rej: $1\backslash 10$: $41\backslash 50$	7	9	10
2): #rej: $11\backslash 20$: $41\backslash 50$	5	6	3
3): #rej: $21\backslash 30$: $41\backslash 50$	3	3	2
4): #rej: $31\backslash 40$: $41\backslash 50$	1	0	2

Comparisons between Phases $11\backslash 20$, $21\backslash 30$ and $31\backslash 40$ with $41\backslash 50$: We make a parallel statistical test between phases $11\backslash 20$ and $41\backslash 50$. The numbers of rej's are summarized in Row 2) of Table 4.5, which are much smaller than those in Row 1). Parallel comparisons are made between $21\backslash 30, 31\backslash 40$ and $41\backslash 50$, which are given in Rows 3) and 4). The numbers of rejections are consistently decreasing as the phase is closer to the last $41\backslash 50$. In particular, 4) means that the individual behaviors are already quite similar between $31\backslash 40$ and $41\backslash 50$.

Assumption of Constant Behaviors over a Temporal Phase: Following our assumption of the constant behavior over a phase, the change in behaviors should occur only between two phases. We made this assumption for an analytic purpose. However, we can see from Rows 3), 4) of Table 4.5 that revisions are gradually occurring during each of those phases, but in the initial phases, revisions occurred in more visible manners. It may be difficult to find an adequate uniform length of a temporal phase. This needs further considerations, but leave them as an open problem.

An Individual Behavior vs. the Aggregated Behavior: Fig.2.1 described the aggregated behavior over the subjects for each treatment. According to the model of individual behavior given in Section 3, it would be more natural to study an individual behavior than the aggregated one. If, however, the aggregation does not loose anything, we could avoid the difficulty caused by the small size of the available data. We formulate the question as a simple binomial test.

Choose a treatment τ. Consider the 28 trajectories of actions $\langle \widehat{\eta}_{41,j}^{\tau,\pi}, ..., \widehat{\eta}_{50,j}^{\tau,\pi} \rangle$, $j = 1, 2$, and $\pi = 1, ..., 14$. Under the assumption that the random variables in $\langle X_{41,j}^{\tau,\pi}, ..., X_{50,j}^{\tau,\pi} \rangle$, $j = 1, 2$, and $\pi = 1, ..., 14$ are independent and follow the same probability $\Pr(X_{t,i}^{\tau,\pi} = d) = p$. Then, the maximum likelihood estimator of p is given as the relative frequency $p^M = \sum_{j=1}^{2} \sum_{\pi=1}^{14} \sum_{t=41}^{50} \widehat{\eta}_{t,j}^{\tau,\pi} / (28 \times 10)$ of d.

Now, let a pair π and a subject i be fixed in addition to τ. We formulate the null hypothesis as follows:

$\mathbf{H}_0^{Ag} : X_{41,i}^{\tau,\pi}, ..., X_{50,i}^{\tau,\pi}$ follow p^M, i.e., $\Pr(X_{t,i}^{\tau,\pi} = d) = p^M$ for $t = 41, ..., 50$.

This is tested as a binomial hypothesis test with one population: We consider only the statistic $K_i(\omega) = \sum_{t=41}^{50} X_{t,i}^{\tau,\pi}(\omega)$ and the probability corresponding to $\Pr(\mathrm{RJ})$ with the probability structure induced by $\Pr(X_{t,i}^{\tau,\pi} = d) = p^M$ and with the level of significance

0.05. The method is simpler than the previous one: Since we have much larger data for p^M, we do not need to consider two populations.

Having the parallel tests for phases 1\10, 11\20, 21\30 and 31\40, we have Table 4.6: For 1\10, the numbers of rejections are small, which means that the individual behaviors are, more or less, the same as the aggregated behavior, since any subject has no sources for differences for individual behaviors. For the other phases, the aggregated data and individual data differ significantly for (QS2,NRS) but not very different for (QS1,NRS) and (T,NRS).

Table 4.6; Individualistic vs. Aggregated Behavior

	QS1	QS2	T
1\10	1	1	5
11\20	6	8	3
21\30	3	15	2
31\40	1	13	3
41\50	3	13	3

We may think of two different possible sources for rejections of $\mathbf{H}_0^{Ag}$, as suggested in Section 3: (1) differences in individual propensities with respect to the aspects described by postulates BH1-BH2, EP1-EP2 and ID1-ID2, and (2) differences in the resulting converged outcomes, i.e., more than one natural predictions. Since we have, effectively, only one prediction, i.e., the dominant strategy criterion for the NRS treatments, the rejection results for (QS1,NRS) and (T,NRS) may be regarded as caused by (1). Many rejections for (QS2,NRS) are caused by the outliers. Table 4.6 cannot be read as implying that it would be enough to think about the aggregated behavior. We will discuss the same tests for the ARS treatment in Section 5.2.

5. Results for Games QS1, QS2 and T with ARS

High ratios of incorrect answers in Table 2.2 give us more room for analysis. In Section 5.1, we scrutinize the cognitive data on payoff answers looking for some new forms of analysis. We then connect the cognitive data to the epistemic postulates EP1 and EP2. In Section 5.2 the analysis is parallel to that given in Sections 4.2 and 4.3, with a focus on the effects of role-switching and ICE. In Section 5.3, we consider ordinal understanding of payoffs by subjects.

5.1. Analysis 1 of the Cognitive Data

There are various sources for incorrect answers to the payoff questionnaire: simple mistreatments of actions and roles, and more structural sources. We are interested in the latter. One such source is: recall would fail for payoffs experienced only a few times,
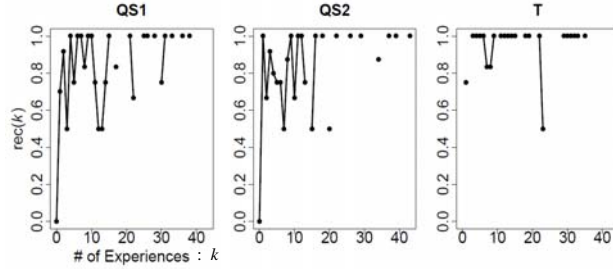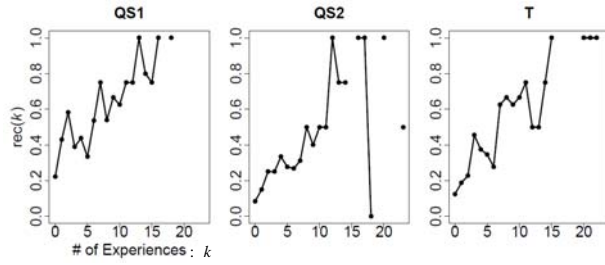
Figure 5.1: Recall Rate $rec(k)$ for NRS

Figure 5.2: Recall rate $rec(k)$ for ARS

or only in the beginning phase. This is related to the postulates EP1 and EP2 and it suggests some way to proceed with our analysis.

In Fig.1.1, each of pairs (d, c), (c, c) occurred only once in rounds $2, 3$,respectively. In Table 1.2, subject 1 gave the correct answers 5 and 1 for (d, c) in role g and for (c, c) in b, even though those rounds are far from the last round 50. He gave only incorrect answers to unexperienced payoffs to (d, c) and (c, c) in roles b and g. On the contrary, subject 2 gave the correct answers only to (c, d) for both roles.

This observation raises the following questions:

C1: What are the correlations between the numbers of experiences and correct answers?

C2: Do the payoff answers give enough information for ordinal comparisons?

In this section, we look at C1 and we wait until Section 5.3 to answer C2.

Question C1 is considered here. Question C2 will be considered in Section 5.3.

Consider the proportion of #subjects giving correct answers relative to #subjects having k experiences of a particular payoff, which we call the *recall rate*. To be precise, let $\xi_i(r; a_b, a_g)$ be the number of experiences, by subject i, of role r and action pair (a_b, a_g), and also define $\xi_i^C(r; a_b, a_g) = 1$ if his answer to $h_r(a_b, a_g)$ is correct, and

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$\xi_i^C(r; a_b, a_g) = 0$ otherwise. We formulate the recall rate $rec(k)$:

$$rec(k) = \frac{\sum_{(r;a_b,a_g)} \left|\{i : \xi_i(r; a_b, a_g) = k \text{ and } \xi_i^C(r; a_b, a_g) = 1\}\right|}{\sum_{(r;a_b,a_g)} \left|\{i : \xi_i(r; a_b, a_g) = k\}\right|}$$

where $(r; a_b, a_g)$ varies over $\{b, g\} \times \{c, d\}^2$.

Fig.5.1 gives the three graphs depicting the recall rates for QS1, QS2 and T for NRS, and Fig.5.2 gives the corresponding ones for ARS. In Fig.5.2, $rec(k)$ appears quite proportional to the number k of experiences, while it takes 1 for many k in Fig.5.1. We find, in Fig.5.2, the tendency for subjects to learn payoffs more correctly as they experience payoffs more, which are suggestive for a more precise structure, such as proportionality, than Postulates EP1, EP2.

5.2. Analysis of the Behavioral Data

We analyze the behavioral data for ARS in a parallel manner to Section 4, and summarize the results in Tables 5.1 and 5.2, which correspond to Tables 4.2 and 4.5. We find several new features in these tables; occurrences of an ICE, and slow payoff learning, relative to the corresponding results for NRS. We look at Tables 5.1 - 5.4 focusing on these features.

Smaller Numbers of Choices d and Slower Convergence: We find that in ARS, the numbers of choices d for period 41\50 in Table 5.1.1) are much smaller than those in NRS, shown in Table 4.2.1). This has a reason; convergent cases to the ICE include convergences to (c, c) in QS1, QS2, and to (c, d) in T, in addition to those to (d, d).

The slow convergence is also observed by comparing between the corresponding Rows 4)-6), of Tables 5.1 and 4.2. Row 4) of both tables are similar, but Row 5) become quite different, and Row 6) show that convergence is slower in terms of standard deviations.

Table 5.1; Summary for ARS

	QS1	QS2		T
1): $f_d^i \geq 8$ ($f_d^i \geq 7$): 41\50	11 (12)	7 (8)		6 (10)
2): $f_d^i \geq 8$ pairwise: 41\50	3	2		2
3): $f_c \geq 8$ ($f_c \geq 7$): 41\50	0 (1)	9 (12)	3): cd ind. ≥ 8 ($f_c \geq 7$)	13 (14)
3'): cc pairwise (both ≥ 8)	0	3	3'): cd pairwise (both ≥ 8)	6
4): $\overline{sd}_{1\backslash 10}$	.49	.48		.50
5): $\overline{sd}_{41\backslash 50}^i$	.46	.34		.32
6): $\#\{sd_{41\backslash 50}^i - sd_{1\backslash 10}^i < 0\}$	14	19		15

Counting c and d based on (c, d) for (T,ARS): The focus in (T,ARS) is the ICE (c, d), and indeed, we have several pairs to converge to (c, d), though we have a few other convergences to (d, d). This is caused by a twist in (T,ARS). In the following, we stipulate

to count c for role b as 1 and d for role g also as 1. For NRS, a subject was identified with a role, but for ARS, a subject takes a role alternately. We focus on the behavior of a subject, rather than that of a role. For example, when the trajectory for phase $41\backslash50$ is given as $(c, d), ..., (c, d)$, such as in Fig.1.1, the behavior of the subject taking b at round 41 for $41\backslash50$ is $c, d, c, d, ..., c, d$, and for the other subject, it is $d, c, d, c, ..., d, c$. The corresponding numerals for QS1,QS2 are $0, 1, 0, 1, ..., 0, 1$, but $1, 1, ..., 1, 1$ for T.

In Tables 5.1, Row 4)-6) for T are calculated in this manner. In Tables 5.2 and 5.3, the calculations for T are also based on this stipulation.

The slow convergence is consistent with the slow cognitive learning discussed in Section 5.1. According to our model of individual behavior in Section 3, in ARS, a subject needs more time to learn the entire payoffs, i.e., more trials/errors remain in later rounds, than in NRS; thus, behavioral convergence must be slow in ARS.

Each of QS1, QS2, T has still a few convergences to (d, d), shown in Row 2). Rows 3), 3') show the convergences to (c, c) in QS1, QS2, and (c, d) in T. No subjects played c in QS1 in the sense of $f_d^i \geq 8$, but quite a few subjects played c in QS2, though only 3 pairs out of 14 went to (c, c). In T, many showed the ICE behavior.

Ut-s behavior: In games QS1, QS2, (c, c) maximizes the utility sum. As observed above, it was played in QS2, but not in QS1. Game T has a twist and the utility sum behavior becomes (c, d). Row 3') for T tells that 6 pairs out of 14 show convergences (in the sense of $f_d^i \geq 8$) to (c, d), including the clear-cut convergence of Fig.1.1. Counting the actions corresponding to (c, d), 13 subjects show convergences to the actions consistent with Ut-s.

We also find some subjects showing Ut-s in QS2, but none in QS1. A high value of the standard deviations in Row 5) for QS1 is interpreted as meaning that trials/errors were still dominant in later rounds[12].

Statistical Tests for Comparisons of Various Phases: In the parallel manner to Section 4.3, we make statistical tests of comparisons of behavior of subjects for $1\backslash10$, $11\backslash20$, $31\backslash40$, vs. $41\backslash50$. The results are given in Rows 1) - 4) of Table 5.2. In Table 4.5 for NRS, the numbers changed drastically from Row 1) to the Row 2). In Table 5.2, this change is less drastic, which is compatible with slow convergences in subjects' behaviors in ARS than in NRS.

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[12]Some readers may think that Fehr-Schmit's [6] theory of inequality aversion (see also Camerer [4]) could explain our experimental results. A direct application of this theory to each of the three games suggests the (d,d) outcome. If we use the payoff sum of two rounds, the result would become exclusively the cooperative outcome. Hence, this theory is not compatible with our behavioral data.

Table 5.2; Behavioral Comparisons for ARS

	QS1	QS2	T
1): #rej: 1\10: 41\50	5	7	7
2): #rej: 11\20: 41\50	3	10	5
3): #rej: 21\30: 41\50	3	2	6
4): #rej: 31\40: 41\50	2	1	2

Implications for the Choice of Temporal Phases: We find in 4) of both Tables 4.5 and 5.2 that for NRS and ARS, individual behavior including trials/errors is already quite stationary for phases 31\40 and 41\50. As already mentioned, we test stochastic independence of individual behavior in Section 6. For this, we choose longer phase 31\50 to keep the data size, which is justified by the results of stationary behaviors.

These results are also suggestive for the conjecture that our results are not sensitive for the choice of the length of a temporal phase to be 10, but this is an open problem.

An Individual Behavior vs. the Aggregated Behavior: This comparison is made in the same way as in Section 4. Focussing on an individual behavior of a subject, we conduct essentially the same statistics tests for (QS1,ARS), (QS2,ARS) and (T,ARS) and each of 1\10, 11\20, 21\30, 31\40, and 41\50. The results are summarized in Table 5.3. We interpret this table as meaning that we should look at the data for each pair of subjects rather than the aggregated data over the subjects.

Table 5.3; Individualistic vs. Aggregated Behavior

	QS1	QS2	T
1\10	1	3	0
11\20	7	8	6
21\30	4	5	7
31\40	3	8	7
41\50	5	11	14

Behavioral Dependence upon Roles: Table 5.4 shows the result of the hypothesis test of dependence upon roles b and g : We divide the data from 31\50 into the odd and even round groups. Then, we conduct a statistical test of whether these two groups follow the same probability structure. We can see some rejection cases; the behaviors of some subjects are dependent upon roles. We will discuss behavioral dependence upon roles once more in Section 6.2.

Table 5.4; Dependence upon Roles for ARS

	QS1	QS2	T
#rej: B31\50: G31\50	5	3	3

5.3. Analysis 2 of the Cognitive Data

Recall that Table 2.2 shows the low rates of correct answers about the payoffs. Nevertheless, we have some numbers of convergences to action d or c in QS2 and T in Table 5.1. As already suggested in Section 5.1, decision making may depend only upon ordinal understanding of payoff values. Here, we look at the payoff answers from the viewpoint of ordinal preferences. To motivate this, let us look at the *two* inequalities determining an ICE for Table 1.2:

$$\text{for subject 1,} \quad 5 + [5] < 2 + 10 \text{ and } 3 + 2 < 2 + 10; \tag{5.1}$$

$$\text{for subject 2,} \quad [1] + [1] < 2 + 10 \text{ and } [1] + [1] < 2 + 10. \tag{5.2}$$

Recall that $[\cdot]$ signifies a numerically incorrect answer. Many answered payoffs are incorrect, but are still correct enough to have an ICE relative to the answered payoffs. Let us consider how often those inequalities hold.

Table 5.5: Subjective Understanding of Behavioral Criteria

		QS1			QS2			T	
	Ut-s	Dom	Br	Ut-s	Dom	Br	Ut-s	Dom	Br
# of 2	12	7	10	11	4	9	22	3	6
# of 1	7	7	12	6	6	7	5	9	13
# of 0	9	14	6	11	18	12	1	16	9
Avg.	1.11	.75	1.1	1	.5	.89	1.75	.54	.89

Table 5.5 summarizes the payoff answers from 28 subjects for each game with ordinal understandings of three decision criteria: Utility-sum, Dom and Br. Utility-sum is defined for the answered payoff functions in the way of (5.1) for subject 1, to which we assign $0, 1, 2$, the number of inequalities correct relative to the objective payoffs. Dom (also Br) takes also a value from $0, 1, 2$, since each subject answered two payoff functions, one for each role.

It is a salient point that in T, 22 subjects out of 28 have values 2 for Utility-sum, though the numerically correct answers are about 45% stated in Table 2.2. Dom and Br take values 2 only for 3 and 6 subjects. Hence, in T, many subjects' understandings are consistent with the ICE prediction, and indeed some of them played (c, d).

On the other hand, in QS1 and QS2, the numbers of subjects giving value 2 to Dom and Br are higher than in T. This is compatible with Table 5.1 for QS1, QS2.

When Br takes value 2, criterion NE holds. In Table 5.5, the numbers of value 2 for Br are quite different from those for Dom. Thus, some subjects might use the NE criterion rather than the Dom criterion.

There are some causalities (or correlations) between payoff understanding and behavior. Also, the above consideration of ordinal understanding suggests a refinement of

EP1 and EP2. Also, as indicated in Section 3.2, Dom and Br are behaviorally indistinguishable for the objective game QS1, QS2 and T. Here, we may distinguish between them, even though behavioral observations are the same. However, a more precise discussion is left to a future study.

6. Statistical Tests of Independent Behavior

We test statistical independence of behavior $X_{t,i}^{\tau;\pi}$ in the temporal phase 31\50, as suggested in Fig.4.1. We formulate the hypothesis test of stochastic independence in Section 6.1, and present the results for NRS and ARS in Section 6.2. The results are positive for independence, which have the game theoretical implication that the deterministic behavior described by $\sigma_{t,i}^{\tau;\pi}$ are regarded as history-independent for 31\50. This together with the results in Sections 4 and 5 is interpreted as meaning that $\sigma_{t,i}^{\tau;\pi}$ is determined by the subjective payoffs and some history-independent criteria.

Here, we take temporal phase 31\50 (30\50) for our consideration in order to keep some data size. Both Tables 4.5 and 5.2 state that this is not problematic since that the behaviors are stable in 31\50.

6.1. A Hypothesis Test of Stochastic Independence

The general notion of stochastic independence is the non-existence of any stochastic dependences. However, even though we restrict our attention to rounds 31\50, we have too many possibilities for such dependences, and at the same time the sizes of experimental data are small. Hence, we restrict[13,14] our independence test to Markov-type dependence. To be more precise, we introduce a certain *statistic* to detect the Markov-type conditional probability. Our general idea is to test whether a trajectory for 31\50 is less likely generated by independent variables than by Markov-type dependent ones. Our answer is "no".

Let triple τ, π, i be fixed. Again, we abbreviate the superscripts τ, π. We restrict the scope of dependences to the domain of the *Markov condition* that $X_{31,i}, ..., X_{50,i}$ satisfy: for $t = 31, ..., 50$, $\eta_1, .., \eta_{t-1} \in \{c, d\}^2$,

$$\Pr(X_{t,i} = d \mid X_1 = \eta_1, ..., X_{t-1} = \eta_{t-1}) = \Pr(X_{t,i} = d \mid X_{t-1} = \eta_{t-1}), \quad (6.1)$$

---

[13]The *runs test* is typically used for testing stochastic independence in the literature (see Gibbons-Chakraborti [8]). It is about "independence" of a series of random variables, and is not applied to a situation including another variables like ours. For example, if $X_{t,1}$'s are independent, and $X_{t,2}$'s follow "Tit-for-Tat", the runs test cannot detect the patterned behavior of the latter, while ours can.

[14]The restriction can be justified by the cognitive limitationsof EP1 and EP2 mentioned in Section 1.1. Since each subject has no source other than his memory to infer in which round he is playing in the experiment, the influence from the immediately previous actions must be dominant to those from earlier rounds.

where this requires nothing if $\Pr(X_{t-1} = \eta_{t-1}) = 0$. Thus, (6.1) states that the probability of $X_{t,i}$ taking d may depend only upon the immediately previous pair of actions. Also, we assume that the conditional probability is constant over $31\backslash 50$: for each $\xi = (\xi_1, \xi_2) \in \{c, d\}^2$, there is some $p_i(d \mid \xi)$ such that for $t = 31, ..., 50$,

$$\Pr(X_{t,i} = d \mid X_{t-1} = \xi) = p_i(d \mid \xi). \tag{6.2}$$

Now, we introduce a certain statistic, R_i, in order to evaluate this $p_i(d \mid \xi)$ from the observed data $\langle \widehat{\eta}_{30}, ..., \widehat{\eta}_{50} \rangle$ (the start from round 30 is due to (6.1) and (6.2)). Then we make the null hypothesis that the trajectory is generated by the independent variables $X_{t,i}$, $t = 30, ..., 50$. If the probability of each observed trajectory is evaluated by the statistic R_i for $p_i(d \mid \xi)$ and drops below the 5% significance level, we reject the null hypothesis.

To introduce the statistic R_i, we partition the rounds $31\backslash 50$ into the odd number rounds $T_O = \{31, ..., 49\}$ and the even number rounds $T_E = \{32, ..., 50\}$. First, we define the vectors of random variables $\{K_{i,\xi}\}_\xi$ and $\{K_{i,(\xi,d)}\}_\xi$: for $\xi \in \{c, d\}^2$ and $\omega \in \Omega$,

$$K_{i,\xi}(\omega) = |\{t \in T_O : X_t(\omega) = \xi\}|; \tag{6.3}$$

$$K_{i,(\xi,d)}(\omega) = |\{t \in T_O : X_t(\omega) = \xi, \ X_{t+1,i}(\omega) = d\}|. \tag{6.4}$$

The first is the number of the rounds having ξ in T_O, and the second is that of successive occurrences of ξ and d. Let φ be the function defined as: for two numbers (x, y), $\varphi(x, y) = y/x$ if $x \neq 0$ and $\varphi(x, y) = 0$ otherwise. Then, we define the statistic $R_i = \{R_{i,\xi}(\omega)\}_{\xi \in \{c,d\}^2} = \{\varphi(K_{i,\xi}, K_{i,(\xi,d)})\}_{\xi \in \{c,d\}^2}$. This gives the relative frequency of d conditional upon ξ with the stipulation that when $K_{i,\xi}(\omega) = 0$, $R_{i,\xi}(\omega) = \varphi(K_{i,\xi}(\omega), K_{i,(\xi,d)}(\omega)) = 0$.

The following lemma states that $R_{i,\xi}$ is an almost "unbiased" estimator of $p_i(x \mid \xi)$ in the following sense.

Lemma 6.1. $E(R_{i,\xi}) = \Pr(K_{i,\xi} > 0) \times p_i(d \mid \xi)$ for each $\xi \in \{c, d\}^2$.

Proof. $K_{i,\xi}(\omega)$ takes a value from $0, 1, ..., 10$. When ξ occurs in round $t \in T_O$, the conditional probability of having d in round $t + 1$ is given as $p_i(d \mid \xi)$ by (6.2). Hence, when $K_{i,\xi}(\omega) = k > 0$, the expected value of $K_{i,(\xi,d)}$ is $k \times p_i(d \mid \xi)$. Hence, $E(R_{i,\xi}) = \sum_{k=1}^{10}(k \times p_i(d \mid \xi))/k \times \Pr(K_{i,\xi} = k) = \sum_{k=1}^{10} p_i(d \mid \xi) \times \Pr(K_{i,\xi} = k) = \Pr(K_{i,\xi} > 0) \times p_i(d \mid \xi)$. ∎

Since $R_{i,\xi}$ is stipulated to take the value 0 whenever $K_{i,\xi} = 0$, our statistic $R_{i,\xi}$ estimates $p_i(d \mid \xi)$ only for ω with $K_{i,\xi}(\omega) > 0$. The coefficient $\Pr(K_{i,\xi} > 0)$ matters for our hypothesis tests.

The partition (T_O, T_E) is introduced to guarantee Lemma 6.1. The other case where the roles of T_O and T_E are switched will be discussed later.

The null hypothesis we test is:

$\mathbf{H}_0^{In} : X_{30,i}, ..., X_{50,i}$ are independent and follow the same probability $p_i^{30 \backslash 50}$,
   i.e., $\Pr(X_{t,i} = d) = p_i^{30 \backslash 50}$ for $t = 30, ..., 50$.

Recall that $p_i^{30 \backslash 50} = \sum_{t=30}^{50} \widehat{\eta}_{t,i}/21$ is the maximum likelihood estimator of $\Pr(X_{t,i} = d)$ under the assumption that $X_{30,i}, ..., X_{50,i}$ are independent and follow the same probability. The reason for the start to be round 30 will be clear presently.

Now, we consider the region in which the statistic $R_i = (R_{i,\xi})_{\xi \in \{c,d\}^2}$ takes a value. Let L_i be the set of 8-dimensional integer vectors $l_i = \{(l_{i,\xi}, l_{i,(\xi,d)})\}_{\xi \in \{c,d\}^2}$ satisfying:

$$\sum_{\xi \in \{c,d\}^2} l_{i,\xi} = 10 \text{ and } l_{i,(\xi,d)} \le l_{i,\xi} \text{ for } \xi \in \{c,d\}^2. \tag{6.5}$$

We also define $\varphi(L_i) := \{(\varphi(l_{i,\xi}, l_{i,(\xi,d)}))_{\xi \in \{c,d\}^2} : l_i \in L_i\}$. Each $\varphi(l_i) = (\varphi(l_{i,\xi}, l_{i,(\xi,d)}))_{\xi \in \{c,d\}^2}$ is a 4-dimensional vector, denoted by r_i. Then, each $r_i = (r_{i,\xi})_{\xi \in \{c,d\}^2} \in \varphi(L_i)$ is regarded as a realization of the statistic $R_i = (R_{i,\xi})_{\xi \in \{c,d\}^2}$.

From the observed trajectory $\langle \widehat{\eta}_{31}, ..., \widehat{\eta}_{50} \rangle$, we define the vector $\widehat{k}_i = \{(\widehat{k}_{i,\xi}, \widehat{k}_{i,(\xi,d)})\}_\xi$

$$\widehat{k}_{i,\xi} = |\{t \in T_O : \widehat{\eta}_t = \xi\}| \text{ and } \widehat{k}_{i,(\xi,d)} = |\{t \in T_O : \widehat{\eta}_t = \xi \text{ and } \widehat{\eta}_{t+1,i} = d\}|. \tag{6.6}$$

This $\widehat{k}_i = \{(\widehat{k}_{i,\xi}, \widehat{k}_{i,(\xi,d)})\}_\xi$ is now regarded as a realization of $\{(K_{i,\xi}, K_{i,(\xi,d)})\}_\xi$. Hence, $\widehat{r}_i = \{\varphi(\widehat{k}_{i,\xi}, \widehat{k}_{i,(\xi,d)})\}_\xi$ is the observed realization of the statistic $R_i = (R_{i,\xi})_{\xi \in \{c,d\}^2}$.

The statistic $R_i = (R_{i,\xi})_{\xi \in \{c,d\}^2}$ is distributed in the region centered at $(E(R_{i,\xi}))_{\xi \in \{c,d\}^2}$. Hence, if the observed $\widehat{r}_i = \varphi(\widehat{k}_i)$ is "far from" $(E(R_{i,\xi}))_{\xi \in \{c,d\}^2}$, then a rare event happened. We evaluate this "far from" by the following set:

$$\mathrm{Cn}_i^O = \{r_i \in \varphi(L_i) : \|r_i - (E(R_{i,\xi}))_{\xi \in \{c,d\}^2}\| \ge \|\widehat{r}_i - (E(R_{i,\xi}))_{\xi \in \{c,d\}^2}\|\}, \tag{6.7}$$

where $\|\cdot\|$ is the Euclidean norm.

Under our hypothesis $\mathbf{H}_0^{In}$, we have $E(R_{i,\xi}) = \Pr(K_{i,\xi} > 0) \cdot p_i^{30 \backslash 50}$ by Lemma 6.1. Now, we say that $\mathbf{H}_0^{In}$ is T_O-*rejected* iff $\sum_{r_i \in \mathrm{Cn}_i^O} \Pr(R_i = r_i) \le 0.05$. That is, if the set Cn_i^O is a "rare" event with respect the probability measure $\Pr$ derived from trajectory $\langle \widehat{\eta}_{30}^{\tau,\pi}, ..., \widehat{\eta}_{50}^{\tau,\pi} \rangle$ together with the null hypothesis $\mathbf{H}_0^{In}$, we regard it as meaning that $\widehat{r}_i = \varphi(\widehat{k}_i)$ is "far from" $(E(R_{i,\xi}))_{\xi \in \{c,d\}^2}$, and will attribute it as caused by the null hypothesis $\mathbf{H}_0^{In}$.

The calculation of the probability distribution of R_i is complicated. Instead of an analytic calculation, we run the Monte Carlo simulation to obtain the probability distribution of R_i approximately and $\sum_{r_i \in \mathrm{Cn}_i^O} \Pr(R_i = r_i)$[15].

We partitioned the rounds $31 \backslash 50$ into the odd rounds T_O and the even rounds T_E. We consider the other test by replacing T_O and T_E with $T_E' = \{30, ..., 48\}$ and $T_O' =$

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[15] We are indebted to Eizo Akiyama of University of Tsukuba for constructing a computer program for this simulation.

$\{31, ..., 49\}$ $(= T_O)$, respectively. We have the above test in the same manner by the replacements of T_O, T_E with T'_E, T'_O, in which case T_O-rejection becomes T'_E-rejection. We say that $\mathbf{H}_0^{In}$ is $\vee$-*rejected* ($\wedge$-*rejected*) iff T_O-rejected or (and) T'_E-rejected. The reason to start with round 30 rather than 31 is to have $T'_E = \{30, ..., 48\}$.

6.2. Results of the Independence Tests

NRS Treatments: The results for the independence test for NRS is summarized in Table 6.1. In (QS1,NRS), the number of rejections is 2 for "or" (0 for "&") out of 28 subjects. In (QS2,NRS) and (T,NRS), the numbers are 4 (1) and 3 (0). In (QS1,NRS) and (T,NRS), the rejections occurred only in either T_O- or T'_E-sense. Only in (QS2,NRS), one subject shows the $\wedge$-rejection.

These mean that the behaviors of a majority of subjects may be regarded as stochastically independent, and as following history-independent behavioral criteria in 31\50. This statistical evidence, together with Tables 4.2 and 4.3, can be taken as a result of many subjects playing dominant strategies or at least best-response for their subjective payoff functions.

Table 6.1; Independence Tests for NRS

	QS1	QS2	T
#rej: $\vee$ / $\wedge$	2 / 0	4 / 1	4 / 0
Avg(p-values)	.58	.58	.51

Our independence results are opposite to the former experimental results such as Selten-Stoecker [23] and Andreoni-Miller [1]. Besides the difference in the cognitive assumptions, we made the experimental design to eliminate the end-game effects, which were important particularly for [23] and [1]. Our results are more compatible with Shubik [24], McCabe *et al.* [16], Oechssler-Schipper [19], Apesteguia [2], and Erev-Greiner [5].

However, Table 6.2 indicates high rates of rejection when we ignore role-switching for the ARS treatments, which is discussed below.

ARS Treatments: Role-switching gave one more piece of information, i.e., role r, to each subject in addition to the previous choices of actions and payoffs. First, however, ignoring this additional information r, we conduct the same hypothesis test of statistical independence as in the NRS case. Then, the results are given in Row 1) of Table 6.2.

The numbers of rejections are significantly higher than the corresponding ones in Table 6.1. Also, the average p-values in Row 1') are much lower than those in Table 6.1. This result is quite consistent with Table 5.3. We suspect that these results are caused by ignoring role-switching.

The trajectory shown in Fig.1.1 (pair 8, T) is a typical example for the rejection caused by ignoring role-switching. For this pair, since $p_1^{30\backslash 50} = 11/21$ and $p_2^{30\backslash 50} =$

10/21, the resulting trajectory by $\mathbf{H}_0^{In}$ must be quite random, but the observed trajectory has the alternating pattern. Hence, we have the $\wedge$-rejection for this pair.

This suggests that we should modify the independence test formulated in Section 6.1 by taking the information about roles into account. We allow each subject's behavior to depend upon the roles, i.e., it is still independent and identical except the dependence of the probability for $X_{t,i}$ upon the assigned role.

Taking Role-dependence into Account: To be precise, we assume that $\Pr(X_{t,i} = d)$ depends upon the assigned role in round t : Let $i = 1$. If t is odd, then subject i assigned to role b takes action d with the probability $\Pr(X_{t,i} = d) = p_i^{b:30\backslash50} := \sum_{t \in T_O} \widehat{\eta}_{t,i}/10$, and if t is even and he is assigned to role g, then he takes d with $\Pr(X_{t,i} = d) = p_i^{g:30\backslash50} := \sum_{t \in T_E} \widehat{\eta}_{t,i}/10$. We have the symmetric definition for $i = 2$.

The null hypothesis is as follows:

$\mathbf{H}_0^{r:In}$: for $i = 1$, $X_{30,i}, ..., X_{50,i}$ are independent and following the same probability
$\Pr(X_{t,i} = d) = p_i^{b:30\backslash50}$ for odd t, and $\Pr(X_{t,i} = d) = p_i^{g:30\backslash50}$ for even t.

The rest is the same as in Section 6.1.

Results are summarized in Row 2) of Table 6.2, which are drastically lower than Row 1) and are similar to the NRS result. That is, almost all rejection cases are explained by dependence upon roles.

<div align="center">

Table 6.2; Independence Tests for ARS

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	QS1	QS2	T
1): #rej: $\vee$ / $\wedge$	6 / 4	4 / 2	11 / 7
1'): Avg(p-values)	.39	.50	.38
2): Counting Roles: #rej: $\vee$ / $\wedge$	1 / 0	5 / 1	0 / 0
2'): Avg(p-values)	.55	.60	.69

Consider the trajectory of Fig.1.1, again. For it, we have $p_1^{b:30\backslash50} = 0$, $p_2^{g:30\backslash50} = 1$, and $p_1^{g:30\backslash50} = 1$, $p_2^{b:30\backslash50} = 0$, from which we have $\Pr(K_{i,(c,d)} > 0) = 1$ but $\Pr(K_{i,\xi} > 0) = 0$ if $\xi \neq (c,d)$. Thus, $R_{i,\xi}$ captures completely the alternating pattern of the trajectory. Hence, the test does not reject $\mathbf{H}_0^{r:In}$; the p-value for this is 1.

After all, in both NRS and ARS treatments, our statistical tests deny the possibilities of history-dependent strategies like the Tit-for-Tat strategy and the Trigger-strategy. While this is contrary to the findings of Selten-Stoecker [23] and Andreoni-Miller [1], it is consistent with our experimental design and the cognitive limitations of IGT expressed in EP1 and EP2. The ARS case did, however, show some statistical evidence of history-dependence on roles, which is also consistent with IGT.

7. Conclusions

We presented an experimental study of behavior and cognition in repeated situations of PD games with/without role-switching from the perspective of IGT. We had 6 experimental treatments {QS1,QS2,T} × {NRS,ARS}. We obtained the behavioral data directly from the experiments and the cognitive data from the payoff questionnaire. For NRS, the behavioral results as well as the answered payoffs are quite conclusive; recall is almost perfect and behavior in the longer term is largely consistent with the dominant strategy criterion. On the other hand, for ARS, the behavioral results are less conclusive, and the payoff answers are diverse. However, the data for ARS have two salient features: Behavioral-wise, we found some convergences to the ICE as well as to the noncooperative outcomes, and cognitive-wise, recall of payoffs was more varied across subjects, providing more room for analysis.

The behavioral results for NRS differ from some existing results on the PD games, such as Selten-Stoecker [23] and Andreoni-Miller [1]. In our NRS results, subjects started trials/errors in early rounds and tended to play non-cooperative actions in later rounds. This together with the cognitive results could be interpreted as meaning that many subjects played dominant strategies in later rounds. It is consistent with Shubik [24], McCabe *et al.* [16], Oechssler-Schipper [19], Apesteguia [2], and Erev-Greiner [5] despite the fact that the first three assumed that each subject knew his own payoff function, while we started with the no-knowledge assumption. The cognitive assumption adopted in [5] is the same as ours, and their results are quite consistent with ours.

For ARS, our results even differ from [24], [16], [19], [2],and [5] as well as the standard literature. The difference comes from the introduction of role-switching together with the no-knowledge assumption. On the other hand, our results are quite consistent with predictions in Kaneko-Kline [13].

The analysis of cognitive and learning aspects in NRS and ARS is also a contribution of the paper. In NRS, each subject had at most 4 payoffs to recall, but the recall was quite strong, which was discussed in Sections 4.1. On the contrary, in ARS, it was difficult for each subject to recall all payoffs, which was discussed in Section 5. This confirmed our epistemic postulates EP1, EP2. Also, as discussed in Section 5.3, subjects were found to tend to simplify the numerical payoffs into ordinal comparisons.

In Section 3, we provided the model of individual behavior based on the informal postulates of IGT. This model together with the independence results is not only a support but also a new development of IGT: It sharpens our two postulates BH1, BH2. The comparisons between phases 1\10, 11\20, 21\30, 31\40 and 41\50 show that there is a tendency of convergence in subject's behavior towards certain outcomes. Such convergences are better understood by looking at our analyses of the cognitive data, given in Sections 5.1 and 5.3.

This paper is only a start of an experimental study of behavioral and cognitive

issues from the IGT perspective. There are a lot of problems we have not touched. For example, we may improve our analysis of payoff learning, e.g., we extend the entire duration to 60 rounds, with the payoff questionnaire to be given after 20, 40 rounds. By this kind of extensions, the analyses of the cognitive issues such as those given in Sections 5.1 and 5.3 will become richer than the present form. This suggests to consider a cognitive model of individual learning, which is an important open problem. Another issue is the stochastic independence discussed in Section 6: We may need more studies such as further experiments of longer durations and also a simulation study to evaluate how good our statistical test of independence is.

We have also various more game theoretical problems: One such problem of the treatment of information, i.e., an information set or an information piece, and another one is the structural understanding of a game situation, which were originally discussed in Kaneko-Kline [10] - [12].

To study those problems from experimental points of view must enrich the entire IGT as a theory. This paper has paved the way, by providing a sound framework and development of IGT for analysis of experimental data on behavior and cognitive learning.

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