Accuracy and Retaliation in Repeated Games with Imperfect Private Monitoring: Experiments and Theory

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Abstract

We experimentally examine repeated prisoners' dilemma with random termination, where monitoring is imperfect and private. Our estimation indicates that a significant proportion of subjects follow generous Tit-For-Tat (g-TFT) strategies, straightforward extensions of Tit-For-Tat. However, the observed retaliating policies are inconsistent with the g-TFT equilibria. Contrarily to the theory, subjects tend to retaliate more with high accuracy than with low accuracy. They tend to retaliate more than the theory predicts with high accuracy, while they tend to retaliate lesser with low accuracy. In order to describe these results as unique equilibrium, we demonstrate an alternative theory that incorporates naïveté and reciprocity.

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1. Introduction

It is a widely accepted view that the long-run strategic interaction facilitates collusion among players whose interests conflict with each other. The premise is that each player observes information about which actions the opponents have selected before. However, even if the monitoring of the opponents' actions is *imperfect* (i.e. each player cannot directly observe the opponents' action choices but can observe informative signals), still the theoretical studies have shown that sufficiently patient players can employ cooperative strategies as equilibrium in a greater or lesser degree.

To be more precise, the folk theorem generally indicates that if the discount factor is sufficient, i.e., close to unity, and each player can not directly but indirectly observe the opponents' action choices through noisy signals, a wide variety of allocations can be attained by subgame perfect equilibria in the infinitely repeated game (Fudenberg, Levine, and Maskin (1994) and Sugaya (2012), for instance). Indeed the folk theorem is applicable to a very wide range of strategic conflicts. However, the theorem does not inform positively what kind of equilibria emerge empirically, as well as the strategies people follow actually associated with the equilibria.

Given the lack of consensus on the strategies people empirically follow, this study experimentally analyses our subjects' behavior in the repeated prisoners' dilemma. Our experimental setup is imperfect monitoring. Each player cannot directly observe her opponent's action choice, but observes a signal instead, which is either a *good* signal or a *bad* signal. The good (bad) signal is more likely to occur when the opponent selects the cooperative (defective) action rather than the defective (cooperative, respectively) action. The probability that a player observes the good (bad) signal when the opponent selects the cooperative (defective, respectively) action is referred as the monitoring accuracy, which is denoted by $p \in (\frac{1}{2}, 1)$. The study experimentally controls the levels of monitoring accuracy as treatments (the high accuracy $p = 0.9$ and the low accuracy $p = 0.6$) to examine the strategies our subjects follow. Specifically, the monitoring technology is *private* in the manner that each player cannot receive any information about what the opponent observes about the player's choices (i.e., the signals are only observable to the receivers).

To examine the prevalence of the strategies our subjects employ, following the recent strand in the experimental repeated game in which the heterogeneity of the strategies people follow is treated explicitly, we employ the Strategy Frequency Estimation Method (SFEM) developed by Dal Bó and Fréchette (2011). In the SFEM framework, we list various strategies that our subjects potentially take, and then estimate the frequencies of each strategy. This list includes the strategies that share significant proportions in existing studies of experimental repeated game, such as Tit-For-Tat (TFT), Grim-Trigger, Lenience, and Long-Term Punishment.

Distinctly from the existing experimental studies (Fudenberg, Rand, and Dreber (2012), Aoyagi, Bhaskar, and Fréchette (2015)), we rigorously include stochastic strategies in our SFEM list. Importantly, we include straightforward extensions of TFT, namely *generous Tit-For-Tat* (g-TFT). G-TFT is a simple stochastic Markovian strategy that makes a player's action choice contingent only on the signal observed at the previous round and permits the stochastic choice between the cooperative action and the defective action at each round.[5]

Because of the permission of stochastic action choices, g-TFT has a great advantage to the equilibrium analysis over the TFT strategy: provided the discount factor is sufficient, there always exist g-TFT equilibria, irrespective of the level of monitoring accuracy. Motivated with such theoretical importance, we regard g-TFT strategies and equilibria as the reasonable benchmarks of the standard repeated game theory with imperfect private monitoring. Indeed, our SFEM estimates do indicate that a significant proportion of our subjects follow g-TFT strategies. Hence, g-TFT is supported even empirically.

Observing that many of our subjects follow g-TFT strategies, we empirically examine their retaliation policies. We focus on the contrast of the probabilities of cooperative action choices contingent on a good signal and a bad signal, which is referred as the *retaliation intensity*.[6] Fixing the discount factor sufficient, the retaliation intensities are common across all g-TFT equilibria, depending on the level of monitoring

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[5] A deterministic version of g-TFT corresponds to the well-known Tit-For-Tat strategy with a slight modification for the case of imperfect private monitoring, according to which, a player always mimics her opponent's action choice at the previous round by making the cooperative (defective) action choice whenever she observes the good (bad, respectively) signal.

[6] Note that TFT corresponds to the g-TFT whose retaliation intensity equals unity.

accuracy. The retaliation intensity implied by the g-TFT equilibria is decreasing in level of monitoring accuracy. Importantly, this decreasing property plays the central role in making use of the improvement of monitoring technology and effectively saving the welfare loss caused by the monitoring imperfection. Hence, it is quite important to examine whether this property holds even empirically.

The retaliation intensities observed in our experimental data, however, contradict with the predictions by the standard equilibrium theory mentioned above. Contrarily to the g-TFT equilibria, our subjects tend to retaliate more in the high accuracy treatment than in the lower accuracy treatment. They tend to retaliate more than the level implied by the g-TFT equilibria in the high accuracy treatment, while they tend to retaliate lesser in the low accuracy treatment. Hence, our subjects' behavior cannot be explained by the standard theory.

As a feedback from our experimental findings to the theoretical development, we demonstrate an alternative theory that is more consistent with our experimental results than the standard theory. This theory associates equilibrium behavior with psychology and bounded rationality as follows. We permit each player to be motivated by not only pure self-interest but also *reciprocity*. We permit each player to be often *naïve* enough to select actions at random. We permit the degrees of such reciprocity and naiveté to be dependent on the level of monitoring accuracy.

By incorporating reciprocity and naïveté into equilibrium analysis, we characterize the underlying behavioral model of preferences that makes the retaliation intensity implied by the g-TFT equilibrium increasing in level of monitoring accuracy, i.e., more consistent with our experimental results. In the contrast with the standard theory, the derived behavioral model guarantees the *uniqueness* of g-TFT equilibrium.

The organization of this paper is as follows. Section 2 reviews the literature. Section 3 shows the basic model. Section 4 introduces g-TFT strategy and equilibrium. Section 5 explains the experimental design. Section 6 shows the experimental results about aggregate behavior. Section 7 explains the Strategy Frequency Estimation Method. Section 8 shows the experimental results about individual strategies. Section 9 demonstrates the behavioral theory. Section 10 concludes.

2. Literature Review

This paper contributes to the long history of research on the repeated game literature. The equilibrium theory demonstrates the folk theorems in various environments, which commonly showed that a wide variety of outcomes are sustained by perfect equilibria provided the discount factor is sufficient. Fudenberg and Maskin (1986) and Fudenberg, Levine, and Maskin (1994) proved their folk theorems for perfect monitoring and imperfect public monitoring, respectively, where they utilized the self-generation nature of perfect equilibria explored by Abreu (1988) and Abreu, Pearce, and Stacchetti (1990), which, however, crucially relies on the publicity of signal observations. For the study of imperfect private monitoring, Ely and Valimaki (2002), Obara (2002), Piccione (2002) explored the belief-free nature as an alternative to self-generation, which motivates a player to select both the cooperative action and the defective action at all times. They showed the folk theorem in prisoners' dilemma game where monitoring is private and almost perfect.[7]

Subsequently, Matsushima (2004) proved the folk theorem in prisoners' dilemma game with imperfect private monitoring by constructing review strategy equilibria as lenient behavior with long-term punishments, where we permit the monitoring technology to be arbitrarily inaccurate. Eventually, Sugaya (2012) proved the folk theorem with imperfect private monitoring for a very general class of infinitely repeated games, by extending self-generation to imperfect private monitoring and then combining it with the belief-free nature.

Matsushima (2013) is related to this paper, which intensively studied g-TFT strategies in a class of prisoners' dilemma games that includes this paper's model [8]. This work corresponds to the theoretical benchmark of this paper, showing that the class of g-TFT strategies has the great advantage of equilibrium analysis compared with TFT.

The literature of experimental studies on repeated games has examined the determinants of cooperation and tested various theoretical predictions, in order to find clues to resolve the multiplicity problem. See Dal Bó and Fréchette (2014) for a review.

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[7] For the survey up to almost perfect private monitoring, see Mailath and Samuelson (2006).

[8] For other studies on g-TFT, see Nowak and Sigmund (1992) and Takahashi (1997).

The Strategy Frequency Estimation Method (SFEM), which is the methodology employed in this study, is frequently used in the literature of experimental repeated games. See Fudenberg, Rand, and Dreber (2012), Dal Bó and Fréchette (2011), Breitmoser (2015), Aoyagi, Bhaskar, and Fréchette (2015), for instance.

Importantly, this study includes g-TFT strategies and their variants in our SFEM list. Inclusion of such stochastic action choices is scant in the literature of experimental repeated game, with the exception of Fudenberg, Rand, and Dreber (2012). However, they include only a few g-TFT strategies just aiming to perform robustness checks for their main claims.[9] In contrast, we rigorously include many variants of g-TFT in our SFEM list to examine our subjects' retaliating policies.

3. The Model

This paper investigates a repeated game played by two players, i.e., player 1 and player 2, in the discrete time horizon. This game has a finite round-length, but the terminating round is randomly determined, and therefore, unknown to players. The component game of this repeated game is denoted by $(S_i, u_i)_{i \in \{1,2\}}$, where S_i denotes the set of all actions for player $i \in \{1, 2\}$, $s_i \in S_i$, $S \equiv S_1 \times S_2$, $s \equiv (s_1, s_2) \in S$, $u_i : S \to R$, and $u_i(s)$ denotes the payoff for player i induced by action profile $s \in S$ in the component game. We assume that each player $i's$ payoff has the following additively separable form:

$$u_i(s) = v_i(s_i) + w_i(s_j) \quad \text{for all} \quad s \in S, \text{ where } j \neq i.$$

The impact of a player's action choice on her (or his) welfare is *additively separable* from the impact of the opponent's action choice on her welfare.

At each round, two noisy signals $\omega_1 \in \Omega_1$ and $\omega_2 \in \Omega_2$ occur after their action choices are made, where Ω_i denotes the set of possible ω_i, $\omega \equiv (\omega_1, \omega_2)$, and $\Omega \equiv \Omega_1 \times \Omega_2$. A signal profile $\omega \in \Omega$ is randomly determined according to a conditional

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[9] The experimental setup in Fudenberg, Rand, and Dreber (2012) is imperfect public monitoring where the stochastic strategies have relatively less importance than the case of imperfect private monitoring.

probability function $f(\cdot \mid s): \Omega \to R_+$, where $\sum_{\omega \in \Omega} f(\omega \mid s) = 1$ for all $s \in S$, and we

assume *full support* in that $f(\omega \mid s) > 0$ for all $\omega \in \Omega$ and $s \in S$.

Let $f_i(\omega_i \mid s) \equiv \sum_{\omega_j \in \Omega_j} f(\omega \mid s)$, and we assume that $f_i(\omega_i \mid s)$ is independent of s_j.

We denote $f_i(\omega_i \mid s_i)$ instead of $f_i(\omega_i \mid s)$. We utilize $\omega_i \in \Omega_i$ to denote *the signal for

player $i's$ action choice.* Player $i's$ action choice s_i influences the occurrence of the

signal for her action choice ω_i, but does not influence the occurrence of the signal for

the opponent's action choice ω_j, where $j \neq i$.

We assume that monitoring is *imperfect*. At every round $t \in \{1, 2, ...\}$, each player i

cannot directly observe either the action, denoted by $s_j(t) \in S_j$, that the opponent $j \neq i$

has selected, or even the realized payoff profile, denoted by

$u(s(t)) = (u_1(s(t)), u_2(s(t))) \in R^2$, where we denote by $s(t) = (s_1(t), s_2(t)) \in S$ the action

profile selected at round t. Instead, player i observes the signal for the opponent $j's$

action choice $\omega_j(t) \in \Omega_j$, where $j \neq i$, through which, player i can not directly but

indirectly and imperfectly monitor the opponent $j's$ action choice $s_j(t)$.[10]

We assume that monitoring is *private*. Each player cannot know about what kind of

signal the opponent receives about her own action choice. Hence, each player i knows

her own action choice $s_i(t)$ and the signal for the opponent's action choice $\omega_j(t)$, but

does not know either the opponent's action choice $s_j(t)$ or the signal for her own action

choice $\omega_i(t)$.

The assumption of imperfect private monitoring, along with the assumption of the

above-mentioned independence, eliminates the impact of a player's observation about the

opponent's observation about her action choices. This environment enables us to focus

on the impact of monitoring imperfection about the opponent's action choices.

Let $h(t) = (s(\tau), \omega(\tau))_{\tau=1}^t$ denote the *history up to round t*. Let us denote by

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[10] Our specification of monitoring structure is in contrast with the previous works such as Green and Porter (1984) and Aoyagi and Fréchette (2009). These studies commonly assumed that the distribution of a noisy signal depends on all players' action choices, while we assume the above-mentioned independence.

$H = \{h(t) \mid t = 0,1,...\}$ the set of possible histories, where $h(0)$ implies the null history. *The average payoff for player i when the history $h(t) \in H$ up to round t occurs* is defined as

$$U_i(h(t)) \equiv \frac{\sum_{\tau=1}^{t} u_i(s(\tau))}{t}.$$

From additive separability, this average payoff can be rewritten as

(1) $U_i(h(t))$

$$= \frac{1}{t} [|\{\tau \in \{1,...,t\} \mid s_i(\tau) = A\}| v_i(A) + |\{\tau \in \{1,...,t\} \mid s_i(\tau) = B\}| v_i(B)$$

$$+ |\{\tau \in \{1,...,t\} \mid s_j(\tau) = A\}| w_i(A) + |\{\tau \in \{1,...,t\} \mid s_j(\tau) = B\}| w_i(B)].$$

This paper specifies the component game as a *prisoners' dilemma with symmetry and additive separability* as follows. For each $i \in \{1,2\}$,

$$S_i = \{A, B\}, \quad v_i(A) = -Y, \quad v_i(B) = 0, \quad w_i(A) = X + Y, \text{ and}$$

$$w_i(B) = X + Y - Z,$$

where X, Y, and Z are positive integers, and

$$Z > Y > 0.$$

This specification implies

$$u_1(A, A) = u_2(A, A) = X,$$

$$u_1(B, B) = u_2(B, B) = X + Y - Z,$$

$$u_1(A, B) = u_2(B, A) = X - Z,$$

and

$$u_1(B, A) = u_2(A, B) = X + Y.$$

Let us call A and B the *cooperative* action and the *defective* action, respectively.

Selecting the cooperative action A instead of the defective action B costs Y, but gives the opponent the benefit Z, which is greater than Y. Note that the payoff vector induced by the cooperative action profile (A, A), i.e., (X, X), maximizes the welfare $u_1(s) + u_2(s)$ with respect to $s \in S$, and is greater than the payoff vector induced by the defective action profile (B, B), i.e., $(X + Y - Z, X + Y - Z)$, because $Z > Y$. Note also

that the defective action profile (B,B) is a dominant strategy profile and the unique Nash equilibrium in the component game.

We further specify the monitoring structure as

$$\Omega_i = \{a,b\}, \quad f_i(a \mid A) = f_i(b \mid B) = p, \text{ and } \frac{1}{2} < p < 1.$$

Let us call a and b the *good* signal and the *bad* signal, respectively. The probability index p implies the level of *monitoring accuracy*. The greater p is, the more accurately each player can monitor the opponent's action choice. The inequality $p > \frac{1}{2}$ implies that the probability of the good signal for a player occurring is greater when this player selects A than when she selects B.

For each history $h(t) \in H$ up to round t, we define the *frequency of cooperative action choice* A, or, the *cooperation rate*, by

$$\rho(h(t)) \equiv \frac{\left|\{\tau \in \{1,...,t\} \mid S_1(\tau) = A\}\right| + \left|\{\tau \in \{1,...,t\} \mid S_2(\tau) = A\}\right|}{2t}.$$

From (1) and symmetry, it follows that the *sum of the average payoffs, i.e., the welfare in average, when the history* $h(t) \in H$ *up to round* t *occurs* is given by

(2) $\qquad U_1(h(t)) + U_2(h(t))$

$\qquad\qquad = 2[\rho(h(t))\{v_1(A) + w_1(A)\} + \{1 - \rho(h(t))\}\{v_1(B) + w_1(B)\}]$

$\qquad\qquad = 2[\rho(h(t))X + \{1 - \rho(h(t))\}(X + Y - Z)]$

$\qquad\qquad = 2[X + \{1 - \rho(h(t))\}(Y - Z)].$

From (2), *the cooperation rate* $\rho(h(t))$ *uniquely determines the welfare* $U_1(h(t)) + U_2(h(t))$.

We assume *constant random termination*, where $\delta \in (0,1)$ denotes the probability of the repeated game continuing at the end of each round t, provided this game continues up to round $t-1$. Hence, the repeated game is terminated at the end of each round $t \geq 1$ with a probability $\delta^{t-1}(1-\delta)$. The expected length of the repeated game is given by

$$\sum_{t=1}^{\infty} \delta^{t-1}(1-\delta)t.$$

Throughout our experiments, we assume that

$\qquad \delta = 0.967 \quad (=29/30),$

implying that the continuation probability is very high, which mimics the discount factor that is sufficiently large to support the existence of equilibria in which players collude with each other in infinitely repeated interactions.

4. Generous Tit-For-Tat Equilibrium

Let $\alpha_i \in [0,1]$ denote a stochastic action choice for player i, implying the probability that she makes the cooperative action choice A. Player $i's$ strategy in the repeated game is defined as $\sigma_i : H \to [0,1]$. According to σ_i, she selects the cooperative action A with the probability of $\sigma_i(h(t-1))$ at each round t, provided the history $h(t-1)$ up to round $t-1$ occurs. Let Σ_i denote the set of all strategies for player i. Let $\sigma \equiv (\sigma_1, \sigma_2)$ and $\Sigma \equiv \Sigma_1 \times \Sigma_2$.

The *expected payoff for player i induced by $\sigma \in \Sigma$ when the level of monitoring accuracy is given by $p \in (0,1)$ is defined as*

$$U_i(\sigma; p) \equiv (1-\delta) E[\sum_{\tau=1}^{\infty} \delta^{\tau-1} u_i(s(\tau)) \mid \sigma, p],$$

or, equivalently,

$$U_i(\sigma; p) = \frac{E[\sum_{t=1}^{\infty} \delta^{t-1}(1-\delta) \sum_{\tau=1}^{t} u_i(s(\tau)) \mid \sigma, p]}{\sum_{t=1}^{\infty} \delta^{t-1}(1-\delta)t}$$

$$= \frac{E[\sum_{t=1}^{\infty} \delta^{t-1}(1-\delta)t U_i(h(t)) \mid \sigma, p]}{\sum_{t=1}^{\infty} \delta^{t-1}(1-\delta)t},$$

where $E[\cdot \mid \sigma, p]$ denotes the expectation operator conditional on (σ, p). *The expected frequency of cooperative action choice A, i.e., the expected cooperation rate, induced by $\sigma \in \Sigma$ when the monitoring accuracy is given by $p \in (0,1)$ is defined as*

$$\rho(\sigma;p) \equiv \frac{E[\sum_{t=1}^{\infty} \delta^{t-1}(1-\delta)t\rho(h(t)) \mid \sigma, p]}{\sum_{t=1}^{\infty} \delta^{t-1}(1-\delta)t}.$$

From additive separability and (2), it follows that

$$U_1(\sigma;p) + U_2(\sigma;p) == \frac{E[\sum_{t=1}^{\infty} \delta^{t-1}(1-\delta)t\{U_1(h(t)) + U_2(h(t))\} \mid \sigma, p]}{\sum_{t=1}^{\infty} \delta^{t-1}(1-\delta)t}$$

$$= 2[X + \{1 - \rho(\sigma;p)\}(Y - Z)].$$

Hence, *the expected cooperation rate* $\rho(\sigma;p)$ *uniquely determines the sum of the expected payoffs, i.e., the welfare in expectation* $U_1(\sigma;p) + U_2(\sigma;p)$. A strategy profile $\sigma \in \Sigma$ is said to be *a (subgame perfect) equilibrium* in the repeated game with monitoring accuracy $p \in (0,1)$ if

$$U_i(\sigma;p) \geq U_i(\sigma_i', \sigma_j; p) \quad \text{for all} \quad i \in \{1,2\} \quad \text{and all} \quad \sigma_i' \in \Sigma_i .^{[11]}$$

We introduce a class of strategies, namely, *generous Tit-For-Tat strategies,* as follows. A strategy $\sigma_i \in \Sigma_i$ is said to be *generous Tit-For-Tat* (*g-TFT*) if there exists $(q, r(a), r(b)) \in [0,1]^3$ such that

$$r(a) > 0,$$

$$\sigma_i(h(0)) = q,$$

for every $t \geq 2$ and $h(t-1) \in H$,

$$\sigma_i(h(t-1)) = r(a) \quad \text{if} \quad \omega_j(t-1) = a,$$

and

$$\sigma_i(h(t-1)) = r(b) \quad \text{if} \quad \omega_j(t-1) = b.$$

At round 1, player i makes the cooperative action choice A with the probability of q. At each round $t \geq 2$, player i makes the cooperative action choice A with the probability of $r(\omega_j)$ when she observes the signal $\omega_j(t-1) = \omega_j$ for the opponent's

[11] The full-support assumption makes the distinction between Nash equilibrium and subgame perfect Nash equilibrium redundant.

action choice at round $t-1$. We will simply write $(q, r(a), r(b))$ instead of σ_i for any g-TFT strategy.

A g-TFT strategy $(q, r(a), r(b))$ is said to be an *equilibrium* in the repeated game with accuracy $p \in (0,1)$ if the corresponding symmetric g-TFT strategy profile is an equilibrium in the repeated game with accuracy p. Let us define

(3)
$$w(p) \equiv \frac{Y}{\delta(2p-1)Z}.$$

Note that

$$0 < w(p) \leq 1 \text{ if and only if } \delta \geq \frac{Y}{(2p-1)Z}.$$

The following theorem shows that a g-TFT strategy $(q, r(a), r(b))$ is an equilibrium if and only if the difference in cooperation rate between the good signal and the bad signal, i.e., $r(a) - r(b)$, is equal to $w(p)$.

Theorem 1: *A g-TFT strategy $(q, r(a), r(b))$ is an equilibrium in the repeated game with accuracy p if and only if*

(4)
$$\delta \geq \frac{Y}{(2p-1)Z},$$

and

(5)
$$r(a) - r(b) = w(p).$$

Proof: Selecting $s_i = A$ instead of B costs player i Y at the current round, whereas at the next round, she (or he) can gain Z from the opponent's response with probability $pr(a) + (1-p)r(b)$ instead of $(1-p)r(a) + pr(b)$. Since she must be incentivized to select both action A and action B, the indifference between these action choices must be a necessary and sufficient condition, i.e.,

$$-Y + \delta Z\{pr(a) + (1-p)r(b)\} = \delta Z\{(1-p)r(a) + pr(b)\},$$

that is,

$$Y = \delta Z(2p-1)\{r(a) - r(b)\},$$

implying (5). Since $r(a) - r(b) \le 1$, $1 \ge \dfrac{Y}{\delta(2p-1)Z}$, i.e., the inequality (4), must hold.

Q.E.D.

From Theorem 1, whenever $\delta \ge \dfrac{Y}{(2p-1)Z}$, by setting $r(a) - r(b) = w(p)$, we can always construct a g-TFT equilibrium. This implies the advantage of the investigation of g-TFT strategies instead of the TFT strategy in equilibrium analyses, because the profile of the TFT strategies is not an equilibrium as long as $\delta \ne \dfrac{Y}{(2p-1)Z}$, while g-TFT equilibrium always exists whenever $\delta \ge \dfrac{Y}{(2p-1)Z}$.[12]

This paper regards the observed difference in cooperation rate between the good signal and the bad signal as the intensity that subjects retaliate against their opponents. We name it *the retaliation intensity*. Note from Theorem 1 that if subjects play a g-TFT equilibrium, then the resultant retaliation intensity is approximately equal to $w(p)$.

Importantly, the retaliation intensity implied by the g-TFT equilibria $w(p)$ is *decreasing in p*. The less accurate the monitoring technology is, the more severely players retaliate against their opponents. This decreasing property is essential for understanding how players overcome the difficulty of achieving cooperation under imperfect private monitoring.

In order to incentivize a player to make the cooperative action choice, it is necessary that her opponent makes the defective action choice when observing the bad signal more often than when observing the good signal. In other words, *the retaliation intensity must be positive*. When monitoring is inaccurate, it is hard for her opponent to detect whether the player actually makes the cooperative action choice or the defective action choice. In this case, the enhancement in retaliation intensity is necessitating for incentivizing the

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[12] Note that the g-TFT equilibrium does not depend on the assumption that ω_1 and ω_2 are independently distributed. Whether a g-TFT strategy is equilibrium or not is irrelevant to whether monitoring is private or public. For instance, any g-TFT strategy that satisfies (4) and (5) is an equilibrium even if each player can observe both ω_1 and ω_2, i.e., even under imperfect public monitoring.

player. Hence, *the retaliation intensity must be decreasing in the level of monitoring accuracy*.

This decreasing property plays the central role in improving the welfare by utilizing the noisy signals as much as possible. Since monitoring is imperfect, it is inevitable that the opponent observes the bad signal even if the player actually makes the cooperative action choice. This inevitably causes the welfare loss to occur, because the opponent might retaliate against the player even when the player actually makes the cooperative action choice. In this case, if the monitoring technology is more accurate, the opponent can well incentivize the player with being less sensitive to whether the observed signal is good or bad, safely making the retaliation intensity lower. This serves to decrease the welfare loss caused by the monitoring imperfection. Hence, it is very crucial in welfare consideration to examine whether the experimental results satisfies this decreasing property.

This study experimentally evaluates the retaliation intensities. We will regard g-TFT strategies as the most appropriate theoretical benchmark. G-TFT strategies are the straight-forward stochastic extensions of the well-known Tit-For-Tat strategy, extended to have simple subgame perfect equilibria in imperfect private monitoring. G-TFT strategies often appear as the canonical strategies in the theoretical development of equilibrium with private monitoring. Not merely is the existence of the equilibria guaranteed, but also, g-TFT strategies are the only equilibrium strategies that provide the simple, analytically tractable characterization. The analytical tractability is appealing in the empirical investigation of retaliation intensities.

5. Experimental Design

We conducted four sessions of the computer-based laboratory experiments[13] at the Center for Advanced Research for Finance (CARF), University of Tokyo in October 2006. We recruited 108 subjects in total from the subject pool consisting of undergraduate and graduate students in various fields. Our subjects were motivated with monetary incentives; the earned points in the experiments were converted into Japanese Yen with a

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[13] The experiment was programmed and conducted with the software z-Tree (Fischbacher (2007)).

fixed rate (0.6 JPY per point). Additionally our subjects are paid a fixed participation fee, which is 1,500 JPY.

As demonstrated in Section 3, to make the structure of the game simplest, we adopt the prisoners' dilemma with symmetry and additive separability for our component game, in which payoff parameters are characterized as $(X, Y, Z) = (60, 10, 55)$. The payoff parameters have a structure in which the cost for cooperation Y is small so that the g-TFT equilibria exist even if the monitoring technology is poor. The payoff matrix employed in the experiment is displayed in Table 1. The labels on the actions and signals are presented in neutral language (i.e. the actions are labeled "A" and "B" instead of "cooperation" and "defection", and the signals are labeled "a" and "b" instead of "good" and "bad").

[TABLE 1 HERE]

The experiments have two treatments on the monitoring accuracy; one treatment is the case in which the monitoring accuracy is high. In this treatment, the signals the player observes and the action choices by the opponent coincide with 90% chance ($p = 0.9$), and mismatch with 10% chance. We refer this treatment as "high accuracy treatment". The other treatment is the case in which the monitoring technology is poorer. The signals match with the opponent's action choices with only 60% chance ($p = 0.6$), which is slightly larger than the chance level (50%). We refer this treatment as "low accuracy treatment".

All subjects in the four sessions received both treatments, but the treatment order is counter-balanced to minimize order effects. First two sessions (52 subjects) started with three repeated games of the low accuracy treatment then proceeded to three repeated games of the high accuracy treatments. Second two sessions (56 subjects) are conducted in the reverse order, which started with the high accuracy treatment then proceeded to the low accuracy treatment. Each treatment is preceded with a short practice repeated game which consists of two rounds, to let the subjects understand the new treatment. Subjects were randomly paired at the start of each repeated game, and the pairs remained unchanged until the end of the repeated game. The summary of the treatment order,

number of subjects, game lengths in repeated games which are determined by the continuation probability that is explained soon, are displayed in Table 2.

[TABLE 2 HERE]

We employ Constant Random Termination in our experiment to mimic the infinitely repeated interactions. Each repeated game is to be terminated at each round with a constant probability. We let the continuation probability be $\delta = 0.967 (= 29/30)$.

With the probability of $1 - \delta \, (= 1/30)$, the repeated game was terminated at the current round, and subjects were re-matched with a new opponent and proceeded to the next repeated game. Indeed our subjects were not informed in advance which round is the final round for each repeated game, otherwise we were not able to mimic infinitely repeated games due to "the shadow of the future" (Dal Bó (2005)). To help our subjects understand that the termination rule is stochastic and the probability of termination at each round is 1/30, we presented 30 cells (numbered from 1 to 30) in the computer screen at the end of each round; one number is selected randomly at the end of each round, and the repeated game is terminated if the number 30 is selected by chance and the 30th cell in the computer screen turns to green, otherwise all the cells numbered 1 to 29 turns to green at once and the repeated game continues. The screen is demonstrated in Figure A.1 and A.2 in Appendix 1.

Each subject is informed of the rule of games demonstrated above and the ways in which the game is processed in the computer screen with the aid of printed experimental instructions. The instruction is also explained aloud by a recorded voice. Moreover, on the computer screen during the experiments, our subjects were always able to look over the structure of the game (the payoff matrix and the accuracy of the signals in the treatment), the history up to the round in the repeated game, that consists of the actions of her own and the signals on the opponent's actions.[14]

6. Aggregate Level Analysis of Experimental Results

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[14] See Appendix 6 for the experimental instructions and the images of the computer screen, translated in English from the original Japanese version.

6.1. Overall Cooperation Rates and Round 1 Cooperation Rates

[TABLE 3 HERE]

Table 3 displays the descriptive summary of the data. The entire 108 subjects made 8,864 decisions in the high accuracy treatment, and 9,144 in the low accuracy treatment. The overall frequency of cooperative choices, i.e., the cooperation rate, is 0.672 in the high accuracy treatment, and 0.355 in the low accuracy treatment. The former is statistically significantly larger than the latter ($p < 0.001$, Wilcoxon matched-pair test for individual-level means). The first look of the cooperation rates suggests that our subjects cooperate more as the monitoring technology is improved. As shown in Section 4, the cooperation rate uniquely determine the welfare of the players in our payoff setting (the additive separable payoff structure). The larger cooperation rate in the high accuracy treatment indicates that the welfare is improved in the high accuracy treatment.

To examine our subjects' attitude for cooperation more directly, we focus on round 1 cooperation rates (the frequency of cooperative action choices at round 1). The round 1 cooperation rates are one of the primary measures that directly reflect subjects' motivation for cooperation under the structure of the game (i.e. payoff parameters, discount factor, and most importantly in our study, monitoring accuracy), independently from the history of the incoming signals in the latter rounds, and also independently from the behavior of the opponent matched in the repeated game.

[TABLE 4 HERE]

Table 4 presents the frequency of cooperation at round 1. The round 1 cooperation rate is 0.781 in the high accuracy treatment, and 0.438 in the low accuracy treatment, which is significantly smaller ($p < 0.001$) than the former. Our subjects tend to start repeated games with cooperative action choices in the high accuracy treatment, however, their motivation for cooperation is discouraged as the noise in the signal is increased, to the extent that they start with cooperative actions with less than 50% chance. This result

is somewhat surprising given that the experimental parameters (i.e. payoff parameters and discount factor) are conductive to the g-TFT cooperative equilibria even in the low accuracy treatment. Despite the favorable environment for cooperation, our results indicate that, from the start, non-negligible number of our subjects turn to be reluctant to cooperate in the low accuracy treatment.

These results also imply that our subjects differentiate their strategies between the two treatments. Reacting to the change of the signal quality, perhaps they switch their strategies from cooperative ones in the high accuracy treatment to less cooperative ones in the low accuracy treatment. We explore the specific strategies our subjects follow in each treatment in Section 9.

6.2. Signal-Contingent Cooperation Rates

Table 4 also displays signal-contingent cooperation rates. The frequency of cooperative actions after observing a good signal, denoted by $r(a; p)$, computed as the simple mean of entire choices, is 0.852. We also report the alternative value which is the mean of individual-level means, concerned with the possibility that the behavior of the cooperative subjects might be over-represented in the simple mean of choices.[15] The mean of the individual-level means is 0.788, which is smaller by 0.064 than the simple mean of choices, which implies that the over-representation might be the case. However, both two measures are consistently high and reaching around 0.8, indicating that our subjects are quite cooperative when they observe a good signal in the high accuracy treatment.

In the low accuracy treatment, the cooperation rate after observing a good signal is not as high as observed in the high accuracy treatment. The simple mean of the cooperative choices is 0.437, and the mean of individual-level means is 0.423. Both low values in the cooperation rates around 0.43 indicate that, similarly to the case of the round 1 cooperation rate, our subjects are reluctant to cooperate even after observing good signals in the low accuracy treatment, opposed to the case in the high accuracy treatment.

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[15] Since the subjects who are cooperative might observe good signals more often and take cooperative actions more, their cooperative choices might be over-represented in the computation of cooperation rates contingent on a good signal.

The direct comparison of the cooperation rates between the two treatments indicates that the cooperation rate in the high accuracy treatment is larger than that in the low accuracy treatment ($p < 0.001$ for both the simple mean and the mean of individual-level means).

As to the case of the cooperation rates after observing a bad signal, denoted by $r(b; p)$, the simple mean of cooperative choices in the high accuracy treatment is 0.344. Again, we also report the mean of individual-level means concerned with the over-representation of the subjects who tend to retaliate more. The value is 0.443, which is larger than the simple mean of choices by 0.104, demonstrating that the concern might be the case here. However, still both measures are below 50%, indicating that our subjects tend to defect rather than cooperate after observing a bad signal in the high accuracy treatment.

This tendency of our subjects taking defections after observing a bad signal is more apparent in the low accuracy treatment. The simple mean of cooperative actions over the entire choices is 0.272 and the mean of the individual-level means is 0.279, which are consistently smaller than those in the high accuracy treatment ($p < 0.001$ for both of the means). Observing a bad signal, our subjects tend to take more defections in the low accuracy treatment than in the high accuracy treatment.

The overall picture on the round 1 cooperation rates and the signal-contingent cooperation rates shown above robustly demonstrate that our subjects take more cooperative actions under the better signal quality, irrespective of signals they observe.

RESULT 1-a: Our subjects tend to cooperate more in the high accuracy treatment than in the low accuracy treatment, adapting their strategies according to the signal accuracy.

6.3. Retaliation Intensity

[TABLE 5 HERE]

Now we focus on the retaliation intensities which is one of our primary concern of the study. We examine whether the observed retaliation intensities coincide with the values implied by the g-TFT equilibria ($w(p)$). Table 5 presents the retaliation intensities

in the aggregate level. In the high accuracy treatment, the retaliation intensity $r(a; 0.9) - r(b; 0.9)$ is 0.508 in the mean of entire choices and 0.352 in the mean of individual-level means. Again, the discrepancy might be due to over-representation. However, both measures of the retaliation intensity consistently differ from zero statistically significantly (p < 0.001 for both measures). These results indicate that our subjects use signal-contingent information in their action choices, perhaps attempting to incentivize the opponent to cooperate.

In comparison to the theoretical values implied by the g-TFT equilibria, both measures of the retaliation intensity in the high accuracy treatment are statistically significantly larger than the theoretical values ($w(0.9) = 0.235$, p < 0.001 for both measures). Thus, empirically, our subjects tend to rely on stronger punishments which are more than enough to incentivize the opponents to take cooperative actions in the high accuracy treatment.

On the other hand in the low accuracy treatment, the observed retaliation intensity $r(a; 0.6) - r(b; 0.6)$ is 0.165 in the simple mean of entire choices, and 0.144 in the mean of individual-level means. The two measures consistently differ from zero significantly (p < 0.001 for both measures), which demonstrates that, similarly to the case of the high accuracy treatment, our subjects also use the signal-contingent information even in the poorer monitoring technology. However, unlike the case of the high accuracy treatment, the observed retaliation intensity in the low accuracy treatment is smaller than the level implied by the g-TFT equilibria. Both measures of the retaliation intensity are outstandingly smaller than the theoretically implied value $w(0.6) = 0.94$ (both for p < 0.001). Although our subjects do retaliate according to the signals in the low accuracy treatment, however, the strength of the retaliation is far below the level enough to incentivize the opponents to cooperate, allowing the opponents to defect permanently to pursue larger payoffs.[16]

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[16] One might concern that the seemingly weaker retaliation intensities observed here do not necessarily imply weak retaliation policies of our subjects, since our subjects might use long-term (multi-round) punishments; long-term punishing strategies punish opponents even observing a good signal during punishing phases, which could lower the retaliation intensity computed here. However, our analysis in Section 8 indicates that only a marginal number of our subjects could take long-term punishing strategies, hence the effect by long-term punishments is minimum.

The retaliation intensities are not only inconsistent with the values implied by the g-TFT equilibria, but also the deviation is systematic. The direct comparison of the retaliation intensities between the two treatments indicates that the retaliation intensity in the high accuracy treatment is larger than that in the low accuracy treatment ($p < 0.001$). This is diametrically opposite to the implication by the g-TFT equilibria in which people should employ weaker retaliating policies in the high accuracy treatment than in the low accuracy treatment.

RESULT 2-a: Our subjects tend to retaliate more than the level implied by the g-TFT equilibria in the high accuracy treatment, while they tend to retaliate weaker in the low accuracy treatments. Moreover, opposed to the implications by the standard theory, the retaliation intensity is larger in the improved monitoring technology.

6.4. Reliance on Long Memories

In relation to the behavioral difference of our subjects along with signal qualities, it is also interesting to examine whether our subjects tend to rely on longer histories of signals (i.e. signals two periods ago). Given the theories in review strategies (Radner (1986), Matsushima (2004), and Sugaya (2012)), one presumably assumes that people rely on signals in longer histories to compensate the informational disadvantages in poorer monitoring technologies.

To test whether our subjects rely on information in a signal occurring two periods ago, here we fit the data with a probabilistic linear regression model, regressing the action choices (a dummy variable which takes one if our subjects play cooperation) on all memory-1 histories which consist of a signal and an action at the previous round, and further include information of a signal two period ago into the set of the explanatory variables to the extent that the non-singularity holds without intercept.[17] The regression coefficients on the signal two period ago capture the additional impact on cooperation probabilities from the signal. The standard error is computed by a cluster-bootstrap

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[17] We borrow this approach in Breitmoser (2015).

(subject and repeated game level) to control subject heterogeneity, which is also used to compute the p-value.

[TABLE 6 HERE]

Table 6 displays the regression results. Opposed to the speculation above, the regression coefficients on the information two period ago are exclusively significant only in the high accuracy treatment, and none is significant in the low accuracy treatment. Even in the high accuracy treatment, the size of the coefficients are only marginal, as the maximum impact on cooperative choices is only 13.2%.

RESULT 3-a: There is no evidence that our subjects tend to review longer periods in the low accuracy treatment. Although their actions partly depend on the information two period ago in the high accuracy treatment, the dependencies are marginal in the aggregate level.

6.5. Impact of Experiences

Several existing studies often reported that the frequency of cooperation changes as people experience playing repeated games (see discussion in Dal Bó and Fréchette (2014)). Since the welfare is uniquely determined by the overall cooperation rates in our payoff setting (the additive separability payoff structure), the shift of the overall cooperation rates imply the shift of welfare of the two players.

To examine the impact of the experience of repeated games on overall cooperation rates, we perform the reduced-form, linear regression analysis, explained in Appendix 2 in details. The results indicate that, although there are some experience effects on action choices, the sizes of the effects are not remarkably large in our data. We also find qualitatively similar results on signal-contingent cooperation rates which are also reported in Appendix 2.

We also investigate the effect of experience on retaliation intensities. Here we perform a similar, reduced-form regression analysis, explained in Appendix 2 in details.

The results indicate that the retaliation intensities do not change remarkably as our subjects gain experience.

7. Estimation of Individual Strategies - Methodology

In this and the following sections, we present the direct estimation of individual strategies of our subjects. Given the recent consensus in the literature of experimental repeated game that there is substantial heterogeneity of strategies subjects employ (see Dal Bó and Fréchette (2014) for a review), we do not specifically pick up only a single class of strategy (i.e. g-TFT) and fit the data to determine the model parameters. Rather, we list various strategies our subjects could take, and estimate the frequency that each strategy emerges among our subjects to assess the prevalence of the strategies. The primary goal of the exercise here is to verify our findings in Section 6 and to perform more detailed analyses on g-TFT strategies and retaliation intensities from the viewpoint of individual strategies.

The methodology we employ here is the Strategy Frequency Estimation Method (SFEM) developed by Dal Bó and Fréchette (2011). The SFEM is a maximum likelihood estimation (MLE) of a finite mixture model of strategies subjects individually use, where model parameters to be estimated are the frequencies of each strategy emerging among subjects, and the parameter γ which controls stochastic mistakes of action choices or implementation error, whose probability of occurrence is $1/(1+\exp(1/\gamma))$. The details of the computation of the likelihood is provided in Appendix 3. The underlying assumption is that each subject keeps employing a specific strategy across all repeated games in each treatment. The validity of this method is verified in the Monte-Carlo simulations in Fudenberg, Rand, and Dreber (2012), in which, closely related to our study, they correctly dissociate g-TFT players from players employing other strategies.

In Appendix 4, we perform robustness checks of the SFEM estimates using only the final two repeated games. The SFEM estimates have little changes in both treatments, which would not occur if our subjects systematically changed their strategies across repeated games. This is also consistent with our findings in Section 6 where we do not find remarkable changes in either the cooperation rates or the retaliation intensities as our

subjects gain experiences across repeated games.

[TABLE 7 HERE]

In the SFEM framework, the strategy set considered in the estimation are pre-specified. Given the difficulty to cover all possible set of strategies, we only include the strategies that share significant proportions in existing studies on experimental repeated games as well as g-TFT which is our primary focus. Table 7 displays the list of the strategies in our SFEM. The list includes TFT, TF2T, TF3T, 2TFT, 2TF2T, Grim (trigger strategy),[18] Grim-2, Grim-3, All-C (always cooperate) and All-D (always defect), which are typically listed in the literature of infinitely repeated games in imperfect monitoring (Fudenberg, Rand, and Dreber (2012) for an instance).[19] Among them All-D is a non-cooperative strategy, while other strategies (TFT, TF2T, TF3T, 2TFT, 2TF2T, Grim, Grim-2, Grim-3, All-C) are regarded as cooperative strategies which play cooperation at the starts of each repeated game, and keep cooperating unless they believe the opponent might switch to defect. TF2T, TF3T, 2TF2T, Grim-2 and Grim-3 are "lenient" strategies (Fudenberg, Rand, and Dreber (2012)) that start punishing only after observing several consecutive occurrence of bad signals. TF2T (TF3T) retaliates once after observing two (three) consecutive bad signals, and 2TF2T retaliate twice after observing two consecutive bad signals, corresponding a simple form of so-called "review strategies" (lenient strategies with long-term punishments in the proof of the limit folk theorem (see Matsushima (2004) and Sugaya (2012))). Grim-2 (Grim-3) is a lenient variant of Grim strategy, which triggers to keep defecting after observing two (three) consecutive deviations from (a, A), the combination of good signal from the opponent and own cooperative choice.

Importantly, motivated with the theoretical importance of g-TFT in imperfect private

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[18] Here the definition of Grim strategy is modified to cover the private monitoring case where no common signals are observable. The player starts to keep playing defection if she observed a bad signal or she played defection in the previous round. Note that she could mistakenly play defection before the "trigger" is pulled, since the implementation error of action choices are allowed in the SFEM framework.

[19] Literature often add D-TFT in the strategy set, which plays defection at round 1 then follows TFT from Round 2. However, we do not find any significant frequency of D-TFT in both treatments in our SFEM estimates even if we include it.

monitoring, we also include g-TFT in the list. Inclusion of g-TFT is scant in the literature of experimental repeated games. The only exception is Fudenberg, Rand, and Dreber (2012), in which they find that at least a certain share of their subjects follow g-TFT even in imperfect public monitoring where g-TFT is relatively less important. However, their discussion on g-TFT is merely incomplete since they include g-TFT just aiming to perform robustness checks for their main claims that are less relevant to g-TFT, and left further discussions unanswered. Rather in this study, to address the implications of g-TFT and associated retaliation intensities more rigorously in imperfect private monitoring, we add many variants of g-TFT in our SFEM strategy to dissociate strategies with various retaliation intensities.

Following Fudenberg, Rand, and Dreber (2012), we pre-specify probabilities of retaliation, or equivalently, probabilities of cooperation after observing a bad signal in g-TFT (i.e. $r(b)$) in our strategy set. We allow the probabilities of cooperation given a bad signal to take nine distinct values with the increment by 12.5%, which are 100%, 87.5%, 75%, 62.5%, 50%, 37.5%, 25%, 12.5%, and 0%. Moreover, to cover the case that our subjects might play defections even after observing a good signal (i.e. $r(a) < 1$), we also allow stochastic defections given a good signal. The probabilities of cooperation given a good signal (i.e. $r(a)$) are allowed to take the nine distinct values with the increment by 12.5%, which are 100%, 87.5%, 75%, 62.5%, 50%, 37.5%, 25%, 12.5% and 0%. Here g-TFT-$r(a)$-$r(b)$ denotes the g-TFT which plays cooperation stochastically after observing a good signal with the probability of $r(a)$, and takes cooperation stochastically after observing a bad signal with the probability of $r(b)$.[20] We list all the possible combinations of $r(a)$ and $r(b)$ in g-TFT in our strategy set as long as the g-TFT has a non-negative retaliation intensity (i.e. $r(a) \geq r(b)$). Specifically we refer the g-TFT strategies playing cooperation with constant probabilities r irrespective of signals as Random strategies (equivalent to g-TFT-r-r), denoted by Random-r, as primitive, signal non-contingent, zero retaliation variants of g-TFT including All-C and All-D as the special cases. We regard a g-TFT strategy as non-cooperative if the g-TFT is less

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[20] For simplicity, we assume the probability of playing cooperation at round 1 coincides with the choice probability given a good signal (i.e. $r(a)$).

cooperative than Random-0.5. More specifically, a g-TFT is regarded as non-cooperative if the $r(a)$ and $r(b)$ in the g-TFT are no more than 0.5, otherwise the g-TFT strategies are cooperative.

Besides including these g-TFT strategies in the list, we also add a family of g-2TFT as the strategies which perform even stronger punishments than TFT. The motivation comes from our earlier analysis in Section 6, in which we find that our subjects aggregately take stronger retaliation intensities than the level implied by the standard theory in the high accuracy treatment. The family of g-2TFT strategies (g-2TFT-r) allows the second retaliations to be stochastic (play cooperation with the probability of r in the second punishment) as the generous variants of 2TFT.[21] Conservatively, we also include a family of g-TF2T (g-TF2T-r) as the generous variants of TF2T which allow stochastic punishments if two consecutive bad signals occur (play cooperation with the probability of r after observing two consecutive bad signals).[22]

8. Estimation of Individual Strategies - Results

8.1. Cooperative Strategies and Non-Cooperative Strategies

[Table 8 HERE]

[Table 9 HERE]

Table 8 presents the estimates for the frequencies of strategies our subjects follow, and Table 9 displays the aggregated frequencies. First, we focus on the share of cooperative strategies in both treatments. Our finding in Section 6 suggests that our

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[21] Unlike g-TFT, in g-2TFT we do not allow defections until punishing phases start. Allowing defections outside of punishing phases start reduce the retaliation intensities, which is contradictory to the motivation for employing stronger (multi-round) punishments than the punishment attainable in only one round. Also, the strategies are assumed to play cooperation at round 1 similarly to TFT, as just multi-round punishing variants of TFT.

[22] Unlike g-TFT, in g-TF2T we do not allow defections until punishing phases start, since defections outside of punishing phases are contradictory to the motivation for employing lenient strategies that allow "giving the benefit of the doubt" to an opponent on the first defection (Fudenberg et al. (2012)). With the same reason, the strategies are assumed to play cooperation at round 1.

subjects take cooperative strategies in the high accuracy treatment, but do not necessarily take cooperative strategies in the low accuracy treatment. Here we further examine the specific shares of the cooperative strategies.

In the high accuracy treatment, cooperative strategies, i.e., other strategies than All-D, Random with the cooperation rate no more than 0.5 and g-TFT which are less cooperative than Random-0.5 (g-TFT-0.5-$r(b)$, g-TFT-0.375-$r(b)$, g-TFT-0.25-$r(b)$, and g-TFT-0.125-$r(b)$), exceed non-cooperative strategies, i.e., All-D, Random with the cooperation rate no more than 0.5, and g-TFT with is less cooperative than Random-0.5 (g-TFT-0.5-$r(b)$, g-TFT-0.375-$r(b)$, g-TFT-0.25-$r(b)$, and g-TFT-0.125-$r(b)$). The share of the cooperative strategies is 83.9%, and that of the non-cooperative strategies is the rest, which is 16.1%. The latter share is statistically significantly smaller than the former (p < 0.001). Although there are considerable heterogeneities in the strategies our subjects follow as seen in Table 8, most of our subjects take cooperative strategies in the high accuracy treatment.

On the contrary, our subjects tend to take non-cooperative strategies more in the low accuracy treatment. The share of cooperative strategies drops to 34.7% and the non-cooperative strategies share 65.3%. The share of non-cooperative strategies in the low accuracy treatment is statistically significantly larger than that in the high accuracy treatment (p < 0.001). Individually, the share of All-D is the most, which is 19.0%.

The finding that the share of non-cooperative strategies is considerable in the low accuracy treatment is consistent with the previous finding in Section 6 that the round 1 cooperation rate remains low, reaching to only 43.3% in the low accuracy treatment. Here, our SFEM estimates further indicate that indeed more than half of our subjects follow non-cooperative strategies in the low accuracy treatment.

This result on the large share of non-cooperative strategies is somewhat surprising given that the payoff parameters and discount factor are conductive to the g-TFT cooperative equilibria even in the low accuracy treatment. The complexity of the equilibrium cooperative strategy is not the primary impediment to follow cooperative strategies since the equilibrium cooperative strategy in the low accuracy treatment is approximately TFT in our experimental setup, which is quite simple to implement. Rather, our result implies that the poor signal quality in the low accuracy treatment somewhat

strongly discourages our subjects to take cooperative strategies.

With respect to this point, Fudenberg, Rand, and Dreber (2012) reported in their imperfect public monitoring experiment that the frequencies of cooperative strategies drop significantly as the level of noise is increased from 1/16 to 1/8. Our study demonstrates that, even by drastically changing signal noise from 1/10 to 4/10 in imperfect private monitoring, similarly the poorer signal quality indeed discourages our subjects to take cooperative strategies even if the experimental parameters are conductive to cooperate.

RESULT 1-b: Most of our subjects take cooperative strategies in the high accuracy treatment, while in the low accuracy treatment, many of our subjects take non-cooperative strategies.

8.2. Proportion of G-TFT Strategies

Secondly, motivated with the theoretical arguments in Section 4, we focus on the share of g-TFT. Our SEFM estimates in Table 8 and Table 9 indicate that the family of g-TFT shares a substantial proportion in our imperfect private monitoring. In the high accuracy treatment, g-TFT-1-0.5 individually shares the most over the entire set of strategies, which is 17.1%, followed by another g-TFT strategy, which is g-TFT-0.875-0.25 (10.7%). The total share of the family of g-TFT (g-TFT-$r(a)$-$r(b)$ including TFT, but excluding signal non-contingent variants of g-TFT (i.e. All-C (g-TFT-1-1), All-D (g-TFT-0-0) and Random-r (g-TFT-r-r)) is as large as 70.6%. The extended family of g-TFT, which includes the signal non-contingent, primitive variants of g-TFT shares 76.8%. Moreover, the further extend family of g-TFT, which includes the family of g-2TFT as multi-round punishing variants, shares 77.7%. As shown in these large numbers, indeed most of our subjects follow one of the strategies in the class of g-TFT.

The share of g-TFT is also substantially large in the low accuracy treatment. The share of the family of g-TFT is 55.6%, and the extended family with signal non-contingent variants shares 94.6%, and the further extended family with multi-round punishing variants share 96.2%. Regardless of the treatment, we find the substantial share

of our subjects following a strategy in the family of g-TFT.

This finding that the many subjects follow g-TFT regardless of treatments indicate that their decisions on retaliation largely depends on a single occurrence of a bad signal (c.f. lenient strategies). This finding is consistent with our previous finding in Section 6 that the action choices only marginally depend on the signals occurring two periods ago in both treatments.[23]

RESULT 4: Our SFEM estimates indicate that the family of g-TFT share substantial proportion among the strategies our subjects follow in both treatments.

8.3. Retaliation Intensity

Thirdly, observing that many of our subjects follow g-TFT, we turn to the issue on retaliation intensities which is one of our primary focuses of the study. Here, we address how many fraction of our subjects take retaliation intensities which are consistent with g-TFT equilibria. Recall that the level of retaliation intensity implied by the g-TFT equilibria is 0.235 in the high accuracy treatment. Approximately, g-TFT-1-0.75, g-TFT-0.875-0.625, g-TFT-0.75-0.50, g-TFT-0.625-0.37.5, g-TFT-0.50-0.25, g-TFT-0.375-0.12.5, and g-TFT-0.25-0 have this intensity of retaliation in our strategy set. However, our SFEM estimates in Table 8 and Table 9 indicate that the joint share of these strategies is only 5.6% which does not significantly differ from zero (p = 0.319), implying that very few of our subjects follow equilibrium g-TFT strategies in the high accuracy treatment.

This finding that only a limited number of our subjects follow equilibrium retaliation intensity is also true in the low accuracy treatment. In the low accuracy treatment, the retaliation intensity implied by the g-TFT equilibria is much larger than that in the high

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[23] The result that our SFEM estimates find many of our subjects playing g-TFT in our imperfect private monitoring is seemingly less consistent with the finding of Fudenberg, Rand, and Dreber (2012), which found only a small proportion of their subjects playing g-TFT in their imperfect public monitoring. However, we are not able to address the exact factors behind the discrepancy between our results and theirs, since our experimental settings are different from theirs in many aspects such as payoff parameters, discount factor, signal accuracy. Perhaps most importantly our setting is a private monitoring environment in which g-TFT play important roles as a benchmark equilibrium strategy. Nonetheless as we discuss later in this section, similarly to Fudenberg, Rand, and Dreber (2012), we find a certain proportion of our subjects following lenient strategies in the high accuracy treatment.

accuracy treatment, which is 0.94. Approximately, the retaliation intensity in TFT is equivalent to the level implied by the g-TFT equilibria. However, the share of TFT in the low accuracy treatment is only 2.7%, again, which is not significantly different from zero (p = 0.221). These results demonstrate that, despite that many of our subjects follow one of the g-TFT strategies, almost all of them do not follow the retaliation intensities implied in the g-TFT equilibria in both treatments.

Observing that almost all of our subjects do not follow the retaliation intensities implied by the g-TFT equilibria, we further address how they tend to deviate from the theory. In Section 6 we find that the aggregate level of retaliation intensity in the high accuracy treatment is larger than that implied by the g-TFT equilibria. Now we examine whether the similar, consistent results emerge here in the SFEM estimates.

Our SFEM estimates in Table 8 and Table 9 indicate that the group of stronger retaliation variants of g-TFT (g-TFT strategies with retaliation intensities more than 0.25 i.e. g-TFT-1-0.625/0.5/0.375/0.25/0.125/0, g-TFT-0.875-0.5/0.375/0.25/0.125/0, g-TFT-0.75-0.375/0.25/0.125/0, g-TFT-0.625-0.25/0.125/0, g-TFT-0.5-0.125/0, g-TFT-0.375-0 and g-2TFT-0.875/0.75/0.625/0.5/0.375/0.25/0.125/0) jointly shares 54.4% in the high accuracy treatment. Previously we find slightly more than 70% of our subjects follow g-TFT. However, the results here imply that roughly three fourth of them retaliate strongly more than the g-TFT equilibria require. Indeed, the share of the weaker retaliation variants of g-TFT, even including signal non-contingent strategies, merely reaches to 17.7% (g-TFT-1-0.875, g-TFT-0.875-0.75, g-TFT-0.75-0.625, g-TFT-0.625-0.5, g-TFT-0.5-0.375, g-TFT-0.375-0.25, g-TFT-0.25-0.125, g-TFT-0.125-0 and signal non-contingent, zero retaliation strategies, which are All-C, All-D, and Random-r), which is statistically significantly smaller than the share by the group of stronger retaliation variants (p < 0.001).

On the other hand in the low accuracy treatment, we previously find weaker retaliation intensities in the aggregate level in Section 6. Now we examine how many of our subjects follow the weaker retaliation strategies in our SFEM estimates. Our SFEM estimates indicate that the group of weaker retaliation variants of g-TFT (g-TFT other than TFT and signal non-contingent, zero retaliation variants of g-TFT which are All-C, All-D, and Random-r) jointly shares 93.5%. Again, we have found that 96.2% of our subjects take strategies in g-TFT, however, weaker retaliation variants of g-TFT

predominantly share almost all of them. On the contrary, strong retaliation variants of g-TFT (here the multi-round punishing variants of TFT, which are g-2TFT-0.875/0.75/0.625/0.5/0.375/0.25/0.125/0) share less than 0.1%, which is statistically significantly smaller than the share by the weaker retaliation variants (p < 0.001).

Previously in Section 6 we found that the mean retaliation intensities deviate from the values implied by the g-TFT equilibria in the aggregate level systematically. Here we further examine whether the finding still hold even if we restrict our attention to the behavior of g-TFT players rather than the aggregate behavior with the entire strategies.

To focus on the behavior of the g-TFT players, we compute the mean retaliation intensities conditional on the g-TFT strategies (including All-C, All-D, and Random-r). The conditional mean retaliation intensity in the high accuracy treatment is 0.426 (s.d. 0.033), again which is significantly larger than the value predicted by the g-TFT equilibria (0.235, p < 0.001). In the low accuracy treatment the mean retaliation intensity is 0.148 (s.d. 0.025), again which is significantly smaller than the value implied by the g-TFT equilibria (0.94, p < 0.001). The direct comparison of the two mean retaliation intensities demonstrate that the conditional mean of retaliation intensities in the high accuracy treatment is significantly larger than that in the low accuracy treatment (p < 0.001). Even restricted to the behavior of g-TFT players, still their behavior deviate from the theoretical predictions systematically similarly to the findings in Section 6.

RESULT 2-b: Our SFEM estimates indicate that, in both treatments, only a small number of our subjects follow the retaliation intensities implied by the g-TFT equilibria. In the high accuracy treatment, the share of stronger retaliation variants of g-TFT outweigh that of weaker retaliation variants. In the low accuracy treatment, the share of weaker retaliation variants of g-TFT outweigh that of stronger retaliation variants. Moreover, the mean retaliation intensity among g-TFT players is larger in the high accuracy treatment than the value implied by the g-TFT equilibria, and is smaller in the low accuracy treatment than that by the equilibria. Furthermore, the mean retaliation intensity by the g-TFT strategies is larger in the high accuracy treatment than that in the low accuracy treatment opposed to the theoretical implications by the g-TFT equilibria.

8.4. Long-Term Punishment

Fourthly, we focus on long-term punishing strategies. We have observed that the aggregate level of retaliation intensity is smaller than the level implied by the g-TFT equilibria in the low accuracy treatment in Section 6. Here we address the concern that the seemingly weak retaliation intensity might spuriously arise when some subjects employ long-term punishing strategies.

Our SEFM estimates in Table 8 and Table 9 indicate this is not the case in our data. The share of the strategies with long-term punishments (a family of 2TFT, 2TF2T, Grim, Grim2 and Grim 3) in the low accuracy treatment is less than 3% which is statistically insignificant (p = 0.435), hence the effect of strategies with long-term punishment is minimum. This is also true in the high accuracy case, where the joint share by the long-term punishing strategies is 6.6%, again, which is statistically insignificant (p = 0.203)

RESULT 2-c: The share of strategies with long-term punishments, which could spuriously reduce the observed retaliation intensities, is small in both treatments.

8.5. Lenience

Finally, we focus on the share of lenient strategies. As seen in Section 6, our subjects do not have tendency to rely on longer histories in the low accuracy treatment. This finding suggests that the share of lenient strategies might not be larger in the poorer monitoring technologies in our imperfect private monitoring, opposed to the speculations in the field of review strategies (Radner (1986), Matsushima (2004), and Sugaya (2012)). Here we examine whether the share of lenient strategies becomes larger as the monitoring technology becomes poorer.

Our SFEM estimates in Table 8 and Table 9 indicate that, in the low accuracy treatment, none of the individual shares by the lenient (review) strategies (the family of g-TF2T including TF2T, TF3T, 2TF2T, Grim-2 and Grim-3) significantly differ from zero. Even jointly, they share only 3.8%, which is not significantly different from zero (p = 0.359). The lenient strategies do not share a remarkable proportion in the low accuracy

treatment. On the contrary, in the high accuracy treatment, the share of lenient strategies raises to 21.4% which is significantly different from zero (p = 0.023) and is marginally significantly larger than that in the low accuracy treatment (p = 0.055). Thus, we conclude that there is no tendency to have more lenient strategies in the poorer monitoring technologies.

RESULTS 3-b: Our SFEM estimates provide no evidence for a larger share of lenient strategies in the low accuracy treatment. Rather, the share is only negligible in the low accuracy treatment, while they share approximately 20% in the high accuracy treatment.

9. Feedback to Theory

Our experimental results indicate that the cooperation rate is greater in the high accuracy treatment, a substantial proportion of the subjects play g-TFT strategies, and the retaliation intensity is greater in the high accuracy treatment.

As a feedback from these experimental findings to the theoretical development, we demonstrate an alternative theory, which is more consistent with observed behavior than the standard theory. This section ignores the heterogeneity of strategies the subjects employed. We replace this heterogeneity with the common knowledge assumption on the strategy that players employ.

The purpose of this section is to associate our subjects' behavior with their aspects of psychology and bounded rationality. To be more precise, we permit each player to be motivated by not only pure self-interest but also *reciprocity*. We permit each player to be often *naïve* enough to select actions at random. We further permit the degrees of such reciprocity and naiveté to be dependent on the level of monitoring accuracy.

By incorporating reciprocity and naïveté into equilibrium analysis, we characterize the *underlying behavioral model of preferences* that makes the retaliation intensity implied by the g-TFT equilibria increasing in the level of monitoring accuracy, i.e., more consistent with our experimental findings.

In order to focus on the incentives at the second and later rounds, this section will simply write $(r(a), r(b))$ instead of $(q, r(a), r(b))$ for any g-TFT strategy. Fix an

arbitrary $\underline{p} \in (\frac{1}{2}, 1)$ as the lower bound of monitoring accuracy.

9.1. Behavioral Model

Consider an arbitrary accuracy-contingent g-TFT strategy, which is denoted by

$$(r(a; p), r(b; p))_{p \in (\underline{p}, 1)}.$$

For each level of monitoring accuracy $p \in (\underline{p}, 1)$, a player makes stochastic action choices according to the g-TFT strategy $(r(a), r(b)) = (r(a; p), r(b; p))$. We assume that the player selects both action A and action B with positive probabilities, i.e.,

(6) $\qquad 0 < r(a; p) < 1$ and $0 < r(b; p) < 1$.

We introduce *naïveté* as follows. At every round, with a probability $2\varepsilon(p) \in [0, \frac{1}{2}]$, the player naively, or randomly, selects between action A and action B, i.e.,

$$\min[r(a; p), 1 - r(a; p), r(b; p), 1 - r(b; p)] \ge \varepsilon(p).$$

With the remaining probability $1 - 2\varepsilon(p)$, the player makes the action choice in the more conscious manner.[24] [25]

We introduce *reciprocity* as follows. Suppose that the player observes signal a, i.e., the good signal for his opponent. He feels guilty when he selects the defective action despite the observation of the good signal. In this case, he can save the psychological cost $c(a; p) \ge 0$ by selecting the cooperative action. Hence, the instantaneous gain from selecting action B is equal to $Y - c(a; p)$, while the resultant future loss is equal to $\delta Z(2p - 1)\{r(a; p) - r(b; p)\}$. From (6), we require the following properties as a part of

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[24] In order to calm the tense relation between rationality and empirical data, economic theory and empirics have used stochastic choice models such as logit and probit models that incorporated random error into equilibrium analysis. For instance, the model of quantal response equilibrium assumed that the deviation errors from the optimal action choice are negatively correlated with the resultant payoffs. See Goerree, Holt, and Palfrey (2008) for a review. In contract, this section assumes that the deviation errors induced by naïveté is independent of either the resultant payoff or the observed signal but depends on the level of monitoring accuracy.

[25] The general experimental literature has often pointed out that social preference facilitates cooperation. See Güth, Schmittberger, and Schwarze (1982), Berg, Dickhaut, and McCabe (1995), and Fehr and Gächter (2000). The literature assumes that preferences depend on various contexts of the game being played. See Rabin (1993), Charness and Rabin (2002), Falk, Fehr, and Fischbacher (2003), Dufwenberg and Kirchsteiger (2004), and Falk and Fishbacher (2005). This paper makes the relevant context parameterized by the level of monitoring accuracy.

the equilibrium constraints in behavioral theory:

(7) $\qquad [Y - c(a;p) > \delta Z(2p-1)\{r(a;p) - r(b;p)\}] \Rightarrow [r(a;p) = \varepsilon(p)]$,

and

(8) $\qquad [Y - c(a;p) < \delta Z(2p-1)\{r(a;p) - r(b;p)\}] \Rightarrow [r(a;p) = 1 - \varepsilon(p)]$.[26]

Next, suppose that the player observes signal b, i.e., the bad signal for his opponent. He is in an ill-temper when he selects the cooperative action despite the observation of the bad signal. In this case, he can save the psychological cost $c(b;p) \geq 0$ by selecting the defective action. Hence, the instantaneous gain from selecting action B is equal to $Y + c(b;p)$, while the resultant future loss is equal to $\delta Z(2p-1)\{r(a;p) - r(b;p)\}$. From (6), we require the following properties as the other part of this section's equilibrium constraints:

(9) $\qquad [Y + c(b;p) > \delta Z(2p-1)\{r(a;p) - r(b;p)\}] \Rightarrow [r(b;p) = \varepsilon(p)]$,

and

(10) $\qquad [Y + c(b;p) < \delta Z(2p-1)\{r(a;p) - r(b;p)\}] \Rightarrow [r(b;p) = 1 - \varepsilon(p)]$.

We define a *behavioral model* as

$$(\varepsilon(p), c(a,p), c(b;p))_{p \in (\underline{p},1)}.$$

An accuracy-contingent g-TFT strategy $(r(a;p), r(b;p))_{p \in (\underline{p},1)}$ is said to be an *equilibrium* in the behavioral model $(\varepsilon(p), c(a,p), c(b;p))_{p \in (\underline{p},1)}$ if the properties (7), (8), (9), and (10) hold for all $p \in (\underline{p},1)$.[27]

9.2. Characterization

A player with behavioral model $(\varepsilon(p), c(a,p), c(b;p))_{p \in (\underline{p},1)}$ is said to be *positively reciprocal* in accuracy p if $c(a;p) > 0$. She is said to be *negatively reciprocal* in p

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[26] Without any substantial change, we can interpret $c(a;p)$ as the psychological benefit, where he feels better by selecting the cooperative action instead of the defective action after observing the good signal. We have the same point about $c(b;p)$.

[27] For simplicity of arguments, we eliminate the incentive constraints for the first-round action choices, and then focus on the action choices at the second and later rounds.

if $c(b;p) > 0$. She is said to be *null-reciprocal* in p if $c(a;p) = 0$ and $c(b;p) = 0$.

We assume that $c(a;p)$ and $c(b;p)$ are continuous in accuracy p, and

either $c(a;p) = 0$ or $c(b;p) = 0$.

With this assumption, we can divide players into three categories, i.e., positively reciprocal players, negatively reciprocal players, and null-reciprocal players.

According to our experimental findings, we assume that

(i) both $r(a;p)$ and $r(b;p)$ are increasing and continuous in p,

and

(ii) the retaliation intensity $r(a;p) - r(b;p)$ is increasing in p.

Since $w(p)$ is decreasing in p, it follows from (ii) that there exists a critical level $\hat{p} \in [\underline{p}, 1]$ such that

$$r(a;p) - r(b;p) > w(p) \qquad \text{if } p > \hat{p},$$

and

$$r(a;p) - r(b;p) < w(p) \qquad \text{if } p < \hat{p}.$$

The retaliation intensity is greater than the retaliation intensity implied by the g-TFT equilibria in standard theory if the level of monitoring accuracy is better than the critical level $\hat{p}$, while the retaliation intensity is lesser than the retaliation intensity implied by the g-TFT equilibria in standard theory if the level of monitoring accuracy is worse than the critical level $\hat{p}$.

The following theorem shows that the above-mentioned equilibrium constraints, i.e., (7), (8), (9), and (10), uniquely determine the underlying behavioral model.

Theorem 2: *The accuracy-contingent g-TFT strategy* $(r(a;p), r(b;p))_{p \in (\underline{p},1)}$ *is an equilibrium in the behavioral model* $(\varepsilon(p), c(a,p), c(b;p))_{p \in (\underline{p},1)}$ *if and only if*

(11) $\qquad r(a;p) = 1 - \varepsilon(p)$ *and* $r(b;p) = 1 - \varepsilon(p) - w(p) - \dfrac{c(b;p)}{\delta(2p-1)Z}$

for all $p > \hat{p}$,

and

$$(12) \qquad r(a; p) = \varepsilon(p) + w(p) - \frac{c(a; p)}{\delta(2p-1)Z} \quad and \quad r(b; p) = \varepsilon(p) \quad for\ all \quad p < \hat{p}.$$

Proof: See Appendix 5.

From Theorem 2, the behavioral model $(\varepsilon(p), c(a, p), c(b; p))_{p \in (\underline{p}, 1)}$ is uniquely determined: for every $p > \hat{p}$

$$\varepsilon(p) = 1 - r(a; p),$$

$$c(a; p) = 0, \text{ and}$$

$$c(b; p) = \delta(2p-1)Z\{r(a; p) - r(b; p) - w(p)\},$$

and for every $p < \hat{p}$,

$$\varepsilon(p) = r(b; p),$$

$$c(a; p) = \delta(2p-1)Z\{w(p) - r(a; p) + r(b; p)\}, \text{ and}$$

$$c(b; p) = 0.$$

Note that

(iii)   the player is null-reciprocal at the critical level $\hat{p}$, i.e., $c(a; \hat{p}) = c(b; \hat{p}) = 0$,

(iv) $\varepsilon(p)$ is single-peaked with the peak at the critical level $\hat{p}$, i.e., increasing in $p \in (\underline{p}, \hat{p})$ and decreasing in $p \in (\hat{p}, 1)$,

(v) $c(a; p)$ is decreasing in $p \in (\underline{p}, \hat{p})$,

and

(vi) $c(b; p)$ is increasing in $p \in (\hat{p}, 1)$.

9.3. Trade-Offs

The behavioral model $(\varepsilon(p), c(a, p), c(b; p))_{p \in (\underline{p}, 1)}$ is said to be *more kind* in p than in p' if either

it is more positively reciprocal in p than in p', i.e., $c(a; p) > c(a; p')$,

or

it is less negatively reciprocal in p than in p', i.e., $c(b; p') > c(b; p)$.

From Theorem 2, the behavioral model has the following *trade-off between kindness and accuracy*:

(vii)   The less kind a player is, the more accurate the monitoring technology is.

Given a sufficient level of monitoring accuracy, players tend to be more negatively reciprocal as monitoring is more accurate. This tendency makes the retaliation intensity severer, and therefore works against the better success in cooperation caused by the improvement of monitoring technology. Given an insufficient level of monitoring accuracy, they tend to be more positively reciprocal as monitoring is less accurate. This tendency makes the retaliation intensity milder, and therefore mitigates the worse success in cooperation caused by the deterioration of monitoring technology.[28]

From Theorem 2, the behavioral model also has the following *trade-off between naïveté and reciprocity*:

(viii)   The more naively a player makes action choices, the less reciprocal he is.

Given that a player is negatively reciprocal, he tends to be more conscious, i.e., less likely to mistakenly select the defective action despite observing the good signal, as he is more negatively reciprocal. Given that a player is positively reciprocal, he tends to be more conscious, i.e., less likely to mistakenly select the cooperative action despite observing the bad signal, as he is more positively reciprocal.

9.4. Uniqueness of G-TFT Equilibrium

We further show that the accuracy-contingent g-TFT strategy $(r(a; p), r(b; p))_{p \in (\underline{p}, 1)}$ is the only plausible accuracy-contingent g-TFT equilibrium in the derived behavioral model $(\varepsilon(p), c(a, p), c(b; p))_{p \in (\underline{p}, 1)}$. In fact, whenever $\underline{p} < \hat{p}$, then there exists no other

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[28] The model here and that in Duffy and Muñoz-García (2012) share the common spirit that the social preferences play an important role in people making collusion in repeated games. However, the implications of the social preferences are different. Duffy and Muñoz-García demonstrated that, motivated with fairness, social preference facilitates people to achieve collusion even if the time discount factor is insufficient. In contrast, our behavioral theory shows that it crucially depends on the monitoring technology whether the social preference helps collusion or not due to the trade-off between the kindness and accuracy; motivated with reciprocity, the social preference facilitate people to collude even under poorer monitoring accuracies, where a larger discount factor is required. However, it inhibits people to collude under better monitoring accuracies.

accuracy-contingent g-TFT equilibrium strategy at all.

If $\underline{p} = \hat{p}$, there exists another accuracy-contingent g-TFT strategy equilibrium, $(\tilde{r}(a;p), \tilde{r}(b;p))_{p \in (\underline{p},1)}$, which is specified as

$$\tilde{r}(a;p) = \varepsilon(p) + w(p) \text{ and } \tilde{r}(b;p) = \varepsilon(p) \text{ for all } p \in (\underline{p},1),$$

where $(\tilde{r}(a;p), \tilde{r}(b;p))_{p \in (\underline{p},1)}$ and $(r(a;p), r(b;p))_{p \in (\underline{p},1)}$ are the only equilibria in the derived behavioral model.

Note that $(\tilde{r}(a;p), \tilde{r}(b;p))_{p \in (\underline{p},1)}$ is quite implausible, because $\tilde{r}(a;p)$ and $\tilde{r}(b;p)$ are decreasing, and the frequency of cooperative action choices is therefore decreasing, in level of monitoring accuracy. Note also that $(\tilde{r}(a;p), \tilde{r}(b;p))_{p \in (\underline{p},1)}$ is less efficient than $(r(a;p), r(b;p))_{p \in (\underline{p},1)}$, irrespective of $p \in (\underline{p},1)$.

The above-mentioned uniqueness is in contract with the standard theory, which has numerous g-TFT equilibria. The uniqueness substantially relies on the inclusions of the psychological costs $c(a;p)$ and $c(b;p)$, which make the equilibrium constraints dependent on the signal occurrence at the previous round.

10. Conclusion

This paper experimentally examines collusion in repeated prisoners' dilemma with random termination where monitoring is imperfect and private; each player obtains information on the opponent's action choice through a signal instead of a direct observation, and the signal the opponent observes is not observable to the player. We assume that the continuation probability is large enough to support collusion even in the poor monitoring technology. Our study is the first experimental attempt to investigate imperfect private monitoring.

Our experimental results indicate that a significant proportion of our subjects employed g-TFT strategies, which are the straightforward stochastic extensions of the well-known TFT strategy. We significantly depart from the experimental literature by focusing on g-TFT strategies, which have attracted less attention in the empirical literature despite its theoretical importance. Our findings that a significant proportion of

our subjects follow g-TFT strategies reveal its empirical importance.

Although many subjects follow g-TFT strategies, their retaliating policies systematically deviate from the predictions by the g-TFT equilibria. Our subjects retaliate more in the high accuracy treatment than in the low accuracy treatment, contrarily to the theoretical implications. They retaliate more in the high accuracy treatment, while they retaliate lesser in the low accuracy treatment. These experimental findings indicate that the subjects fail to improve their welfare by effectively utilizing the monitoring technology as the standard theory predicted.

As a feedback from these experimental findings to the theoretical development, we characterize a behavioral model of preferences that incorporates reciprocity and naïveté. Our behavioral theory describes the signal-contingent behavior consistent with our experimental results as the unique, plausible g-TFT equilibrium. This feedback could be expected as a clue to establish a pervasive theory that has more relevancies to real behavior and more predictive power.

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Table 1:
Prisoner's Dilemma with Symmetry and Additive Separability
$(X, Y, Z) = (60, 10, 55)$

	A	B
A	60 60	5 70
B	70 5	15 15

Table 2:
Features of Experimental Design

	Number of Subjects	Treatment order (sequence of game lengths)
October 5, 2006 (10:30 ~ 12:30)	28	0.6 (24, 40, 25), 0.9 (28, 33, 14)
October 5, 2006 (14:30 ~ 16:30)	24	0.6 (20, 23, 37), 0.9 (34, 34, 19)
October 6, 2006 (10:30 ~ 12:30)	28	0.9 (38, 21, 25), 0.6 (25, 28, 29)
October 6, 2006 (14:30 ~ 16:30)	28	0.9 (25, 35, 23), 0.6 (36, 30, 21)

Table 3:
Decisions and Signal

	$p = 0.9$			$p = 0.6$		
	N	Mean	St. Dev.	N	Mean	St. Dev.
Cooperative-choice	8,864	0.672	0.469	9,144	0.355	0.479
Good signal	8,864	0.637	0.481	9,144	0.483	0.500

Table 4:
Means of Cooperative Action Choice

	$p = 0.9$	$p = 0.6$	p-values
$q(p)$ (round 1)	0.781 (0.042)	0.438 (0.035)	< 0.001
$r(a; p)$	0.852 (0.033)	0.437 (0.018)	<0.001
Individual-level means	0.799 (0.032)	0.423 (0.027)	$< 0.001+$
$r(b; p)$	0.344 (0.026)	0.272 (0.030)	< 0.001
Individual-level means	0.448 (0.026)	0.279 (0.032)	$< 0.001+$

Notes: The standard errors (shown in parentheses) are block-bootstrapped (subject and repeated game level) with 5,000 repetitions, which is used to calculate p-values. The null hypothesis is that the values are identical across the two treatments.

+ Furthermore, Wilcoxon matched-pair test within individual rejects the null hypothesis that the values are identical across the two treatments ($p < 0.001$ for each).

Table 5:
Retaliation Intensities

	Mean	S.E.	p-value
$r(a;0.9) - r(b;0.9)$	0.508	0.028	$< 0.001+$
Individual-level means	0.352	0.028	$< 0.001+$
$r(a;0.6) - r(b;0.6)$	0.165	0.025	$< 0.001+$
Individual-level means	0.144	0.023	$< 0.001+$
$(r(a;0.9) - r(b;0.9)) - (r(a;0.6) - r(b;0.6))$	0.344	0.031	< 0.001
Individual-level means	0.208	0.029	< 0.001

Notes: The standard errors are block-bootstrapped (subject and repeated game level) with 5,000 repetitions, which is used to calculate p-values.

+ Hypothesis tests for the comparison to the value implied by the standard theory (w(p)), which is 0.235 in the high accuracy treatment and 0.94 in the low accuracy treatment. The null hypothesis is that the mean is identical to the implied value.

Table 6:
Reduced form regression results on signal contingency

	p = 0.9	p = 0.6
aA	0.887*** (0.019)	0.766*** (0.038)
aB	0.502*** (0.040)	0.255*** (0.035)
bA	0.506*** (0.038)	0.582*** (0.049)
bB	0.106*** (0.021)	0.110*** (0.042)
aAa	0.062*** (0.022)	0.037 (0.031)
aBa	0.017 (0.054)	-0.055 (0.034)
bAa	0.125*** (0.041)	-0.045 (0.046)
bBa	0.132*** (0.037)	0.022 (0.016)
Observations	8,216	8,496
R2	0.816	0.531
Adjusted R2	0.816	0.531

Notes: xYz in the regressors denotes that the player takes action Y, observes signal x on the opponent's choice, and the player has observed signal z in the previous round. Similarly, xY denotes that the player takes action Y and observes signal x on the opponent's choice. The standard errors (shown in parentheses) are block-bootstrapped (subject and repeated game level) with 5,000 repetitions, which is used to calculate p-values. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 7:
Strategy set in our SFEM

Strategy	Description
All-C	Always cooperate
TFT	Tit-For-Tat
g-TFT- $r(a)$ **-** $r(b)$	Generous Tit-For-Tat, cooperate if a good signal occurs with the probability of $r(a)$, and forgive a bad signal and cooperate with the probability of $r(b)$
All-D	Always defect
TF2T	Tit for Two Tat (retaliate if bad signals occur in all of the last two rounds)
g-TF2T- r	Generous Tit for Two Tat, playing cooperation stochastically with probability of r even after observing two consecutive bad signals
TF3T	Tit for Three Tat (retaliate if a bad signal occurs in all of the last three rounds)
2TFT	Two Tit-For-Tat (retaliate twice consecutively if a bad signal occurs)
g-2TFT- r	Generous-Two Tit-For-Tat, retaliate for sure if a bad signal occurs, however, forgive and cooperate with the probability of r in the next round if a good signal occurs (second punishment)
2TF2T	Two Tit for Two Tat (retaliate twice consecutively if a bad signal occurs in all of the last two rounds)
Grim	Cooperate until player chose defection or observed a bad signal, then play defection forever
Grim-2	Cooperate until the case happens twice in a row in which player chose defection or observed a bad signal, then play defection forever
Grim-3	Cooperate until the case happens three times in a row in which player chose defection or observed a bad signal, then play defection forever
Random- r	Cooperate with the probability of r irrespective of signals

Table 8:
Maximum Likelihood Estimates of individual strategies

	p = 0.9	S.E.	p = 0.6	S.E.
All-C (g-TFT-1-1)	0	(0.029)	0.037**	(0.019)
g-TFT-1-0.875	0	(0.009)	0	(0)
g-TFT-1-0.75	0	(0)	0	(0.002)
g-TFT-1-0.625	0	(0.040)	0	(0)
g-TFT-1-0.5	0.171***	(0.063)	0	(0)
g-TFT-1-0.375	0	(0)	0	(0)
g-TFT-1-0.25	0.041	(0.031)	0	(0)
g-TFT-1-0.125	0	(0.007)	0.010	(0.014)
TFT (g-TFT-1-0)	0.026	(0.016)	0.027	(0.022)
Ramdom-0.875 (g-TFT-0.875-0.875)	0.002	(0.014)	0	(0)
g-TFT-0.875-0.75	0.033	(0.024)	0.027	(0.017)
g-TFT-0.875-0.625	0.022	(0.033)	0	(0.015)
g-TFT-0.875-0.5	0.042	(0.041)	0.004	(0.015)
g-TFT-0.875-0.375	0.055	(0.048)	0	(0)
g-TFT-0.875-0.25	0.107***	(0.041)	0	(0)
g-TFT-0.875-0.125	0	(0.006)	0.010	(0.011)
g-TFT-0.875-0	0	(0)	0.010	(0.009)
Random-0.75 (g-TFT-0.75-0.75)	0	(0)	0	(0)
g-TFT-0.75-0.625	0	(0.001)	0.038	(0.024)
g-TFT-0.75-0.5	0	(0.017)	0.017	(0.022)
g-TFT-0.75-0.375	0.003	(0.023)	0.026	(0.027)
g-TFT-0.75-0.25	0	(0)	0	(0.004)
g-TFT-0.75-0.125	0.011	(0.015)	0	(0)
g-TFT-0.75-0	0.009	(0.008)	0	(0)
Random-0.625 (g-TFT-0.625-0.625)	0.011	(0.010)	0.014	(0.018)
g-TFT-0.625-0.5	0	(0.005)	0	(0.012)
g-TFT-0.625-0.375	0.023	(0.029)	0.089*	(0.046)
g-TFT-0.625-0.25	0	(0)	0	(0.015)
g-TFT-0.625-0.125	0.026	(0.021)	0	(0)
g-TFT-0.625-0	0	(0.010)	0	(0)
Random-0.5 (g-TFT-0.5-0.5)	0	(0.013)	0.023	(0.024)
g-TFT-0.5-0.375	0.053	(0.034)	0.050	(0.045)
g-TFT-0.5-0.25	0.003	(0.011)	0.038	(0.029)
g-TFT-0.5-0.125	0	(0)	0	(0.006)
g-TFT-0.5-0	0.019	(0.014)	0	(0)
Random-0.375 (g-TFT-0.375-0.375)	0.021	(0.019)	0.044	(0.045)
g-TFT-0.375-0.25	0	(0.006)	0.090	(0.060)
g-TFT-0.375-0.125	0	(0)	0	(0.012)
g-TFT-0.375-0	0	(0.003)	0.014	(0.013)
Random-0.25 (g-TFT-0.25-0.25)	0	(0)	0.063	(0.053)
g-TFT-0.25-0.125	0	(0)	0.069*	(0.041)
g-TFT-0.25-0	0.008	(0.014)	0.001	(0.011)
Random-0.125 (g-TFT-0.125-0.125)	0	(0.001)	0.033	(0.028)
g-TFT-0.125-0	0.029	(0.021)	0.037	(0.022)
All-D (g-TFT-0-0)	0.028	(0.017)	0.190***	(0.035)
g-TF2T-0.875	0.074*	(0.040)	0	(0)
g-TF2T-0.75	0	(0.021)	0	(0)
g-TF2T-0.625	0	(0.010)	0	(0.003)
g-TF2T-0.50	0.022	(0.028)	0	(0)
g-TF2T-0.375	0	(0.020)	0	(0)
g-TF2T-0.25	0	(0.024)	0.009	(0.009)
g-TF2T-0.125	0	(0.001)	0	(0)

TF2T (g-TF2T-0)	0	(0.004)	0	(0)
TF3T	0.070	(0.045)	0	(0.004)
g-2TFT-0.875	0	(0)	0	(0)
g-2TFT-0.75	0.009	(0.016)	0	(0)
g-2TFT-0.625	0	(0.024)	0	(0)
g-2TFT-0.50	0	(0.005)	0	(0)
g-2TFT-0.375	0	(0)	0	(0)
g-2TFT-0.25	0	(0)	0	(0)
g-2TFT-0.125	0	(0)	0	(0)
2TFT (g-2TFT-0)	0	(0)	0	(0)
2TF2T	0	(0.013)	0.009	(0.010)
Grim	0.009	(0.008)	0	(0)
Grim-2	0.013	(0.016)	0	(0.007)
Grim-3	0.035	(0.025)	0.020	(0.024)
Gamma	0.280***	(0.035)	0.247***	(0.059)

Notes: The standard errors (shown in parentheses) are cluster-bootstrapped (individual-level) with 100 repetitions, which is used to calculate p-values. *p < 0.1, **p < 0.05, ***p < 0.01.

Table 9:
**Frequency of Cooperative strategies, g-TFT, Retaliation Intensities (RI)**

|	p = 0.9		p = 0.6	
Cooperative strategies		83.9%		34.7%
Non-cooperative strategies		16.1%		65.3%
Family of g-TFT		70.6%		55.6%
Including signal non-contingent, zero RI strategies (All-C, All-D, Random-r)		76.8%		96.2%
Including multi-round punishing strategies (g-2TFT)		77.7%		96.2%
Equilibrium RI	(RI = 0.25)	5.6%	(RI = 1)	2.7%
Stronger RI	(RI > 0.25)	54.4%	(RI > 1)	0.0%
Weaker RI (positive RI only)	(0 < RI < 0.25)	11.4%	(0 < RI < 1)	53.0%
Including zero RI strategies	(RI < 0.25)	17.7%	(RI < 1)	93.5%
Mean RI conditional on g-TFT		0.426		0.148
Median RI conditional on g-TFT		0.5		0.125
Lenient strategies		21.4%		3.7%

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Appendix 1: Screens in Constant Random Termination
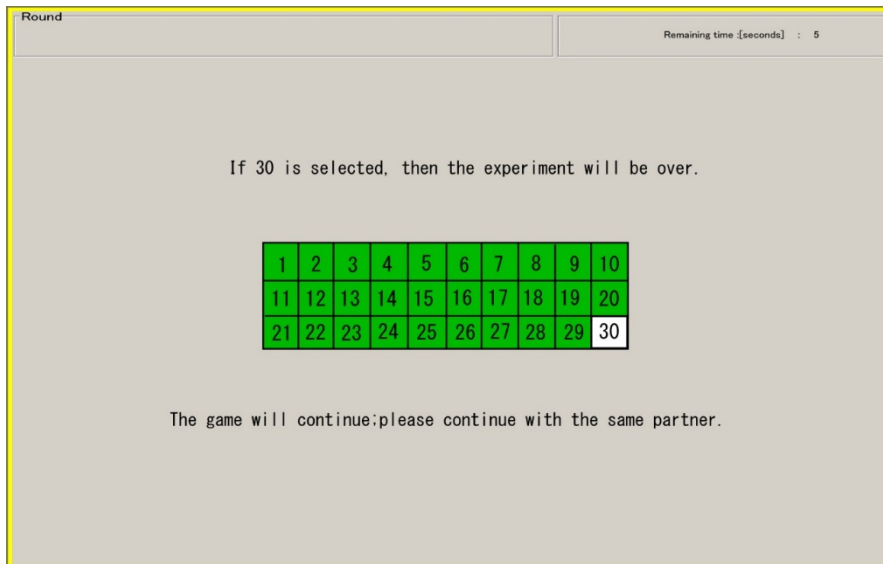
Figure A. 1: Screen when the repeated game continues
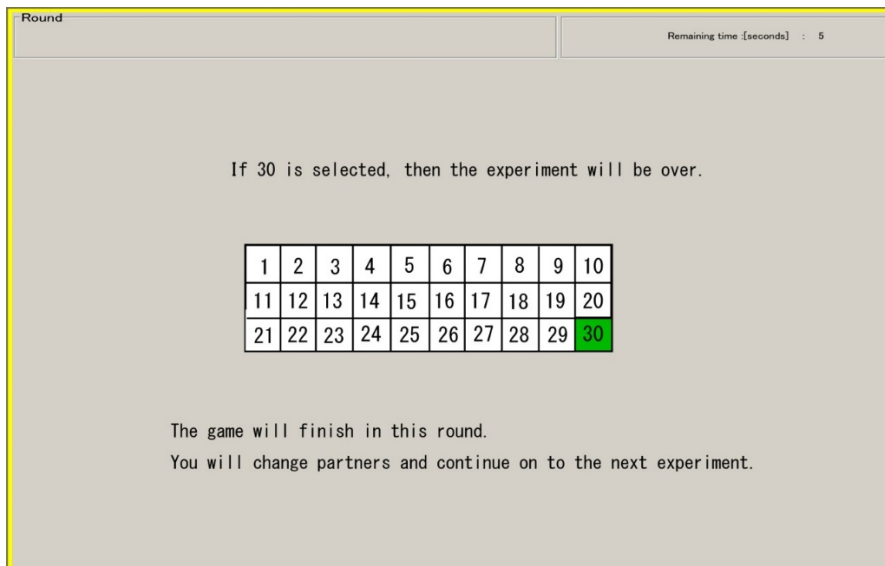
Figure A. 2: Screen when the repeated game is terminated

Appendix 2: Impact of Experience

Several existing studies often reported that the frequency of cooperation changes as people experience playing repeated games (see discussion in Dal Bó and Fréchette (2014)). The overall cooperation rates might rise with experiences of repeated games when the experimental parameters are conductive for cooperation. Since the welfare is uniquely determined by the overall cooperation rates in our payoff setting (i.e. the additive separability payoff structure), the shift of the overall cooperation rates imply the shift of welfare of the two players.

To examine the impact of the experience of repeated games on overall cooperation rates, we perform the following reduced-form, linear regression analysis; we regress the action choices on the two explanatory variables, "RG2" and "RG3". The dummy variable "RG2" ("RG3") takes one if the choice is made in the second (third) repeated games in each treatment. Moreover, to further examine the change of the cooperation rate with-in a repeated game, we also include the dummy variable "First 14 Rd." which takes one if the choice is made in the first 14 rounds of each repeated game. The regression model is a fixed-effect model in which the individual heterogeneity in tendencies to take cooperative choices is controlled by individual fixed effects.

[TABLE A. 1 HERE]

Table A. 1 displays the regression results. In the high accuracy treatment, the coefficient on the second repeated game is 0.029 (insignificant), and that on the third repeated game is 0.105 (significant, $p < 0.001$). These positive values in the regression coefficients indicate that our subjects tend to cooperate more as they gain experience, indicating that the welfare of the two players is improved by experience. However the size is at most 11%, which is only a marginal effect.

In the low accuracy treatment, the coefficient on the second repeated game is -0.071 (significant, $p < 0.05$), and that on the third repeated game is -0.118 (significant, $p < 0.001$). On the contrary to the case in high accuracy treatment, our subjects tend to become less cooperative as they gain experience even in the situation where the

experimental parameters are conductive for cooperation, rather indicating that the welfare is worsen by the experience. However, the sizes of the effect of experience is at most 12%, again, which is only a marginal effect.

As to the effect with-in a repeated game, the coefficients on the first 14 rounds are statistically significantly larger than zero in both treatments (p < 0.001 for both treatments), although the sizes are at most 8%. Our subjects tend to become less cooperative as the rounds proceed in each repeated game, however the effect is small.

These results indicate that, although there are some experience effects on action choices, however, the sizes of the effects are not remarkably large in our data. We also perform the identical analysis to the signal contingent cooperation rates, and find qualitatively similar results (Table A. 2 and Table A. 3).

[TABLE A. 2 HERE]

[TABLE A. 3 HERE]

In addition to the cooperation rate, we also investigate the effect of experience on retaliation intensities. Here we perform a similar, reduced-form regression analysis, regressing the action choices on the dummy variable "Signal" which takes one if the signal is good. The coefficient on the dummy variable captures the contrast between the cooperation rate contingent on the good signal and that on bad signal, which is the retaliation intensity. To examine the experience effects on retaliation intensities across repeated games and with-in a repeated game, we add the cross-product terms with "RG2", "RG3" and "First 14 Rd." in the set of the explanatory variables. Again, the regression model is a fixed-effect model in which the individual heterogeneity in tendencies to take cooperative choices is controlled by individual fixed effects.

[TABLE A. 4 HERE]

Table A. 4 displays the regression results. None of the coefficient on the joint effect of "Signal" and repeated games ("RG2" and "RG3") is significantly different from zero in both treatments, implying that the retaliation intensities do not differ either in the second repeated games or in third repeated games from that in the first repeated games.

Furthermore, the coefficient on the cross-product of "Signal" and "RG2" does not differ from that on the cross-product of "Signal" and "RG3" in both treatments (p = 0.702 for the high accuracy treatment, and p = 0.672 for the low accuracy treatment). These results jointly indicate that the retaliation intensities are stable across repeated games.

As to the with-in repeated game difference, only the coefficient on the joint effect of "Signal" and "First 14 Rd." in the high accuracy treatment significantly differs from zero, although the size of the effect is approximately 5%. Our subjects tend to rely on stronger retaliation intensities as the rounds proceed in a repeated game, however, the difference is not remarkably large.

Overall, the results here indicate that the retaliation intensities do not change remarkably as our subjects gain experience.

Table A. 1:
Fixed-effect model regression results on the experience effect on overall cooperation rates

	p = 0.9	p = 0.6
RG2	0.029 (0.031)	-0.071** (0.027)
RG3	0.105*** (0.031)	-0.118*** (0.029)
First 14 Rd.	0.062*** (0.014)	0.080*** (0.015)
Observations	8,864	9,144
R2	0.021	0.025

Notes: Cluster-robust (individual-level) standard errors in parenthesis. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$. The coefficient on "RG3" is significantly larger than that on "RG2" in the high accuracy treatment (F-test, p = 0.016). The coefficient on "RG3" is significantly smaller than that on "RG2" in the low accuracy treatment (F-test, p = 0.027).

Table A. 2:
Fixed effect model regression results on the experience effect on cooperation rates contingent on good signals

	p = 0.9	p = 0.6
RG2	0.014 (0.016)	-0.055* (0.029)
RG3	0.076*** (0.021)	-0.104*** (0.034)
First 14 Rd.	0.018 (0.011)	0.073*** (0.018)
Observations	5,453	4,265
R2	0.005	0.021

Notes: Cluster-robust (individual-level) standard errors in parenthesis. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table A. 3:

Fixed effect model regression results on the experience effect on cooperation rates

contingent on bad signals

	p = 0.9	p = 0.6
RG2	0.025 (0.030)	-0.070** (0.030)
RG3	0.052 (0.036)	-0.123*** (0.029)
First 14 Rd.	0.061*** (0.018)	0.070*** (0.016)
Observations	3,087	4,555
R2	0.009	0.027

Notes: Cluster-robust (individual-level) standard errors in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A. 4;

Fixed-effect model regression results on the experience effect on retaliation intensities

	p = 0.9	p = 0.6
Signal	0.392*** (0.030)	0.118*** (0.025)
Signal: RG2	-0.015 (0.027)	0.020 (0.022)
Signal: RG3	0.007 (0.038)	0.034 (0.027)
Signal: First 14 Rd.	-0.048** (0.019)	0.005 (0.018)
RG2	0.029 (0.034)	-0.077** (0.030)
RG3	0.070* (0.039)	-0.130*** (0.029)
First 14 Rd.	0.068*** (0.018)	0.072*** (0.016)
Observations	8,540	8,820
R2	0.021	0.025

Notes: Cluster-robust (individual-level) standard errors in parenthesis. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. The coefficient on the cross-product term "Signal: RG2" is not significantly different from that on the cross-product term "Signal: RG3" in the high accuracy treatment (F-test, $p = 0.702$). The coefficient on the cross-product term "Signal: RG2" is not significantly different from that on the cross-product term "Signal: RG3" in the low accuracy treatment (F-test, $p = 0.672$).

Appendix 3: Derivation of Likelihood

The likelihood function in SFEM frameworks is derived as follows. The choice probability of subject i employing strategy s at round r of the repeated game k, given the history of her past choices and signals obtained from the opponent up to the round, is defined as

(A. 1) $$P_{ikr}(s) = \frac{1}{1 + \exp(-1/\gamma)},$$

if the observed choice is matched with the predicted choice by strategy s given the history up to the round. Otherwise, the choice is classified as implementation error and

the choice probability is

(A. 2)
$$P_{ikr}(s) = \frac{1}{1 + \exp(1/\gamma)},$$

where γ captures the probability of the implementation error.

The likelihood of subject i employing strategy s is

$$P_i(s) = \prod_k \prod_r P_{ikr}(s).$$

Now in the SFEM framework, the likelihood of subject i over all strategies is a finite mixture of $P_i(s)$ over the entire strategy set. We denote the frequency of occurrence of strategy s by $P(s)$. Then the log likelihood of the MLE is

$$LH = \sum_i \ln \prod_s P(s) P_i(s).$$

The choice probabilities in (A. 1) and (A. 2) are defined over deterministic strategies. Since our list of strategies considered in our SEFM (Table 7) includes stochastic strategies, the choice probabilities should be extended to cover stochastic cases. Following Fudenberg, Rand, and Dreber (2012), the choice probabilities (A. 1) and (A. 2) are extended to cover stochastic strategies as follows,

(A. 3)
$$P_{ikr}(s) = s_{ikr}\left(\frac{1}{1 + \exp(-1/\gamma)}\right) + (1 - s_{ikr})\left(\frac{1}{1 + \exp(1/\gamma)}\right)$$

if the observed choice is A,

(A. 4)
$$P_{ikr}(s) = (1 - s_{ikr})\left(\frac{1}{1 + \exp(-1/\gamma)}\right) + s_{ikr}\left(\frac{1}{1 + \exp(1/\gamma)}\right)$$

if the observed choice is B,

where s_{ikr} is the probability of playing A in the stochastic strategy s given the history up to the round. Observe that the new formulations of the choice probabilities (A. 3) and (A. 4) are reduced to the previous definition (A. 1) and (A. 2) when s_{ikr} takes either one or zero as deterministic choices.

The standard error of the MLE is computed through a cluster-bootstrap (subject-level) with 100 resamples, which is also used to perform the hypothesis tests presented in Section 8.

Appendix 4: Robustness Checks of Our Strategy Estimation

In this Appendix we discuss the robustness of the SFEM estimates. In the main text we use all the three repeated games of each treatment in our estimation. Here we demonstrates that the estimation results almost show little changes even only using the final two repeated games in each treatment (Table A. 5 and A. 6).

The mean retaliation intensity in the high accuracy treatment decreases slightly in the final 2 repeated games, which is closer to the value implied by the g-TFT equilibria (0.235), which might suggest that our subjects learn optimal retaliation intensities by experience in the high accuracy treatment.

Table A. 5
Aggregated estimates for high accuracy case (p = 0.9)

	All	Final 2
Cooperative Strategies	83.9%	88.3%
Family of g-TFT (including zero RI strategies)	76.8%	75.2%
Equilibrium RI	5.6%	7.6%
Stronger RI	54.4%	49.0%
Weaker RI (including zero RI strategies)	17.7%	20.8%
Mean RI conditional on g-TFT (including zero RI strategies)	0.426	0.360
Lenient Strategies	21.4%	21.6%

Table A. 6
Aggregated estimates for low accuracy case (p = 0.6)

	All	Final 2
Cooperative strategies	34.7%	37.6%
Family of g-TFT (including zero RI strategies)	96.2%	96.5%
Equilibrium RI	2.7%	2.4%
Stronger RI	0.0%	0.0%
Weaker RI (including zero RI strategies)	93.5%	94.0%
Mean RI conditional on g-TFT (including zero RI strategies)	0.148	0.135
Lenient strategies	3.7%	2.5%

Appendix 5: Proof of Theorem 2

The proof of the "if" part is straightforward from (7), (8), (9), (10), (11), and (12).

Fix an arbitrary $p \in (\underline{p}, 1)$. From continuity, we can assume without loss of generality that

$$1 - r(a; p) \neq r(b; p).$$

Suppose $p > \hat{p}$, i.e.,

$$r(a; p) - r(b; p) > w(p) > 0.$$

This, along with $w(p) \equiv \dfrac{Y}{\delta(2p-1)Z}$ and $c(a; p) \geq 0$, implies the inequality of (8), and

therefore,

$$r(a; p) = 1 - \varepsilon(p) \quad \text{and} \quad r(b; p) < 1 - \varepsilon(p).$$

Hence, from (9) and (10), either $r(b; p) = \varepsilon(p)$ or

$$Y + c(b; p) = \delta Z(2p-1)\{r(a; p) - r(b; p)\},$$

which implies (11), where $r(b; p) \neq \varepsilon(p)$ holds because $r(a; p) = 1 - \varepsilon(p)$ and $1 - r(a; p) \neq r(b; p)$.

Next, suppose $p < \hat{p}$, i.e.,

$$r(a; p) - r(b; p) < w(p).$$

This, along with $w(p) \equiv \dfrac{Y}{\delta(2p-1)Z}$ and $c(b; p) \geq 0$, implies the inequality of (9), and

therefore,

$$r(b; p) = \varepsilon(p) \quad \text{and} \quad r(a; p) > \varepsilon(p).$$

Hence, from (7) and (8), either $r(a; p) = 1 - \varepsilon(p)$ or

$$Y - c(a; p) = \delta Z(2p-1)\{r(a; p) - r(b; p)\},$$

which implies (12), where $r(a; p) \neq 1 - \varepsilon(p)$ holds because of $r(b; p) = \varepsilon(p)$ and $1 - r(a; p) \neq r(b; p)$.

Q.E.D.

Appendix 6: Experimental Instruction
(October 6, 2006, Translation from Japanese into English)

Please make sure all the contents are in your envelope. The envelop should have the following items.

1. Pen - 1
2. Instruction – 1 copy
3. Printed computer screen images – 1 copy
4. Bank transfer form – 1 sheet
5. Scratch paper – 1 sheet

If you have any missing item, please raise your hand quietly. We will collect the items at the end of the whole experiments, except for the scratch paper which you could keep with you.

Please look at the instruction (this material). Your will be asked to make decisions on a computer terminal. You will earn "points" according to your performance in the experiments. The points will be converted into monetary rewards at the exchange rate of 0.6 yen per point, which will be paid in addition to the participation fee (1,500 yen). The total amount of money you will receive from the experiments is,

<p style="color:red; text-align:center;">The number of points earned × 0.6 yen + participation fee of 1,500 yen.</p>

Any communication with other participants (i.e. conversation, exchange of signals) is not allowed during the experiments, otherwise you may be asked to leave the experiments. Furthermore, you are not allowed to leave in the middle of the experiments unless a experimenter allows or askes to do so. Please turn off your cell phones during the experiments.

Outline of Experiments

We will conduct 6 experiments across 2 sessions. Each session includes 3 experiments with one practice experiment preceding to them. The 6 experiments are independent of each other; the records of one experiment is not transferred to the other experiments. The experiments is conducted via computer network. You are asked to make decisions in a computer terminal and interact with other participants through the computer network.

All of the participants will be divided into pairs in each experiment. The pairs are made randomly by the computer.

Each experiment consists of several rounds (i.e. Round 1, Round 2, Round 3 and so forth). Later we will explain the rule that decides the number of rounds conducted in an experiment. In each round, you are asked to choose one from two alternatives, which will be also explained below.

Those who have any question, please raise your hand quietly.

Decision Making

You will be asked to choose either A or B in each round. Your partner will also asked to choose either A or B. Please look at the table.

You \ Your partner	A		B	
A	**60**	60	**5**	70
B	**70**	5	**15**	15

The table summarizes the points you and your partner earn according to the combination of the choices made by the two players. The characters in the left column marked by red color indicates your choice, which is either A or B. The characters in the top row marked by light blue

color indicate the choice of your partner, which is also either A or B. In each cell, the numbers in red on the left side indicate the points you earn, and the numbers in light blue on the right side indicate the points your partner earns.

If both you and your partner select A,

both of you and your partner earns 60 points.

If you select A and your partner selects B,

you earn 5 points, and your partner earns 70 points.

If you select B and your partner selects A,

you earn 70 points, and your partner earns 5 points.

If both you and your partner select B,

both of you and your partner earns 15 points.

Please look at the table carefully, and ensure that you understand how the points will be awarded to you and your partner according to the choices made by the two players. Your earning does not only depend on your choice, but also depends on the choice of the partner. Similarly, your partner's earning also depends on your choice as well as on her own choice.

Those who have any questions, please raise your hand quietly.

Session 1

Session 1 consists of three experiments, Experiment 1, Experiment 2, and Experiment 3 respectively. The three experiments follow the identical rules and will be conducted consecutively.

Observable Information

You are not allowed to observe whether your partner selected A or B directly. However, you will receive signal a or signal b which has information on your partner's choice. According to the following rules, the computer determines stochastically whether signal a or signal b appears to you;

If your partner selects A, you will observe,

signal a at the probability of 90% and signal b at the probability of 10%.

If your partner selects B, you will observe,

signal b at the probability of 90% and signal a at the probability of 10%.

In the same way, your partner will not know whether you selected A or B. However, your partner will also observe signal a or signal b which have information on your choice. According to the following rules, the computer determines stochastically whether signal a or signal b appears to your partner;

If you selects A, your partner will observe,

signal a at the probability of 90% and signal b at the probability of 10%.

If you select B, your partner will observe,

signal b at the probability of 90% and signal a at the probability of 10%.

The signal you receive and the signal your partner receives are decided independently and have no correlation. Furthermore, the computer determines the signals independently in each round.

We refer the stochastic rules for this signal generating process as **signaling with 90% accuracy.**

Those who have any question, please raise your hand quietly.

Number of Rounds

The number of rounds in each experiment will be determined randomly. At the end of each round, the computer will randomly select a number from 1 to 30 without replacement, so there is 1/30 chance for any number being selected by the computer. The number selected by the computer is uniformly applied to all participants.

The experiment will be terminated when the number 30 is selected by chance.

The experiment will continue if any number other than 30 is selected. However, you will be only noticed that the number other that 30 is selected, instead of the specific number selected by the computer. Then you will move on to the next round, and are again asked to make a decision faced with the same partner.

The probability that the experiment is terminated in a round remains the same, which is 1/30, regardless of the number of the rounds (Round 1, Round 2, Round 3, and so forth). However, the maximum possible number of rounds in an experiment is experimentally controlled, which is 98.

When Experiment 1 is terminated, you proceed to Experiment 2 and you will be randomly paired with a new partner. When Experiment 2 is terminated, you proceed to Experiment 3 and again you will be randomly paired with a new partner. Session 1 will be over when Experiment 3 is terminated.

Those who have any questions, please raise your hand quietly.

Description of Screens and Operations for Computers

Please look at the booklet with printed computer screen images.

Please look at Screen 1 and Screen 2. Screen 1 displays the screen which will be presented to you at the decision phases. Screen 2 is the screen which will be presented to your partner at the decision phases. Please look at the top left portion of each screen, which indicates that the current round is Round 4. The left portion of Screen 1 displays the information available to you up to the round. The left portion of Screen 2 presented to your partner displays the information available to her up to the round.

You are asked to select either "A" or "B" in the bottom right portion of the screen by mouse clicking. Then, the selection will be confirmed by clicking the "OK" button right below the alternatives.

Next, please look at Screens 3 and Screen 4. Screen 3 is the screen that presents the results to you. Screen 4 is the screen that presents the results to your partner. The screens capture the situation that, at Round 4, both of you and your partner chose A. Screen 3 presents to you that, at Round 4, "your partner's signal (accuracy: 90%) is b," indicating to you that the signal you observe on the partner's choice is "b". On the other hand, Screen 4 presents to your partner that, at Round 4, "your partner's signal (accuracy: 90%) is a", indicating to your partner that the signal your partner observe on your choice is "a". Recall that your partner will observe signal a with the probability of 90%, and observe signal b with the probability of 10% when you choose "A".

Then we move on to the Lottery screens. Please turn the page and look at Screen 5 and Screen 6, which display the lottery. A number from 1 to 30 will be randomly selected with the identical probability of occurrence, which is 1/30. Then the cells turn to green according to the number selected. If the 30 is selected, the cell numbered 30 will turn to green and the message below explains that the current experiment is terminated.

Otherwise, Screen 5 is presented in which all the cells numbered from 1 to 29 turn to green at once (you do not know which number is selected specifically), and the message below explains that the experiment continues with the same partner. Screen 6 is presented when the number 30 is selected and the cell numbered 30 turns to green, indicating that the current experiment is terminated at the round. Again, please make sure that the experiment is terminated when the cell numbered 30 turns to green.

Finally, please look at Screen 7. This screen is presented at the end of experiment. The screen displays the total number of points you earned in that experiment, the average number of points per round, the total number of points your partner earned, and the average number of points per round of your partner. Then you will be rematched with a new partner and move on to the next experiment.

Those who have any question, please raise your hand quietly.

Session 2

Please look at page 6 of your instruction. In session 2, you will participate in three experiments, namely, Experiment 4, Experiment 5, and Experiment 6 with a practice experiment preceding to them.

The three experiments follow identical rules and will be conducted consecutively. Session 2 proceed similarly to Session 1, however, the signal accuracy of Session 2 is different from that of Session 1. Except for the signal accuracy, the two sessions are identical.

Observable Information

You are not allowed to observe whether your partner selected A or B directly. However, you will receive signal a or signal b which have information on your partner's choice. According to the following rules, the computer determines stochastically whether signal a or signal b appears to you;

If your partner selects A, you will observe,

signal a at the probability of 60% and signal b at the probability of 40%.

If your partner selects B, you will observe,

signal b at the probability of 60% and signal a at the probability of 40%.

In the same way, your partner will not know whether you selected A or B. However, your partner will also observe signal a or signal b which has information on your choice. According to the following rules, the computer determines stochastically whether signal a or signal b appears to your partner;

If you selects A, your partner will observe,

signal a at the probability of 60% and signal b at the probability of 40%.

If you select B, your partner will observe,

signal b at the probability of 60% and signal a at the probability of 40%.

The signal you receive and the signal your partner receives are decided independently and have no correlation. Furthermore, the computer determines the signals independently in each round.

We refer the stochastic rules for the signal generating process as **signaling with 60% accuracy.**

Those who have any question, please raise your hand quietly.

Description of Screens and Operations for Computers

Please look at the booklet with printed computer screen images.

Please look at Screen 8 and Screen 9. Screen 8 displays the screen which will be presented to you at the decision phases. The left portion of Screen 8 displays the information available to you up to the round. Please make sure the current signal accuracy with the message "Signal accuracy for your partner's selection: 60%." Screen 9 is the screen which will be presented to your partner at the decision phases. The left portion of Screen 9 presented to your partner displays the information available to her up to the round.

Please look at Screen 10 and Screen 11 on page 6. Screen 10 is the screen that presents the results to you. Screen 11 is the screen that presents the results to your partner. The screens capture the situation that, at Round 4, both of you and your partner chose A, however, you observed signal b, and your partner observed signal a. Please make sure that the bottom right portion of Screen 10 and Screen 11 displays the signal you or your partner observed respectively.

The choices you made and the signals you observe about your partner's choices are only available to you, and are not available to the partner. Please make sure this point in Screen 10 and Screen 11.

The screens for the lottery on continuation of the experiment is identical to the case of Session 1, which shows numbers from 1 to 30. Please refer back to Screen 5 and Screen 6. The

results screen at the end of experiment is also identical to that in Session 1 (Screen 7).
Those who have any question, please raise your hand quietly.

Now, all the process of the experiments are completed, and all the points awarded to everyone are recorded on the computer.

Please answer the questionnaire which will be distributed now.

Take out the bank transfer form in the envelop and fill out it accurately, otherwise we are not able to process the payment correctly for you.
Those who have any question, please raise your hand quietly.

Please make sure that you fill out the questionnaire and the bank transfer form correctly.
Those who have any question, please raise your hand quietly.

Please put all the documents in the envelope. Please leave the pen and the ink pad on the desk. Make sure you take all your belongings with you when you leave.

Please do not to disclose any details regarding the experiments to anyone until Saturday. Thank you very much for your participation. Please follow the instructions by the experimenters to leave the room.

2. Computer Screen Images
(October 6, 2006, Translation from Japanese into English)

Screen 1: Your Selection Screen

The Current round

Round

4

Remaining time :[seconds] : 5

Round	Your Choice	Signal accuracy for partner's choice 90%
1	A	b
2	A	a
3	A	a

Your history up to the previous round

You \ Your partner	A	B
A	**60** 60	**5** 70
B	**70** 5	**15** 15

Click on choice A or B and then click OK

Signal accuracy is 90%.

If you choose A, then there is a 90% chance that your partner will receive signal a and a 10% chance that he/she will receive signal b. If you choose B, then there is a 90% chance that your partner will receive signal b and a 10% chance that he/she will receive signal a.

Check either A or B with your mouse and then click on OK.

Choice ○ A ○ B

OK

Screen 2: The Selection Screen of Your Partner

The Current round

Round

4

Remaining time :[seconds] : 5

Round	Your Choice	Signal accuracy for partner's choice 90%
1	B	a
2	A	a
3	A	b

Your history up to the previous round

You \ Your partner	A	B
A	**60** 60	**5** 70
B	**70** 5	**15** 15

Click on choice A or B and then click OK

Signal accuracy is 90%.

If you choose A, then there is a 90% chance that your partner will receive signal a and a 10% chance that he/she will receive signal b. If you choose B, then there is a 90% chance that your partner will receive signal b and a 10% chance that he/she will receive signal a.

Check either A or B with your mouse and then click on OK.

Choice ○ A ○ B

OK

Screen 3: Your Results Screen

The current round

Round

4

Remaining time :[seconds] : 5

Round	Your Choice	Signal accuracy for partner's choice 90%
1	A	b
2	A	a
3	A	a
4	A	b

The results of round 4 are recorded in your history.

You \ Your partner	A		B	
A	**60**	60	**5**	70
B	**70**	5	**15**	15

Signal accuracy is 90%.

The results of this round

Your choice	A
Your partner's signal	b ← You recieved signal B.

If your partner chooses A, then there is a 90% chance that you will receive signal A and a 10% chance that you will receive signal B.
If your partner chooses B, then there is a 90% chance that you will receive signal B and a 10% chance that you will receive signal A.

OK

Screen 4: The Results Screen of Your Partner

The current round

Round

4

Remaining time :[seconds] : 5

Round	Your Choice	Signal accuracy for partner's choice 90%
1	B	a
2	A	a
3	A	b
4	A	a

The results of round 4 are recorded in your history.

You \ Your partner	A		B	
A	**60**	60	**5**	70
B	**70**	5	**15**	15

Signal accuracy is 90%.

The results of this round

Your choice	A
Your partner's signal	a ← Your partner recieved signal a.

If your partner chooses A, then there is a 90% chance that you will receive signal a and a 10% chance that you will receive signal b.
If your partner chooses B, then there is a 90% chance that you will receive signal b and a 10% chance that you will receive signal a.

OK

Screen 5: Lottery (experiment continues)

Screen 6: Lottery (experiment is over)

Screen 7: The Results Screen

These are your results for this experiment:
you will now change partners and continue on to the next experiment.

Your total number of points	7 2 5
Your average number of points per round	4 4
Your partner's total number of points	6 8 5
Your partner's average number of points per round	4 0

Screen 8: Your Selection Screen

The Current round

Round

Round	Your Choice	Signal accuracy for partner's choice 60%
1	A	b
2	A	a
3	A	a

Your history up to the previous round

Click on choice A or B and then click OK

Signal accuracy is 60%.

If you choose A, then there is a 60% chance that your partner will receive signal a and a 40% chance that he/she will receive signal b. If you choose B, then there is a 60% chance that your partner will receive signal b and a 40% chance that he/she will receive signal a.

Check either A or B with your mouse and then click on OK.

Choice ⦿ A ○ B

OK

Screen 9: The Selection Screen of Your Partner

Screen 10: Your Results Screen

Screen 11: The Results Screen of Your Partner

The current round

Round

4

Remaining time :[seconds] : 5

Round	Your Choice	Signal accuracy for partner's choice 60%
1	B	a
2	A	a
3	A	b
4	A	a

The results of round 4 are recorded in your history.

Your partner		A		B	
You					
A		**60**	60	**5**	70
B		**70**	5	**15**	15

Signal accuracy is 60%.

The results of this round

Your choice	A
Your partner's signal	a

Your partner recieved signal a.

If your partner chooses A, then there is a 60% chance that you will receive signal a and a 40% chance that you will receive signal b.

If your partner chooses B, then there is a 60% chance that you will receive signal b and a 40% chance that you will receive signal a.

OK