Does Strategic Play Explain the Decay in Contributions in a Public Goods Game? Experimental Evidence

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Abstract

In finitely repeated laboratory public goods games contributions start at about 40 to 60 percent of the social optimum and decay from over time with increasing free-riding. There is controversy regarding the reasons behind the decay in contributions. We start from the premise that the existence of reciprocal preferences transforms the public goods games into a problem of equilibrium selection with high contributions being an efficient equilibrium and low contributions being an inefficient equilibrium with others in between. We demonstrate that beliefs held by players about the contributions of their peers play a crucial role in determining their own subsequent contributions. We argue that it is social learning about the heterogeneity of types in the population that is the key explanation to the familiar pattern of decay.

JEL Classification: C71, C91

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1. Introduction

A public good is one which is non-rival and non-excludible in consumption. Non-rival means that the consumption of the public good by one person does not affect others' consumption. Non-excludible means that no one can be excluded from enjoying the benefits, even if that person did not contribute any money towards the public good. Examples of public goods include clean environment, national defense, police and fire services as well as public schools, hospitals and public libraries. While all of these are not non-rival or non-excludible to the same extent, they all share the basic feature that once the good is provided, it is difficult, if not impossible, to exclude those who may not have paid for the good's provision. Therefore, a common problem in the context of public goods is the tendency on the part of self-interested individuals to free-ride on others' contributions.

Economists have used laboratory experiments extensively to study the tension between making voluntary contributions to a public good and free riding on others' contributions.[1] In a typical one-shot play of the public goods game, a group of n participants is told that each of them has an endowment of m tokens. Each participant i must make a decision on how to allocate those tokens between a private account and a public account, typically in whole numbers. Contributions by all the participants in a group are made simultaneously and without any communication. In addition to the tokens allocated to the private account, each participant i receives a fixed percentage (α) of the total group contribution to the public account, where $0<\alpha<1<n\alpha$. The term α is referred to as the *marginal per capita return (MPCR)* from the public good. At the end of a round

[1] For an overview of the research in this area till the 1990s see Ledyard (1995). Chaudhuri (2010) surveys the literature post 1995 on three related issues in public goods experiments: (1) conditional cooperation, (2) the use of costly monetary punishments and (3) the creation and role of cooperative norms in sustaining high contributions in this game.

participants get to see (1) either the vector of contributions made by individual members of the group or (2) the total (and therefore average) contributions to the public account without learning the identity of the group members. Each participant's personal earning is the sum of the tokens kept in the private account plus the return from the public account.

In a finitely repeated version of this game, the one-shot game described above is played over a number of rounds where each successive round proceeds in the same manner, starting with a new endowment of *m* for each participant. Participants know *ex ante* how many rounds they will be playing.

The dominant strategy in the stage game is full free riding, which is also the subgame perfect equilibrium in finitely repeated games. However, the social optimum is for each participant to contribute his entire token endowment to the public account in each round.

Prior experimental research looking at voluntary contributions to a public good reports that: (1) in a one-shot public goods game, the average contribution into a public account ranges between 40% and 60% of the total endowment with wide variations in individual contributions ranging between 0% and 100% (Andreoni, 1988, Iaac & Walker, 1988, Ledyard, 1995). (2) In repeated public goods game, the average contributions in the first round range between 40% and 60% but then contributions decline as participants choose to "*free ride*" over time. The result implies that cooperation declines gradually over time, though the strong free-riding hypothesis of zero contribution is seldom borne out.

There is substantial controversy regarding this familiar pattern of declining contributions over time. While the behavior of those subjects who free-ride from the outset may not be difficult to understand, why do some subjects start out making high contributions and reduce their contribution over time?

Andreoni (1988) is the first to attempt to carefully explore the phenomenon of contributions decay in such public goods games. Andreoni suggests two hypotheses for the reasons behind the decay in contributions: “learning” and “strategies”. The learning hypothesis holds that boundedly-rational subjects may not pick up on the dominant strategy immediately but take time to learn this. Therefore contributions decay over time as more subjects learn the dominant strategy to free-ride. The strategies hypothesis suggests that some players may realize that free-riding is the dominant strategy but they do not want to educate their peers about the dominant strategy. These more sophisticated subjects mimic the rest by contributing more in the initial stages of the game in order to get the others to contribute as well but then they bail-out and free-ride as the end period approaches.[2]

In order to test the strategies hypothesis Andreoni sets up two treatments: “*partners*” and “*strangers*”. In the partners treatment the group composition remains unchanged for the entire duration of the experiment, whereas in the strangers treatment participants are randomly re-matched at the end of each round. The aim is to isolate *strategic behavior* in the following way. Suppose a subject learns in round *t* that free-riding is a single shot dominant strategy, then, in the partners set up, players might choose to continue their contribution because they are able to signal their strategy to the other players in the group. While in a strangers set up, this signaling mechanism is not available, and hence there is no incentive to continue the contribution. This implies that if a subject is a partner playing strategically then she might continue to contribute to the public account. But if a subject is a stranger then she has no incentive to continue cooperation because every game for a stranger is an end-game. This suggests that the partners treatment should elicit higher contribution than the strangers treatment.

[2] The strategies hypothesis is derived from Kreps et al. (1981) "Rational Cooperation in a Finitely Repeated Prisoner's Dilemma".

To isolate the *learning* hypothesis, the experiment includes a surprise "*restart*" where after subjects have finished playing 10 rounds, they were told to continue playing the game and after the additional 3 rounds they were told to stop playing the game. Most subjects would have figured out the dominant strategy of free-riding by this time and contributions should continue to decay with further repetitions. So if learning to play the dominant strategy is primarily responsible for decay, both partners and strangers should be unaffected by the restart.

Andreoni, however, finds that strangers contribute more than partners for the initial 10 rounds and the percentage of partners choosing to free-ride is greater than the percentage of strangers choosing to free ride. Both of these findings contradict the strategies hypothesis. After the re-start, both partners and strangers return to high levels of contribution. The re-start has a longer lasting effect on partners whereas strangers appear to be only temporarily affected by the re-start. This finding contradicts the learning hypothesis which suggests that if learning is primarily responsible for decay then both partners and strangers should be *unaffected* by the restart. Hence Andreoni's findings do not provide support for either the learning or the strategies hypothesis.

Croson (1996) replicates Andreoni's (1988) experiment. In Croson's experiment subjects play for 10 more rounds after the initial 10 rounds. Unlike Andreoni, Croson finds that partners contribute more than strangers, a finding that is consistent with the strategies hypothesis. But Croson also finds that once the game restarts contributions jump up for partners, which is inconsistent with the learning hypothesis. A number of subsequent studies have analysed the pattern of contributions decay using a partners versus strangers set-up with different subject pools. Table 1 summarizes the results derived from other partners versus strangers experiments. As is clear from the table, the findings regarding the relative contributions of partners and strangers are not consistent across these studies.

<< Table 1 about here>>

We adopt a different approach to explain the decay in contributions in a public goods experiment. We believe that subjects play the public goods game differently than visualized by Andreoni. According to Rabin (1993), if one assumes the existence of reciprocal preferences then it is possible to think about the public goods game as a "coordination problem" with high contribution being an efficient equilibrium and low contribution being an inefficient equilibrium with others in between. Rabin's model though is designed for one-shot normal form games and is not immediately applicable to finitely repeated public goods games. Dufwenberg and Kirchsteiger (2004) extend the Rabin model to apply to a finitely repeated linear public goods game like the one we study here. Therefore we suggest that the problem facing subjects in this game is essentially one of equilibrium selection.[3]

Furthermore "*learning*" can take one of two types: (1) "*Introspective*" learning, where a person learns on his own simply by doing something over and over again; (2) "*social*" learning, where a person learns by observing the actions of others. None of the previous studies distinguish between these two types of learning.

We elicit beliefs held by players regarding the contributions to be made by their peers prior to the start of play and demonstrate that these beliefs play a crucial role in

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[3] However, our model and eventual explanation differs from those of Dufwenberg and Kirchsteiger (2004) is significant ways. In the Dufwenberg and Kirchsteiger model there is no incompleteness of information as regards the type of players. The only source of informational asymmetry is via imperfect information, given that in each round players move simultaneously and are unaware of the decisions made by other players prior to making their own decision. In contrast, our explanation relies on incomplete information about players types. We argue that players in this game choose their best responses given their beliefs about the distribution of types. Over time as they observe the actions of other players they update those beliefs and adjust their best responses accordingly. We, however, do not attempt to provide a theoretical model of this behavior in this paper.

determining players' subsequent contributions. We show that subjects have very different beliefs about the contributions to be made by their group members and choose contribution levels based on those beliefs. Subjects with optimistic beliefs start out with high contributions but over time as they observe the fall in average contributions they start to reduce their contributions. The fact that contributions depend more on beliefs about others' contributions and not on the availability of signaling opportunities provides evidence against the strategies hypothesis. Furthermore the fact the contributions decay more rapidly when players get to observe the contributions of their peers provides evidence supporting social learning arguments. We argue that it is social learning about the heterogeneity of types in the population that explains the familiar pattern of decay.

Finally, we adopt a "*partners*" protocol where group composition does not change from one round to the next. This of course allows for signalling and reputation building between the group members. We do this because social learning opportunities are available in a strangers protocol as well. But a strangers protocol offers no or limited scope for signalling and reputation building. Thus the use of the partners protocol provides the strategies hypothesis its best shot. If we can demonstrate that the strategies hypothesis does not perform well in the partners protocol then we can effectively rule this strategy out as a good explanation of perceived behaviour.

We proceed as follows: section 2 outlines the experimental design and procedures. We report our results in three different sections. Section 3 looks at patterns of decay in contributions and explores to what extent this is explained by the strategies hypothesis. One thing we learn from this section is that beliefs about others' contribution play a crucial role in determining contributions. So in Section 4 we look more closely at how beliefs influence contributions. In Section 5 we study how factors such as the number of rounds played, the number of feedbacks received and the potential earning in the game influence learning about the game and therefore contributions to the public account. We provide some concluding remarks in Section 6.

2. Experimental Design and Procedures

Three hundred and twenty-eight subjects were recruited from the University of Auckland. Participants are undergraduate and postgraduate business and economics students, who are inexperienced in the public goods game. All experiments were conducted in a computer laboratory on campus using an internet based public goods game.

At the beginning of each session, the instructions of the game were read out loud to the subjects (see Appendix for a set of sample instructions). Once they log-on to the website, subjects can also read this instruction privately on their computer screen. Subjects are given 10-15 minutes to read through online instructions and ask any questions that they might have.

Subjects are grouped into four. We adopt a “partners” protocol so that the composition of the group always remains unchanged. In each round each subject is endowed with a particular number of tokens at the beginning of each round. (In all but one of our treatments each subject gets an endowment of 10 tokens in each round while each subject gets 40 tokens in the other treatment. We explain below.) In each round each participant has to decide how to allocate his token endowment either to a public account or a private account. The decisions are made simultaneously. Subjects are restricted to making decisions in whole numbers. Tokens contributed to the public account are doubled by the experimenter and redistributed equally among the 4 members of the group. Tokens contributed to the private account remain unchanged. In each round the total payoff to a subject is the number of tokens held in the private account plus the number of tokens obtained from the public account. The payoff to subject *i* in each round is given by

$\pi_i = e - c_i + 0.5\sum_{j=1}^{4} c_j$ where e is the endowment provided to each subject at the beginning of each round, c_i is contribution to the public account by subject i, 0.5 is the marginal per capita return for each token contributed to the public account, and $\sum_{j=1}^{4} c_j$ is sum of contribution to the public account by all four players in the group.

In all treatments subjects play the stage game for a number of rounds and they know the number of rounds prior to the start of play. In some sessions, in order to replicate the "re-start" effect, we have the subjects play some additional rounds at the conclusion of the pre-announced number of rounds. In those sessions, at the beginning we told the subjects that they were going to play for 24 rounds. Once those 24 rounds were over, we told them that we got done earlier than we thought and that there was time to play for another 8 rounds. Subjects were given the opportunity to withdraw if they wished to do but no one did in any of the sessions.

At the end of the session a subject's total earnings in tokens is converted into cash at the rate of NZ $0.05 per token. Participants were paid $4 for showing up. The sessions lasted about one hour and on average subjects earned $18. The highest earning was Z$30.48 and the lowest NZ$10.60.[4]

Our experiment consists of seven different treatments. The first treatment - "*Round-by-Round Feedback*" treatment – is a standard public goods game where subjects play the public goods game for 24 rounds. At the end of each round they receive feedback regarding the total tokens contributed to the public account and their returns from the public account and therefore at the end of each round they know how much they earned in that round. There are 36 subjects in this treatment.

[4] At the time the experiments were run in 2006 NZ $1 was roughly equivalent to US $0.78.

Here prior to starting the first round, we elicit subjects' beliefs about the other group members' contributions by asking each subject to fill out a questionnaire. The questionnaire asked them to predict the average contribution to the public account from the other three member of their group in round 1. Subjects are paid according to the accuracy of their prediction using a quadratic scoring rule (see Appendix). We use these elicited beliefs to classify subjects into three categories: (1) those who expect their group members to contribute either 0, 1, 2, or 3 tokens will be referred to as the "*pessimists*"; (2) those who expect their group members to contribute either 4, 5 or 6 tokens will be referred to as the "*realists*" and finally (3) those who expect their group members to contribute either 7, 8, 9 or 10 tokens will be referred to as the "*optimists*" [5]. Since subjects are restricted to making allocation decisions in whole numbers the predictions can only take discrete values of 0, 1, …10 tokens and since the endowment is out of 10 tokens, in that follows we will often use percentages rather than the actual number of tokens.

In the rest of the paper we will refer to this treatment as ***RBR24-S***, where ***24*** refers to the number of rounds and ***S*** refers to the fact that in this treatment beliefs are elicited only once as opposed to other treatments where we elicit beliefs multiple times. This treatment serves as our control treatment.

The second treatment is the "*Intermittent Feedback*" treatment which has 60 subjects. In this treatment, subjects play the public goods game for 24 rounds but get feedback at the end of every fourth round. That is subjects learn about total contributions to the public account and their returns from it and therefore their earnings for any round at the end of every fourth round. This means that subjects learned about contributions to the

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[5] We use 4 - 6 tokens as the benchmark because prior studies have found that the average contribution in round 1 starts at around 30% - 70% of the endowment. Later in the paper we show that this classification gives very robust results when tested against models without belief classification - where we treated beliefs as given.

public account and their returns from each round during rounds 1 through 4 at the end of round 4. Similarly they learned what happened during rounds 5 through 8 at the end of round 8.

Given that the subjects played 24 rounds and received feedback after every fourth round, they therefore receive feedback 6 times in all, at the ends of rounds 4, 8, 12, 16, 20 and 24. Here again, prior to round 1 we elicit subject beliefs by asking them to fill out questionnaire as in the first treatment. Henceforth we refer to this treatment as ***IF24-S***, where ***24*** refers to the number of rounds and ***S*** refers to the fact that in this treatment beliefs are elicited only once at the beginning of the game.

Since we are interested in studying the role of social learning in contributions decay, we wish to understand how subjects respond to information regarding the contributions of their peers. This intermittent feedback treatment allows us to hone in on the role of information about peer contributions and allows us to focus on how subjects respond to this information.

The third treatment is the "*No Feedback*" treatment. It consists of 64 subjects. In this treatment, subjects play the public goods game for 24 rounds but they do *not* receive any information about the total contributions to the public account or their returns from the public account for any round till the very end of the session. Thus the only thing a subject knows at the end of any given round is how he allocated his token endowment between the public and private accounts but has no idea about the choices made by others or his earnings.

The idea behind this no feedback treatment is as follows. Suppose the main reason behind contributions decay in these games is the fact that boundedly-rational agents need time to learn that the dominant strategy is to free-ride. Then a process of introspective learning, where the subjects play the stage game a number of times, even if they cannot observe the actions of their peers and there is no scope for social learning, should suffice to teach the subjects the merits of free-riding. Therefore if it is introspective learning that explains the decay in contributions then we should observe substantial decay even in this treatment which does not provide any scope for social learning. We elicit subject beliefs once prior to round 1. The procedure of belief elicitation is the same as the first treatment.

Henceforth we refer to this treatment as ***NF24-S***, where ***24*** refers to the number of rounds and ***S*** refers to the fact that in this treatment beliefs are elicited only once at the beginning of the game.

We also replicate the re-start effect found by Andreoni (1988) in one session of the RBR24-S treatment and one session of the IF24-S treatment with 16 subjects participating in each session. We included the surprise "restart" where subjects were told to play an additional 8 rounds after they finished playing the initial set of 24 rounds.[6]

Notice that in the IF24-S treatment, while subjects play for 24 rounds they receive feedback only 6 times. In order to distinguish the importance of the number of rounds played as opposed to the number of feedbacks received we introduce two additional treatments.

Our fourth treatment has 44 subjects where they play the stage game for only 6 rounds and get feedback about total contributions to the public account and their earnings in each round. Thus this treatment is similar to the first treatment, RBR24-S, except that subjects play for 6 rounds only. Again we elicit subject beliefs once prior to round 1. The procedure of belief elicitation is the same as the first treatment. Henceforth we refer to this treatment as ***RBR6-S***, where ***RBR*** stands for round-by-round feedback of total contributions and earnings, ***6*** refers to the fact that subjects in this treatment play the game

[6] We find a re-start effect similar to Andreoni (1988) and Croson (1996). But we do not elaborate on this any further in the current paper since that is not our primary focus and we do not have much to add to what has been written about this phenomenon already.

for 6 rounds and ***S*** refers to the fact that beliefs are elicited only once at the beginning of the game.

This however poses a problem because subjects who play for 6 rounds only, will potentially make only one-fourth the earnings of those subjects who play for 24 rounds. Thus the disparity in potential earnings may lead to differences in behavior.

In order to control for any possible income effect we introduce fifth treatment which is identical to the previous RBR6-S treatment except here in each round each subject has four times the token endowment. That is, subjects in this treatment have 40 tokens each in each round as opposed to the subjects in the other four treatments who have 10 tokens each in each round. Thus the subjects in this treatment can potentially make the same earning as those playing 24 rounds with 10 tokens in each round. We have 28 subjects in this treatment. Again we elicit subject beliefs once prior to round 1. The procedure of belief elicitation is the same as the first treatment. Henceforth we refer to this treatment as ***RBR6-S-High***, where ***6*** refers to the number of rounds, ***S*** refers to single belief elicitation prior starting round 1, and ***High*** refers to higher endowment of 40 tokens rather than 10 tokens as in other treatments.

Our sixth treatment is the same as the RBR24-S treatment (where subjects play the game for 24 rounds and receive feedback regarding the total tokens contributed to the public account and their returns from the public account at the end of each round) except for the number of times we asked subjects to predict the average contribution to the public account from the other three member of their group. In this treatment we asked subjects once before they make the decision for round 1 and every 4 rounds after they receive feedback for round 4, 8, 12, 16 and 20 but before they make decision for round 5, 9, 13, 17 and 21, respectively. Hence subjects make 6 predictions in total, one before round 1, 5, 9, 13, 17 and 21. There are 60 subjects for this treatment. Henceforth we refer to this treatment as ***RBR24-M***, where ***24*** comes from the fact that subjects in this treatment play the game for 24 rounds and ***M*** stands for the fact that in this treatment beliefs are elicited multiple times during the course of the game.

The seventh and last treatment is the same as the IF24-S treatment (where subjects play the game for 24 rounds and they receive feedback regarding the total tokens contributed to the public account and their returns from the public account at the end of every four rounds) except that in this treatment subjects are asked to make a multiple predictions. They are asked to make a prediction once before round 1 and every 4 rounds after they receive the feedback but before they make the decision for round 5, 7, 13, 17 and 21. We have recruited 36 subjects for this treatment. Henceforth we refer to this treatment as ***IF24-M***.

Table 2 provides a summary of the different treatments.

<< Table 2 about here> >

3. Results

3.1 The Role of Social Learning in Contributions Decay

In this section we argue that the main cause of decaying contributions is social learning rather than strategic play or introspective learning. In providing evidence to support this claim in this section of the paper we will focus only on the first three treatments described above, that is, the RBR24-S, IF24-S and NF24-S treatments.

We start off with a preliminary analysis of these treatments. The average contribution to the public account is 47% in the RBR24-S treatment, 41% in the IF24-S treatment, and 42% in the NF24-S. Figure 1 illustrates the temporal pattern of average contributions in these three treatments over 24 rounds. Two facts stand out from Figure 1. First, in the two treatments where the subjects receive feedback about the contributions made by others in the group – that is, the RBR24-S and the IF24-S treatments – average contributions show the familiar pattern of decay. In the RBR24-S treatment average contributions start at 54% in round 1 and decay to 34% in round 24 while in the IF24-S treatment average contributions start at 50% in round 1 and decay to 29% in round 24. Second, we observe little to no decay in average contributions in the NF24-S treatment where average contribution starts at about 45% in round 1 and end at about 42% in round 24. Of the three treatments, the IF24-S treatment exhibits the steepest decline in contributions compared to the other two treatments.

<< Figure 1 about here>>

We use multivariate regression analysis to understand the pattern of contributions in the three different treatments. What we have here is a cross-section of subjects making a series of decisions over time. Thus the appropriate way to treat the data generated is to use a panel data model. In the RBR24-S, we have 36 subjects, each making 24 decisions. In the IF24-S treatment, we have 60 subjects, each making 24 decisions. In the NF24-S treatment, we have 64 subjects, each making 24 decisions. Hence we have a total of 3840 observations.

Let C_{it} be the contribution of player i in round t. This observed contribution C_{it} equals the desired contribution, C_{it}^{*} (which is a latent variable), if and only if $0 \le C_{it}^{*} \le 10$. Therefore we have:

$$C_{it} = \begin{cases} 0 & if \quad C_{it}^{*} < 0 \\ C_{it}^{*} & if \quad 0 \le C_{it}^{*} \le 10 \\ a & if \quad C_{it}^{*} > 10 \end{cases}$$

and C_{it}^{*} is determined by the following equation:

$$C_{it}^{*} = X_{it}^{'}\beta + v_i + C_{i0}\xi_0 + X_i^{'}\xi + \varepsilon_{it}$$

for $i = 1, \ldots, n$ and $t = 1, \ldots, T$. The random effects (ν_i) are IID $N(0, \sigma_\nu^2)$ and the errors (ε_{it}) are $N(0, \sigma_\varepsilon^2)$ independent of ν_i. We use random effects rather than fixed effects because each subject has individual-specific effects such as gender, university degree and family background. Here X_{it} denotes a vector of time invariant effects (like treatment effects), time varying variables (like an individual's contribution in the previous round), and an overall time effect, which is common to all players. Each subject's contribution is in whole numbers which are bounded by zero from below and by ten (the token endowment) from above and thus we estimate this model as a random effects Tobit (maximum likelihood).[7]

To analyse the contribution patterns of the RBR24-S treatment, the IF24-S treatment and the NF24-S treatment, we include the following independent variables in our specification; (1) two dummies - one for the RBR24-S treatment and one for the IF24-S treatment with the NF24-S treatment being the reference category, (2) round, and (3) two interaction terms - one each for the RBR24-S dummy and round, and the IF24-S dummy and round. Here and in what follows, we look at a number of different specifications but in order to make for easier reading we report results only for the specification that provides the best fit for our data.

Table 3 reports results of the above specification. The results show that estimated coefficients of treatment dummies are not significantly different. This implies that subjects start out their contributions at a similar amount regardless of the treatment they

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[7] The token endowment is bounded by 10 from above in all treatments except for the RBR6-S-High treatment where contribution to the public account is bounded by zero from below and by forty from above. But we are not discussing the RBR6-S-High treatment in this section and do not need to consider this difference here.

are in. This suggests that the different instructions provided to participants at the beginning of the session do not have an effect on initial contributions.

The estimated coefficient for round variable (which is used as a reference category for the NF24-S treatment) is negative and significant. The two interaction terms between treatment dummies and round are also negative and significant. The estimated coefficient of the interaction term between the IF24-S dummy and round has the largest negative coefficient followed by the interaction term between the RBR24-S dummy and round. A Wald test finds a significant difference between the estimated coefficients of the interaction term between the IF24-S dummy and round and the interaction term between the RBR24-S dummy and round (with $\chi^2(1) = 4.23$, probability> $\chi^2 = 0.0397$). This implies that contributions decay at the greatest rate in the IF24-S followed by the RBR24-S treatments, and then the NF24-S treatment.

<< Table 3 about here> >

When subjects cannot see the contributions of others, i.e. no scope for social learning, in the NF24-S treatment we find that contributions do not decay as much as when they get to see what their peers are doing. Subjects start their contributions at a similar level regardless of the treatment they are in. However, over time, subjects in the treatment where they receive feedbacks on how much others have been contributing every four rounds (the IF24-S treatment) reduce their contributions at the fastest rate followed by those who receive feedback at the end of each round (the RBR24-S treatment) and finally by those who do not receive any feedback at all until the last round of the game (the NF24-S treatment).

The regression reports that estimated coefficient of round variable is negative and significant, which suggests that contributions do decay in the NF24-S treatment. This result supports the argument that part of the decay in contribution comes from *introspective learning* i.e. learning the dominant strategy of free riding from repeating the action.

However introspective learning seems to explain a small part of the decay since the rate of decay in contribution in the NF24-S treatment is small compared to treatments where subjects get to observe how much others are contributing during the experiment, i.e. the RBR24-S and the IF24-S treatments. Given that the decay is more pronounced in the RBR24-S and the IF24-S treatments than the NF24-S treatment, we conclude that in an addition to the introspective learning which causes subjects to decrease their contributions, there is also evidence of social learning. In treatments where subjects get to see how much others are contributing during the game, they contribute high at the outset; however their contributions decrease significantly more than the treatment with no feedback as they play more rounds. In sections 3.3.1 and 3.3.2 we explore these behavioral differences more carefully.[8]

3.2 Contribution profiles for different types of subjects

As mentioned before, prior to the beginning of round 1 we elicit players' beliefs about the contributions of their peers by asking them what they think the other group members will contribute in round 1 on average. The conditional cooperation hypothesis which recasts the public goods game as essentially a problem of equilibrium selection holds that subjects best-respond to their beliefs. Those who expect their peers to make high (low) contributions do so themselves.

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[8] Neugebauer, Perote, Schmidt and Loos (2009) also look at contributions to a public good when subjects get feedback about others' contributions and when they do not. Neugebauer et al. also collect data on subjects' guesses about the contributions to be made by other group member. They report a similar finding that while contributions show the typically pattern of decay over time when subjects receive feedback about others' contributions, contributions are stable over time in the treatment with no such feedback. They go on to argue that the decay in contribuitions is caused by an element of serlf-serving bias in conditionally cooperative behavior and to subjects adapting to this bias over time.

We now turn to the behavior of subjects with different beliefs. We classify our subjects into three types: (1) ***optimists*** who expect their peers to contribute 7 tokens or more in the first round, (2) ***realists*** who expect their peers to contribute between 4 and 6 tokens, and (3) ***pessimists*** who expect their peers to contribute 3 tokens or less. (Free-riders would be included in the group of pessimists, except that there are very few subjects who free-ride for the entire time.) The vast majority of our subjects (at least 50% or more across different treatments) fall in the category of realists, i.e., they expect their peers to contribute between 4 and 6 tokens. This possibly explains why average contributions typically start in that range across a large number of studies.

Gunnthorsdottir, Houser & McCabe (2007) uses similar classification to separate subjects into two types; one for "free-riders" who contribute 30% or less of her endowment in the first round and another group for "cooperators" who contribute more than 30%. Furthermore, Ones and Putterman (2007) show that early contributions can serve as a significant predictor of contributions in later periods and therefore early beliefs and behavior can serve as reliable predictors of behavior later in the game.[9]

Figures 2 and 3 show the average contributions (in percentages) for the two experiments treatments of interest, the NF24-S and the IF24-S treatments respectively. In each figure the contributions of the pessimists are indicated with circles, those of realists with squares and those of optimists with triangles.

Figure 2 shows the contribution behavior of subjects in the NF24-S treatment where subjects do not get to see what the other are contributing or what their earnings are in any of the rounds. There are 48 (75%) realists in this treatment and 8 (12.5%) each of

[9] To ensure that our classification of dividing subjects into three types provides robust regression results, for each of the following regressions we test it against the exact same specification except we replace type dummies with the actual predictions stated by subjects. Then we use a likelihood-ratio test to examine the robustness of our classification. We find that for all of the following regressions, a likelihood-ratio test reports that dividing subjects into three categories in this manner provides robust results.

optimists and realists. A few things stand out here. The optimists, who expect others to contribute 7 tokens or more, contribute 6.4 tokens on average. Realists, who expect others to contribute between 4 and 6 tokens, contribute 4.3 tokens on average. Finally, pessimists, who expect others to contribute 3 tokens or less, contribute 1.7 tokens on average. Notice that these contributions are relatively stable over time. There is a sharp spike in the average contribution of pessimists in the last period which we attribute to an end-game effect.[10]

<< Figure 2 about here>>

Figure 3 shows the contribution pattern by the three different types of subjects in the IF24-S treatments, respectively. Here we do observe a pattern of decaying contributions but this is true mostly for the optimists and the realists. For the pessimists, contributions are relatively stable, and if anything, show a very slight upward trend. We address this in greater detail below. The patterns are very similar in our control RBR24-S treatment and hence we have chosen not to include a separate figure for this treatment.

< <Figure 3 about here>>

According to the strategies hypothesis we would expect those sophisticated players, who figure out the dominant strategy quickly but who engage in mimicking of less sophisticated players, to start with high contributions in the initial rounds and then free ride more towards the end. This predicted contribution pattern fits the contribution pattern of the optimists and realists in the IF24-S treatment. This is also true of the RBR-24S treatment which is not depicted in detail. But if it is indeed the case that these two groups

[10] As mentioned above there are only 8 pessimists in this treatment and the sharp increase in the very last period is mostly due to the contributions of two subjects. One subject, who contributed only 1 token to the public account in round 23, put in all 10 tokens in the public account in the last period. Another subject, who had put in 2 tokens in the public account in round 23, contributed 8 tokens to the public account in round 24. Notice that the spike is in the opposite direction of the strategies hypothesis.

of subjects are engaging in mimicking of less sophisticated players then when we look at the NF24-S treatment, where there are no signaling opportunities, we would expect these same subjects to contribute very little to the public account. If these subjects are indeed sophisticated and realize that they should free ride then, in the absence of any signaling opportunities in the NF24-S treatment, we expect these subjects to either totally free ride or at least contribute a very small amount for the entire game. But instead, we find a steady pattern of 63.5% contribution from the optimists and 42.5% contributions from the realists.

We hasten to point out that there were indeed 9 subjects in the NF24-S treatment who did free-ride for all 24 rounds. 5 of those were classified as realists (i.e. they expected others to contribute between 4 and 6 tokens), 3 were classified as pessimists (i.e. they expected others to contribute 3 tokens or less), and only 1 was classified as an optimist (i.e. expected greater than 7 tokens contribution from the others). There are no subjects who free-ride for all 24 rounds on the other two treatments.

Hence we observe some evidence supporting the strategies hypothesis - 14% of the subjects in the NF24-S treatment contributed nothing to the public account for all rounds. Nevertheless, the contribution behavior of a majority of subjects in the NF24-S treatment is inconsistent with the strategies hypothesis.

Thus a better explanation for the decaying contributions seems to be that subjects do indeed behave as conditional co-operators and choose their contributions on the basis of their beliefs about the contributions of their peers. Later in this paper we show that our data support this hypothesis.

3.3 Analysis of contribution patters in the NF24-S and IF24-S Treatments

This section uses random effects Tobit regression to undertake a more detailed analysis of contribution patterns in the two experimental treatments of interest NF24-S and IF-24S. Table 4 and 5 present the results from Tobit regressions with random effects for the NF24-S treatment and the IF24-S treatment, respectively.

3.3.1 Analysis of Contribution Patters in the NF24-S Treatment

The section above shows that contributions decay even in the treatment where subjects do not receive feedback about others' contribution even though this decay is not as pronounced as the treatments with feedback. This suggests that introspective learning does play a role, albeit a small one.

In this section we look closely at contribution patters in the NF24-S treatment. For this part of the analysis we exclude data for 9 (out of 64) subjects who contributed zero for all 24 rounds.[11] We use a random effects Tobit regression to analyse the contribution pattern where we include among the independent variables (1) two dummy variables - one each for the optimists and one for the pessimists with the realists being the reference category, (2) round, (3) two interaction terms - one for the optimist dummy interacted with round, and one for the pessimist dummy interacted with round, (4) lag contribution - own contribution in the previous round, and (5) two interaction terms - one for optimist dummy interacted with lag contribution and another for pessimist dummy interacted with lag contribution. In our regression specification we typically include lagged values of the dependent variable (contribution) among the independent variables. Therefore, we also

[11] All of these 9 subjects predicted the average contribution by the other three group members is higher than 0 in round 1. Six out of these 9 predicted that the average contribution by the other three group members will be 4 tokens or higher. It seems to us that these subjects chose to contribute zero because they realised that the dominant strategy is to free ride at the outset of the game, rather than believing that the other will also contribute zero. Thus the behavior of these subjects is not relevant in exploring issues of learning since they seem to understand the dominant strategy at the outset.

include C_{i0}, the first observation of C_{it} (or initial condition) and X_i = (X_{i1}, …, X_{iT}) as independent variables to obtain unbiased coefficient estimates.[12]

Table 4 reports that the optimist dummy is not significant whereas the pessimist dummy is negative and significant. This implies that contributions by the pessimists start out significantly lower than the realists and the optimists. The estimated coefficient for round variable is negative and significant, suggesting that realists decrease their contributions to the public account as they play more rounds. The two estimated coefficients for interaction terms between the optimist dummy and round, and the pessimist dummy and round are positive and significant. This implies that the optimists and the pessimists increase their contributions over time with respect to contributions by the realists.

The estimated coefficient for the optimist dummy interacted with round is not significantly different from the estimated coefficient for pessimist dummy interacted with round ($\chi^2 = 0.01, \Pr = 0.9147$), suggesting that the optimists and the pessimists increase contributions with respect to the realists at the same rate over time. The estimated coefficients for lag contribution, optimist dummy interacted with lag contribution, and pessimist dummy interacted with lag contribution are positive and significant. This implies that if a player contributes more (less) in the previous round, then she will contribute more (less) in the current round, and the magnitude of the effect of lag contribution on the current contribution is bigger for the optimists and the pessimists than the realists.

<<Table 4 about here>>

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[12] This is the correction suggested by Woolridge (2002, pp. 542=544) for dynamic panel data models of this nature. We do not report the results for the estimated coefficients of C_{i0} and X_i.

This analysis is consistent with what Figure 2 shows. Given the above, we conclude that the pessimists start out their contributions lower than the realists and the optimists. Over time, we find that the realists decrease their contributions as the number of round increases while the optimists and the pessimists increase their contributions with respect to contributions by the realists. Hence decaying contributions in the NF24-S treatment comes from the fact that the majority of subjects (75%) are realists learn the dominant strategy by doing and decrease their contributions to the public account as number of round increases.

3.3.2 Analysis of Contribution Patterns in the IF24-S Treatment

It is clear that feedback has an effect on contributions, hence the IF24-S treatment where subjects in this treatment receive feedback on how much others have been contributing in the past four rounds at the end of every four rounds allows us to hone in on the effect of that feedback.

We use a random effects Tobit model again and pay particular attention to what happens to contributions in rounds immediately after the subjects receive feedback about others' contribution. The independent variables include: (1) lag contribution, (2) round and (3) two interaction terms - one for optimist dummy interacted with round, and another for pessimist dummy interacted with round. To analyze the impact of information we include among the independent variables (4) new information dummy which is a dummy for the rounds after subjects receive feedback, (5) two interaction terms - one for the new information dummy interacted with optimist dummy, and another one for the new information dummy interacted with pessimist dummy, (6) lag difference - difference between the average own contribution and average contribution by the other three group members *over the past four rounds*, and (7) two interaction terms - one for lag difference and optimist dummy, another for lag difference and pessimist dummy. [13]

Table 5 reports the results of the random effects Tobit regression of the above specification. The estimated coefficient of lag contribution is positive and significant. This implies that if a player contributes more (less) in the previous round, then she will contribute more (less) in the current round. Estimated coefficient for round variable is negative and significant. The interaction term between optimist dummy and round is not significant while the interaction term between pessimist dummy and round is positive and significant. This suggests that the realists and the optimists decrease their contributions over time, while the pessimists increase their contributions with respect to the realists over time. This contribution pattern of increasing in contributions by the pessimists with respect to the decreasing in contributions by the realists is shown in Figure 3.

The estimated marginal effect[14] of the interaction term between new information dummy and optimist dummy is negative and significant at 5% level whereas the estimated marginal effect of new information dummy is a positive but not statistically significant. This implies that when the optimists receive the information on how much their group members have been contributing in the past four rounds, they decrease their average contributions by 0.73 token in the next round. This decrease in contributions can be explained by the fact that at the end of every four rounds when the optimists realize that they have been contributing higher than the other group members, and they react to this new information by reducing the amount of contributions significantly.

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[13] We used the realists as the reference category for all possible comparisons.

[14] We calculate the change in the dependent variable (contribution) with respect to the change in the independent variables by calculating estimates of $E\left(c^* \mid x = x_{it}, v_i = 0\right)$, where $c^* = 0$ if $c \leq 0$, $c^* = 10$, if $c \geq 10$, and $c^* = c$ otherwise.

The overall insignificance of the estimated coefficient of the new information dummy can be explained by the fact that the more than half of the total participants (58%) fall into the realist category. Hence the new information on the total contributions of the past four rounds is not considerably different from what they have been contributing.

As for the pessimists, the estimated marginal effect for the interaction term between new information dummy and pessimist dummy is positive but not statistically significant. This result needs to be studied in conjunction with the fact that the regression reports a positive and significant value for the pessimist dummy coefficient interacted with round. This suggests that the pessimists increase their contribution over 24 rounds as compared to the realists but this increase in gradual over time rather than sudden spikes upon seeing the contribution of others.

The estimated coefficients for lag difference interacted with optimist dummy and lag difference interacted with pessimist dummy are both negative and significant. This suggests that both optimists and pessimists react to information about the average contribution of group members over the past rounds in a similar way. If her own contribution was higher (lower) than the past four round average contribution by the other three group members, then in the current round she will decrease (increase) her contribution to the public account.

<<Table 5 about here>>

3.3.3 Testing for convergence in contributions

The contribution pattern in the IF24-S treatment shown in Figure 3 suggests a degree of convergence in contributions by the three types of subjects in this IF24-S treatment. This patterns is similar is to the RBR24-S treatment, which we have not shown.

We now turn to the question of whether or not each subject’s contribution converges to their group average contribution. We are primarily interested in testing if this convergence is statistically significant for treatments where subjects get to see how much others are contributing (i.e., the RBR24-S and IF24-S treatments) as opposed to where they do not get such information (as in the NF-24S treatment). For the sake of completeness we look at the both the treatments with feedback.

We have already posited the argument that subjects perceive a public goods game as an equilibrium selection problem, where essentially subjects are attempting to merge to the same contribution level. To provide support for this hypothesis we again use a random effects Tobit regression with absolute values of the difference between own contributions and the group average contribution as a dependent variable. Among the independent variables we have (1) round, (2) two dummies - one for the optimist, and one for the pessimist with the realist being the reference category, and (3) two interaction terms – one for optimist dummy interacted with round, and another for pessimist dummy interacted with round.

Table 6 reports the results of the above specification with the second column showing estimated coefficients for the RBR24-S treatment and the third one showing estimated coefficients for the IF24-S treatment.

For the IF24-S treatment, the estimated coefficient for round is negative and significant. The two dummies and the two interaction terms between these two dummies and round are not statistically significant. This implies that the difference between one's contribution and the group average contribution decreases over time and that it decreases at a similar rate regardless of subject type.

For the RBR24-S treatment the estimated coefficient for round is negative and significant once again suggesting convergence. However, here the optimist dummy interacted with round is positive and significant while the pessimist dummy interacted with round is not statistically significant. This implies that for the realists and the pessimists the difference between contributions and their group average contribution gets smaller as the number of round increases. However this difference is increasing over time for the optimists with respect to the realists.

These results suggest that subjects in the two feedback treatments are essentially attempt to coordinate their contributions at the same level as the group average.[15] However, the pattern of convergence is more pronounced in the IF24-S treatment where the feedback is intermittent. The optimists in the RBR24-S treatment hang on to their optimism and continue to contribute above the group average even in the face of mounting evidence that the others are contributing less than they are.

These results also suggest that initial contributions by subjects depend crucially on their beliefs about how much others will contribute. But as sbjects receive feedback, as in the RBR24-S and the IF24-S treatments, their focus shifts away from initial beliefs and become more dependent on average group contribution. Those with optimistic belief start out with high contribution but once they observe that others are contributing lower than them, they respond to that information by decreasing their contributions. Likewise for the pessimists, they started off with low contribution but once they observe that the others are contributing higher than them, they adjust their beliefs by actually increasing their contributions to the public account. In the next section we explore the role of beliefs more carefully.

[15] Croson (2007) reports a similar conclusion except in Croson' study the preponderance of evidence suggests convergence to the median rather than the mean. We are unable to make this distinction because in our study subjects get feedback only about the total (and therefore average) contributions to the public and *do not* get to see individual contributions as in Croson's study. But both these studies suggest that subjects are essentially trying to coordinate to a particular contribution level which lies somewhere between the social optimum and the free-riding equilibrium.

4. Role of beliefs in social learning

In this section we focus on the *RBR24-M* and the *IF24-M* treatments where subjects are asked to predict the average contribution of the other three group members multiple times during the course of the game; one at the beginning of round 1 and then at the end of every 4 rounds thereafter. However, we do not collect beliefs at the end of round 24. Recall, in the RBR24-M treatment subjects get to see contributions by their peers at the end of each round whereas in the IF24-M treatment subjects get to see contributions by their peers only at the end of every 4 rounds. Thus for ease of comparison we only compare beliefs at the end of every fourth round.

4.1 Overview of contributions in treatments with multiple belief elicitations

Figure 4 shows the average contribution for the RBR24-M and the IF24-M treatments. The overall average contribution to the public account is 42% of the token endowment for the RBR24-M treatment and 36% for the IF24-M treatment. In the RBR24-M treatment the average contribution starts at 53% in round 1 and decays to 27% in round 24, while in the IF24-M treatment the average contribution starts at 47% in round 1 and decays to 21% in round 24. The IF24-M treatment exhibits the steeper decline in contribution compared to the RBR24-M treatment. This result is consistent with findings in section 3.1, where we find a faster decay in contributions in the intermittent feedback treatment (IF24-S) compared to the treatment with round-by-round feedback. (RBR24-S).[16]

<<Figure 4 about here>>

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[16] We run a random effects Tobit regression to analyze in these two treatments. The dependent variable is contribution to the public account. The independent variables include (1) IF24-M treatment dummy with RBR24-M treatment as the reference category, (2) round, and (3) interaction term between IF24-M treatment dummy and round. The results suggest that contributions decay more quickly in the IF24-M treatment compared to the RBR24-M treatment. This is along the lines of our results reported in Section 3.1 above where we compared treatments with single belief elicitation. We do not present these results in detail here. They are available from the corresponding author upon request.

Next, we turn to studying how feedback about others' contributions in the previous round affect one's belief and subsequently how those beliefs affect contributions in the following round by investigating two following issues. First, we investigate how feedback contributes to the belief updating process. Second, we test whether subjects' beliefs about their peers' contributions differ from their own contributions to the public account. If the strategies hypothesis is the main explanation for the decay in contribution, then we should observe smaller and smaller correlation between beliefs about others' contributions and one's own contribution. At least many – if not a majority of subjects – must believe that other will make high contributions while their own contributions to the public account drop off as the game gets closer to the end. We show that this is not the pattern that we observe in our date. Rather, there is strong positive correlation between beliefs about others' contributions and one's own contribution pretty much throughout the session with little noticeable end-game effect.

4.2 Impact of feedback on the belief updating process

First, we look at how feedbacks on others' contribution influence the belief updating process. Our conjecture is that subjects make their predictions about others' contributions based on what they know about others' contribution in the past rounds. Subjects then adjust their beliefs accordingly. To prove our conjecture, we conduct a random effect Tobit regression with beliefs as a dependent variable. The independent variables include: (1) IF24-M treatment dummy with the RBR24-M treatment being the reference category, (2) round, (3) interaction term between IF24-M treatment dummy and round, (4) lag beliefs difference, the difference between one's own lag beliefs and others' average contribution of the past 4 rounds before belief elicitation[17], and (5) interaction term between IF24-M treatment dummy and lag beliefs difference.

Table 7 reports estimated coefficients derived from a random effects Tobit regression of the above specification. We find that IF24-M treatment dummy is not statistically significant, suggesting that prediction of others' average contribution for round 1 is not significantly different across the two treatments. Estimated coefficients for round, and the interaction term between IF24-M treatment dummy and round are negative and significant. This implies subjects' beliefs about others' contributions decays as they play more rounds. This decay is faster in the IF24-M treatment compared to the RBR24-M treatment. The estimated coefficients of the lag beliefs difference, and the interaction term between IF24-M dummy and the lag beliefs difference are negative and significant.

This suggests that if one's lag belief is higher than the past 4 rounds others' average contribution, she will adjust her belief by reducing the amount that she thinks the other will contribute in the next prediction. This effect is more prominent in the IF24-M treatment, that is, the magnitude in which subjects adjust their beliefs is larger in the IF24-M treatment than the RBR24-M treatment giving the same level of the difference. This is one of the explanations why contributions in the treatments where subjects receive feedbacks at the end of every 4 rounds decay faster than the treatments where subjects receive feedbacks at the end of every round. We find that subjects react more to the

[17] We have compared others' average contribution of the past 4 rounds before belief elicitation with others' average contribution in round before belief elicitation using the information criterion test. Information criterion test reports that including the difference between lag beliefs and others' average contribution of the past 4 rounds before belief elicitation as an independent variable explains our data better than the difference between lag beliefs and others' average contribution in round before belief elicitation. Information criterion test reports Akaike information criterion (AIC) of 929.23 and Bayesian information criterion (BIC) of 962.62 for the specification including the difference between beliefs and others' average contribution in round before belief elicitation. It reports AIC of 915.80 and BIC of 959.19 for the specification including the different between beliefs and others' average contribution of the past 4 rounds before belief elicitation.

information when feedback on what others are doing is given to them discretely rather than continually.

<< Table 7 about here>>

4.3 Relationship between one's belief about others' contributions and one's own contribution

In Figures 5(a), 5(b) and 5(c) we show the average contributions and beliefs about others' contributions over 24 rounds for the three types of subjects in the RBR24-M treatment. Figures 6(a), 6(b) and 6(c) show the same information for the IF24-M treatment. These figures illustrate a strong positive correlation between average belief and average contributions.

This finding is confirmed by a non-parametric Kruskal-Wallis test, which tests for the equality of distribution between contributions and beliefs. That is, we test whether beliefs before round 1 come from the same distribution as contributions for round 1 for each type – optimist, realist and pessimist. We then run the same comparison between beliefs and contributions for each of round 5, 9, 13, 17, and 21. Kruskal-Wallis test shows no significant difference between the distribution of beliefs and contributions either in the RBR24-M treatment or in the IF-24M treatment (except for the comparison for round 9 in the RBR24-M treatment).[18] These findings suggest that subjects best-respond follow their beliefs about their peers' contribution and this is true both early on and in the later stages of the game. We do not see any evidence of the bailing out that one would expect to see if the strategies hypothesis was a significant explanation of the decay phenomenon.

<<Figures 5(a), 5(b) and 5(c) about here>>

<<Figures 6(a), 6(b) and 6(c) about here>>

[18] We have not provided the detailed results of these tests, which are available upon request. We also use regression analysis to look at the correlation between beliefs and contributions. We have omitted the details of these results here.

To conclude, the evidence presented in this section shows that subjects start the game with prior beliefs (which are quite heterogeneous) about others' contributions. They then observe others' contributions over time and update their beliefs as they go along. The past contributions by the other group members determine subjects' beliefs in the current round and those beliefs, in turn, impact upon a subject's current contribution.

5 The role of income, feedback and experience

The discussion in Sections 3 and 4 suggest an alternative view than the ones proposed before about how subjects approach the linear public goods game. It appears that subjects start the game with prior beliefs about their peers (and the contributions to be made by them) and choose their own contributions on the basis of those beliefs. When there is no opportunity to update those priors they choose a contribution level commensurate with their beliefs. However, when they get to see what others are doing they update those prior beliefs and adjust their contributions accordingly which leads to a convergence in contributions towards the group average.

We also find, by comparing behaviour in the RBR24-S and IF24-S treatments, that when the information about others' contributions appear at longer intervals rather than at the end of every round, the feedback seems to make more of an impression on the subjects and leads to more pronounced decay in contributions. But the comparison between these two treatments in not quite exact because in the RBR24-S treatment, subjects play for 24 rounds and get feedback 24 times at the end of each round, while in the IF24-S treatment, they play for 24 rounds and get feedback only 6 times at the end of the every fourth round. This in turn raises the question: in terms of learning about the heterogeneity of types, what is more important? Is it the experience gained by playing many rounds or is it the amount of feedback received?

In this section we explore this question by undertaking a number of different comparisons in order to try and understand the interplay between experience and feedback.

First, we compare behaviour in the RBR6-S treatment with that in the first six rounds of the RBR24-S treatment. Here, of course, subjects play for six rounds in each case and also receive six feedbacks at the end of each round. However, the comparison suffers from a drawback, since, in the RBR24-S treatment, the subjects know that they are going to play for 24 rounds and therefore subjects in the RBR24-S treatment can potentially make four times more money than those in the RBR6-S treatment.

So to control for any possible income effects arising out of the first comparison, we next look at the RBR6-S-High treatment, where subjects play for six rounds and get the same number of feedbacks at the end of each round. But here subjects have four times the token endowment in each round compared to the RBR6-S treatment and so can potentially make as much money as they can make in the RBR24-S treatment. Hence potential earnings over the course of the game should not be a factor in this treatment as opposed to the RBR6-S treatment.

The comparisons between RBR6-S, RBR6-S-High and the first six rounds of the RBR24-S treatments, all keep the number of feedbacks constant, i.e. six feedbacks at the end of each round. But this does not allow us to gauge the impact of the extra experience gained by playing additional rounds. In order to control for that, we can also compare behaviour during rounds 1, 5, 9, 13, 17 and 21 in the IF24-S treatment. Here, course, the number of feedbacks is six as well but subjects gain additional experience by playing some rounds in between receiving that feedback. So when we compare behaviour in the RBR24-S treatment with that in the IF24-S treatment in Section 3, we varied the number of feedbacks while keeping the number of rounds fixed. When we look at the rounds immediately after receiving feedback in the IF24-S treatment, and compare that to the first six rounds of the RBR24-S treatment, we are keeping the both the number of rounds and the number of feedbacks the same. When we compare rounds 1, 5, 9, 13, 17 and 21 in IF24-S with the RBR6-S and RBR6-S-High treatments, we are keeping the number of feedbacks constant but varying the rounds and also controlling for potential income effects.

Figure 7 shows what happens for the above comparisons. Two things stand out. First, there is little or no decay in contributions in the RBR6-S treatment and the first six rounds of the RBR24-S treatment and very little difference in behaviour between the two treatments. This observation, in fact, provides more evidence against the strategies hypothesis. If subjects are going to bail out as the end-game approaches, in keeping with this hypothesis, then one would expect to see much more pronounced decay in the RBR6-S treatment which is just not there. What this suggests to us is that six rounds is not enough for subjects to draw conclusions about player types and subjects need more experience by playing more rounds.

The second fact that stands out is that there is much more pronounced decay in the RBR6-S-High treatment and for the rounds immediately following feedback in the IF24-S treatment. In fact, behaviour in these two treatments is very similar and quite distinct from behaviour in the other two treatments.

<<Figure 7 about here>>

Table 8 reports the results of a random effects Tobit regression for a comparison of contributions between the RBR6-S, the RBR6-S-High, the first six rounds of the RBR24-S and for rounds 1, 5, 9, 13, 17, 21 of the IF24-S treatments. Since the tokens endowment (contribution choice subjects can make) in the RBR6-S-High treatment is higher than the other two treatments, we use the *percentage contribution* to the public account as a dependent variable. Independent variables included in the specification are (1) three treatment dummies - one for the first six rounds of the RBR24-S treatment, another for the RBR6-S-High treatment and a third for the rounds immediately following feedback in the IF24-S treatment with the RBR6-S treatment as a reference category, (2) round, (3) three interaction terms – one each for the three treatment dummies interacted with round.

The results essentially corroborate what we see in Figure 7. The estimated coefficients of the treatment dummies are not statistically significant. This suggests that contribution starts at a similar level for all four treatments. The estimated coefficients for round is not statistically significant whereas the RBR6-S-High dummy interacted with round, and contributions for rounds 1, 5, 9, 13, 17, 21 of the IF24-S dummy interacted with round are negative and significant. This implies that contributions in the RBR6-S-High treatment decay faster than the RBR6-S treatment. Hence high potential earnings accelerate the decaying contributions process. Moreover, contributions in those rounds following immediately after feedback in the IF24-S treatment decay faster than the RBR6-S treatment. Using a Wald test we do not find a significant difference between the estimated coefficients of RBR6-S-High dummy interacted with round and contributions for rounds 1, 5, 9, 13, 17, 21 of the IF24-S dummy interacted with round (χ^2 (1 d.f.) = 0.08, Pr>χ^2 = 0.7740) suggesting that contributions of these two treatments decay at a similar rate.

<<Table 8 about here>>

The above findings suggest that feedback, by itself, is not enough. Subjects need both experience gained by playing multiple rounds coupled with feedback in order to learn the distribution of types in the group and update their beliefs accordingly. They also suggest, along the lines of Cooper et al. (1999) that increasing the per-round payoff may serve as a possible substitute for greater experience. When the per-round earnings are much higher, as in the RBR6-S-High treatment, the pattern of behaviour mimics that in the IF24-S treatment.

6. Concluding Remarks

In this paper we argue that subjects approach a public goods game differently than the way envisioned in Andreoni (1988). Our results do not rule out strategic play and/or introspective learning as possible causes for the decay in contribution. But we argue that neither of these are major causes behind the decay in contributions. We believe that the decay in contributions comes mostly from social learning. By this, we mean that subjects start the game with a set of prior beliefs. Then they observe how much others have contributed in the previous rounds and update their beliefs accordingly, and then choose future contributions in order to converge to the group average.

Many of our subjects are conditional cooperators who are willing to match the contributions of others. Those with optimistic beliefs start out with high contributions. But there are two problems here: one is that not all conditional cooperators have equally optimistic beliefs about others' contributions. We do have a group of pessimists who contribute low amounts to start with since they expect others to do the same. Over time as they find that others are contributing more they do increase their contributions, but this increase is gradual and is not enough to offset the sharp drop in contributions coming from the disillusioned optimists. The second problem, which reinforces the first, is the presence of a small number of free-riders which also contributes to the decay in contributions.

Therefore the pattern of learning that is going on is much more complex than simply figuring out the dominant strategy of free-riding. Rather what the subjects are learning over time is the heterogeneity in subject types and the consequent difficult of coordinating to the high-contributions equilibria. The decay in contributions arises from the attempt to converge to an equilibrium which is in between the efficient and inefficient outcomes.

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TABLE 1: Results from previous Partners versus Strangers experiments (taken from Andreoni & Croson (2002))

Study		**Which Group Gives More**		
		Partners	Strangers	Neither
Andreoni (1988)			•	
Croson (1996)		•		
Palfrey and Prisbrey (1996)			•	
Weimann (1994)				•
Keser & van Winden (2000)		•		
Burlando & Hey (1997),	UK:		•	
	Italy:	•		
Brandts & Schram (2001)				•
Brandts, Saijo & Schram (1997)	US:	•		
	Spain:		•	
	Japan:			•
	The Netherlands:			•
Sonnemans, Schram & Offerman (1999)		•		

TABLE 2: Summaries and abbreviations of all seven treatments conducted in the experiment

Treatments	Number of Rounds	Number of Belief Elicitations	Number of Feedbacks	Number of Subjects	Abbreviation
Round-by-Round Feedback	24	1 (single)	24 (at the end of each round)	36	***RBR24-S***
Intermittent Feedback	24	1 (single)	6 (at the end of every fourth rounds)	60	***IF24-S***
No Feedback	24	1 (single)	1 (at the very end of the experiment)	64	***NF24-S***
Round-by-Round Feedback	6	1 (single)	6 (at the end of each round)	44	***RBR6-S***
Round-by-Round Feedback - 40 tokens	6	1 (single)	6 (at the end of each round)	28	***RBR6-S-High***
Round-by-Round Feedback	24	6 (multiple)	24 (at the end of each round)	60	***RBR24-M***
Intermittent Feedback	24	6 (multiple)	6 (at the end of every fourth rounds)	36	***IF24-M***

Table 3: Random effects Tobit regression analysis of contribution patterns in the RBR24-S, IF24-S and NF24-S treatments

Contribution	Estimated coefficients
RBR24-S dummy	1.52 (0.99)
IF24-S dummy	1.10 (0.86)
Round	-0.05*** (0.01)
RBR24-S dummy*Round	-0.04** (0.02)
IF24-S dummy*Round	-0.08*** (0.02)
Constant	3.96*** (0.60)
Wald χ^2	160.57
Number of observation	3840
Number uncensored	2530
Number lower censored	891
Number upper censored	419

Note: ***,**,* denote 1, 5 and 10 percent significance respectively.
Standard errors are presented in parentheses.

Table 4: Random effects Tobit regression analysis of contribution pattern in the NF24-S treatment

Contribution	Estimated coefficients
Optimist dummy	-1.48 (1.27)
Pessimist dummy	-2.76** (1.22)
Round	-0.06*** (0.01)
Optimist dummy*Round	0.09** (0.04)
Pessimist dummy*Round	0.09** (0.04)
Lag contribution	0.11*** (0.04)
Optimist dummy*Lag contribution	0.36*** (0.11)
Pessimist dummy*Lag contribution	0.31** (0.14)
Constant	2.20*** (0.74)
Wald χ^2	119.96
Number of observation	1265
Number uncensored	992
Number lower censored	121
Number upper censored	152

Note: ***, **, * denote 1, 5 and 10 percent significance respectively.
Standard errors are presented in parentheses.

Table 5: Random effects Tobit regression analysis of contribution pattern in the IF24-S treatment

Contribution	Estimated coefficients
Lag contribution	0.54*** (0.05)
Round	-0.13*** (0.02)
Optimist dummy*Round	0.03 (0.03)
Pessimist dummy*Round	0.09** (0.04)
New information dummy	-0.19 (0.30)
New information dummy*Optimist dummy	-0.98* (0.51)
New information dummy*Pessimist dummy	0.36 (0.68)
Lag difference	0.10 (0.08)
Lag difference*Optimist dummy	-0.24** (0.11)
Lag difference*Pessimist dummy	-0.29** (0.15)
Constant	1.36 (0.86)
Wald χ^2	388.91
Number of observation	1200
Number uncensored	694
Number lower censored	362
Number upper censored	144

Note: ***,**,* denote 1, 5 and 10 percent significance respectively.
Standard errors are presented in parentheses.

Table 6: Random effects Tobit regression testing for convergence between one's own contribution and the average group contribution in the RBR24-S and the IF24-S treatments

Absolute difference between own contribution and group average contribution	RBR24-S Estimated coefficients	IF24-S Estimated coefficients
Round	-0.02*** (0.01)	-0.04*** (0.01)
Optimist dummy	0.27 (0.35)	0.05 (0.36)
Pessimist dummy	0.42 (0.41)	-0.09 (0.51)
Optimist dummy*Round	0.03** (0.02)	-0.02 (0.01)
Pessimist dummy*Round	-0.01 (0.02)	-0.01 (0.02)
Constant	1.94*** (0.21)	2.71*** (0.21)
Wald χ^2	17.36	67.13
Number of observation	864	1440
Number uncensored	805	1333
Number lower censored	57	103
Number upper censored	2	4

Note: ***,**,* denote 1, 5 and 10 percent significance respectively.
Standard errors are presented in parentheses.

Table 7: Random effects Tobit regression analysis of beliefs in the RBR24-M and the IF24-M treatments

Beliefs	Estimated coefficients
IF24-M dummy	-0.01 (0 .31)
Round	-0.06** (0.03)
IF24-M dummy*Round	-0.08* (0.05)
Lag beliefs difference	-0.26*** (0.03)
IF24-M dummy*Lag beliefs difference	-0.10* (0.05)
Constant	-0.04 (0.18)
Wald χ^2	177.07
Number of observation	480
Number uncensored	310
Number lower censored	170
Number upper censored	0

Note: ***,**,* denote 1, 5 and 10 percent significance respectively.
Standard errors are presented in parentheses.

Table 8: Comparison of contributions in the RBR6-S, the RBR6-S-High, the first six rounds of the RBR24-S and rounds 1, 5, 9, 13, 17 and 21 of the IF24-S treatments

Percentage Contribution	**Estimated coefficients**
First 6 rounds of RBR24-S dummy	1.30 (9.82)
RBR6-S-High dummy	8.59 (10.50)
Round 1, 5, 9, 13, 17, 21 contributions of the IF24-S dummy	-3.78 (8.68)
Round	-0.44 (1.10)
First 6 rounds of RBR24-S dummy*Round	-1.31 (1.65)
RBR6-S-High dummy *Round	-5.19*** (1.76)
Round 1, 5, 9, 13, 17, 21 contributions of the IF24-S dummy*Round	-4.71*** (1.48)
Constant	57.68*** (6.56)
Wald χ^2	55.04
Number of Observations	1008
Number Uncensored	715
Number Lower Censored	164
Number Upper Censored	129

Note: ***,**,* denote 1, 5 and 10 percent significance respectively.
Standard errors are presented in parentheses.

Figure 1: Average contributions across 24 rounds of the RBR24-S, IF24-S and NF24-S treatments

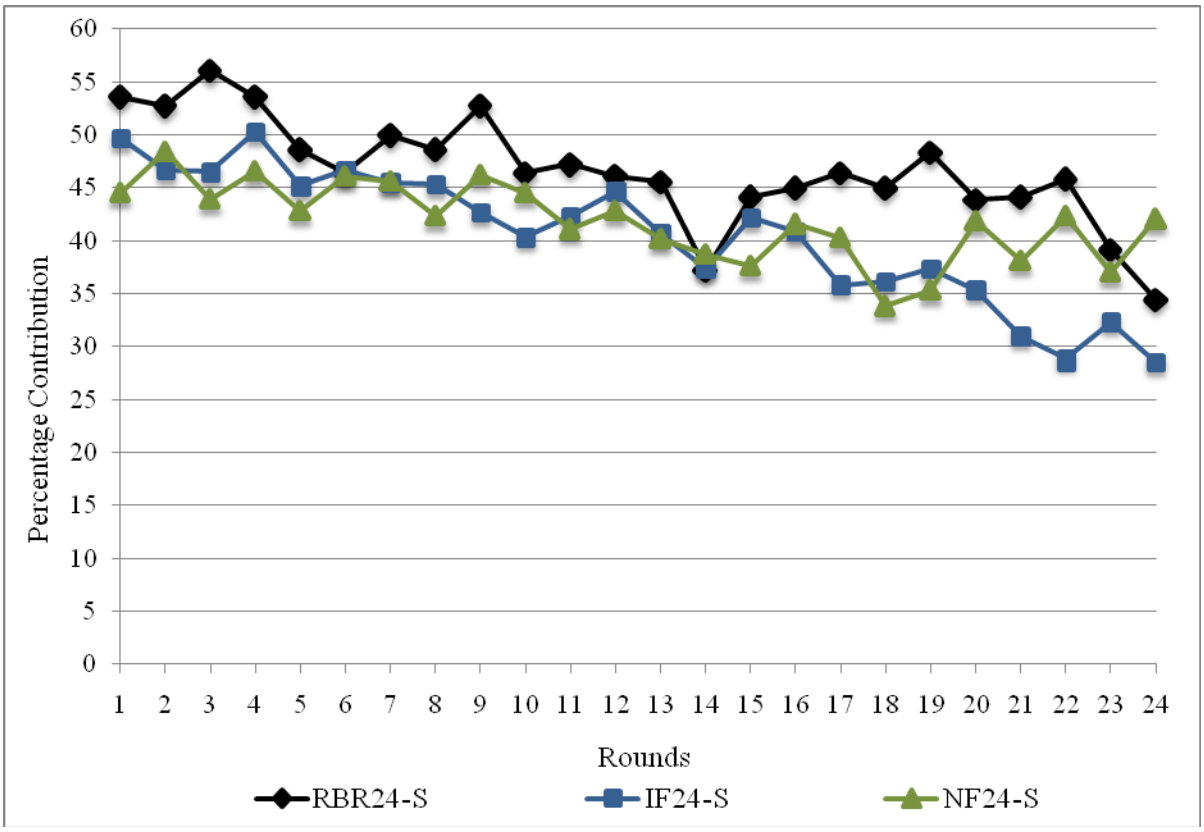


Figure 2: Average contributions by the three types of subjects – Pessimists, Realists and Optimists – in the NF24-S treatment

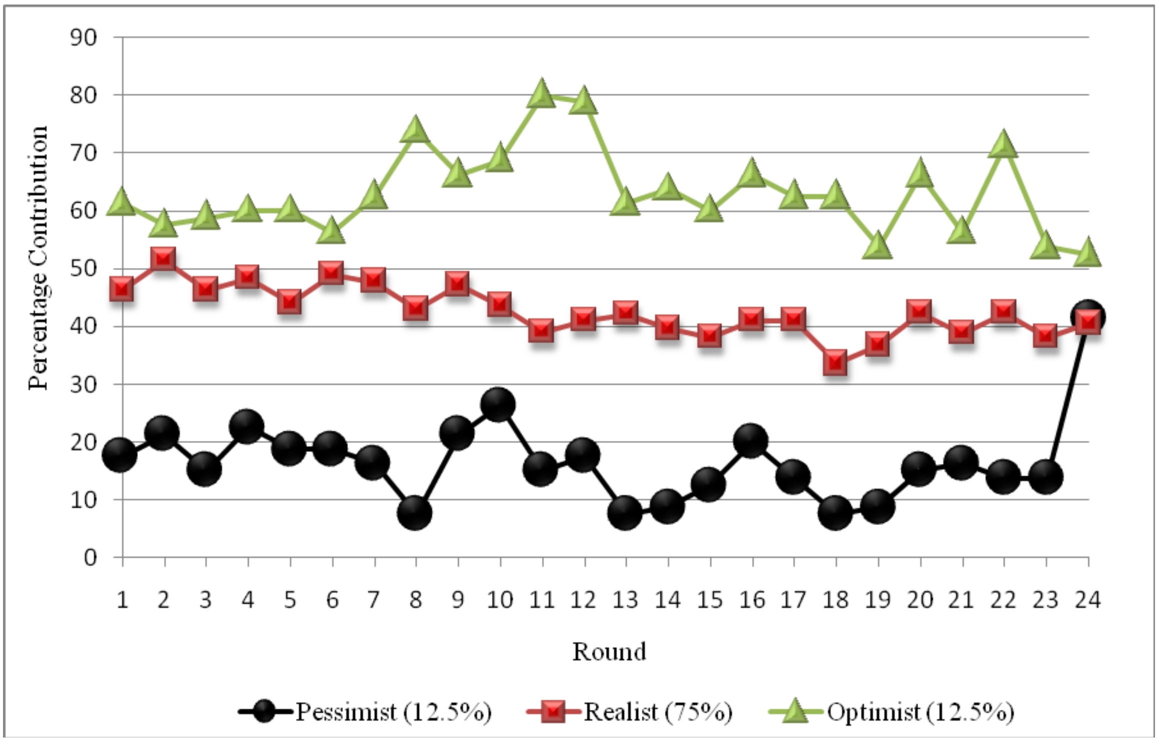


Figure 3: Average contributions by the three types of subjects – Pessimists, Realists and Optimists – in the IF24-S treatment

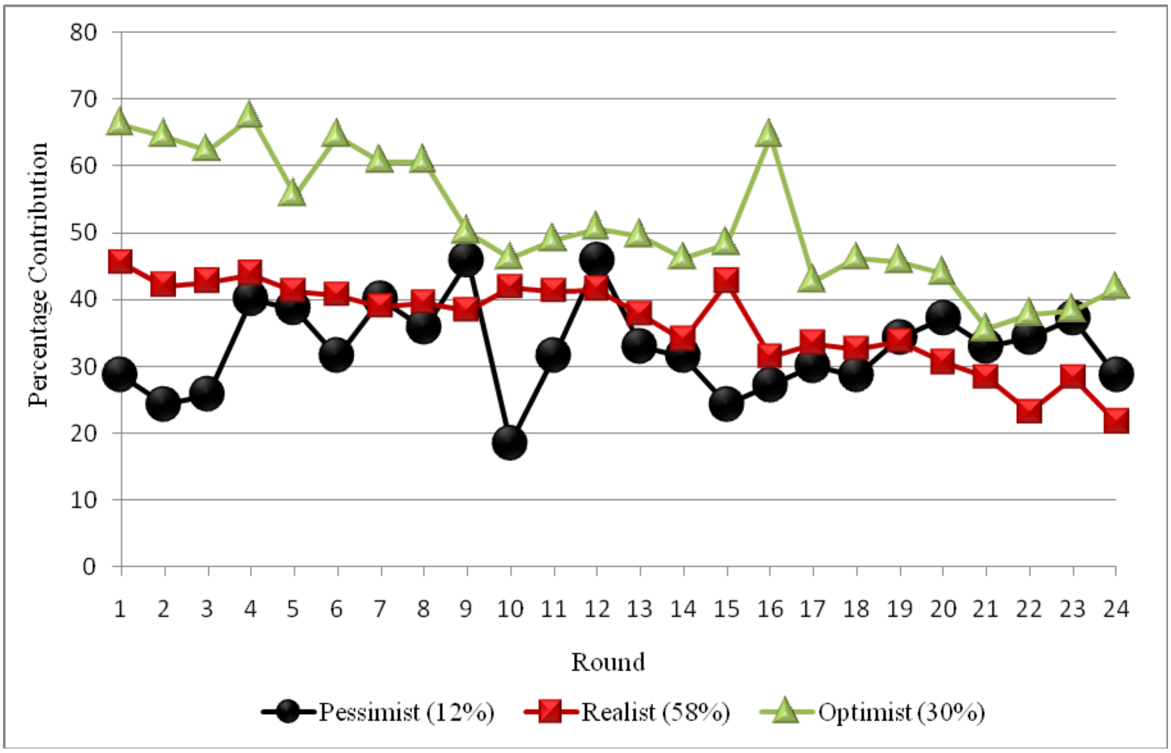


Figure 4: Average contribution across 24 rounds of the RBR24-M and IF24-M treatments

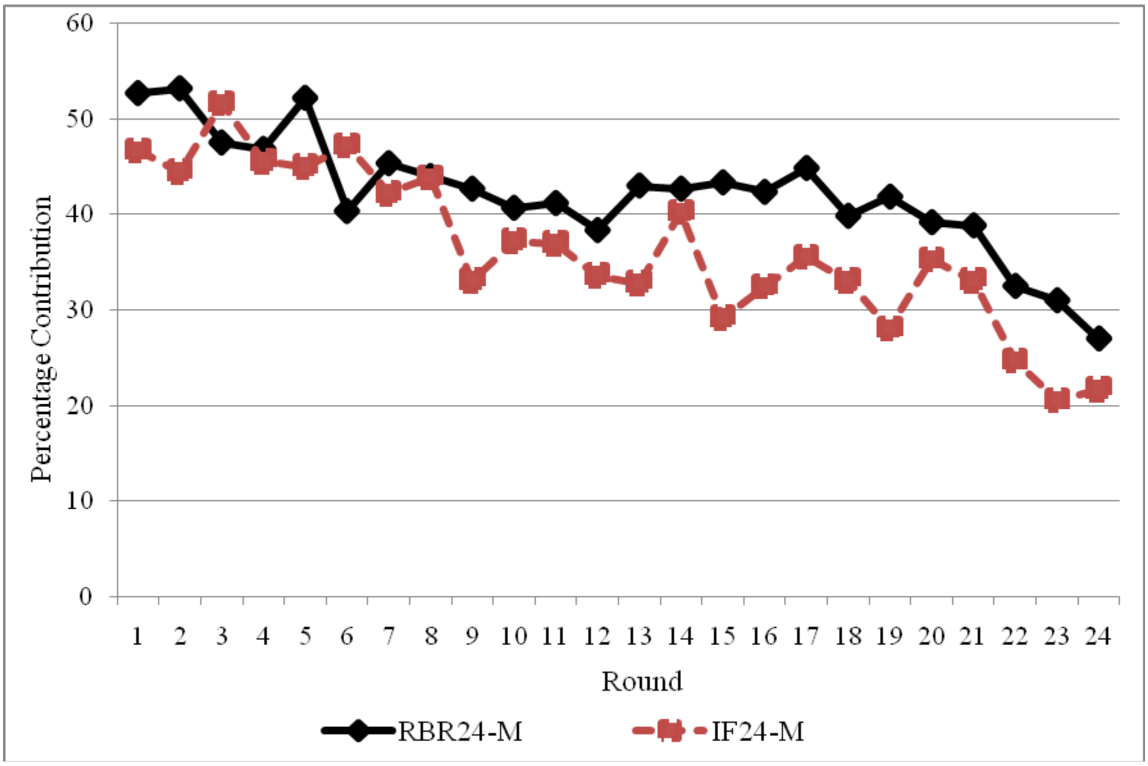


Figure 5 (a): Average predictions and average contributions by the pessimists in the RBR24-M treatment

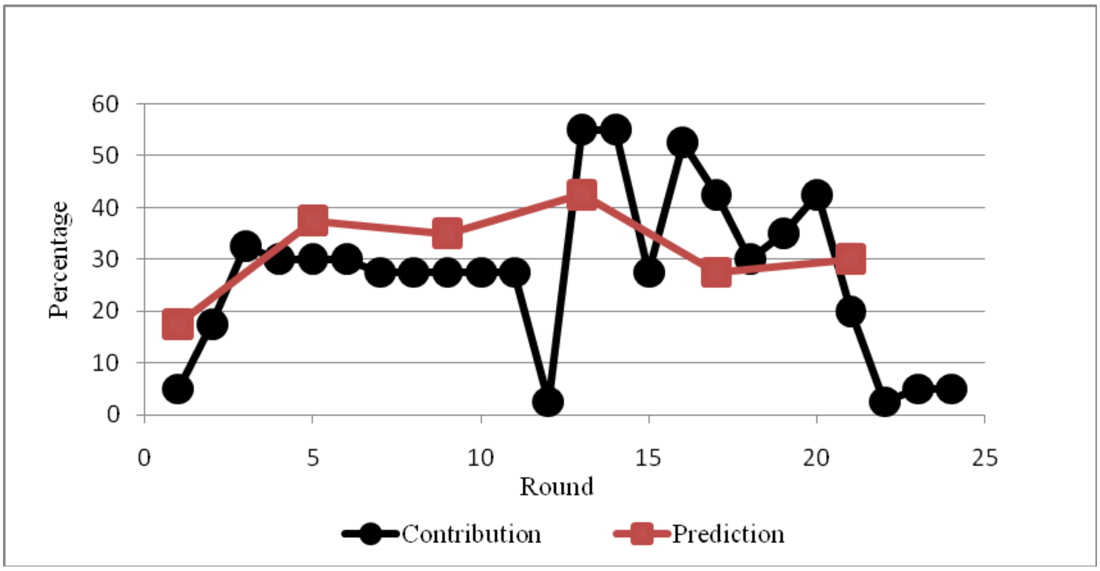


Figure 5 (b): Average predictions and average contributions by the realists in the RBR24-M treatment

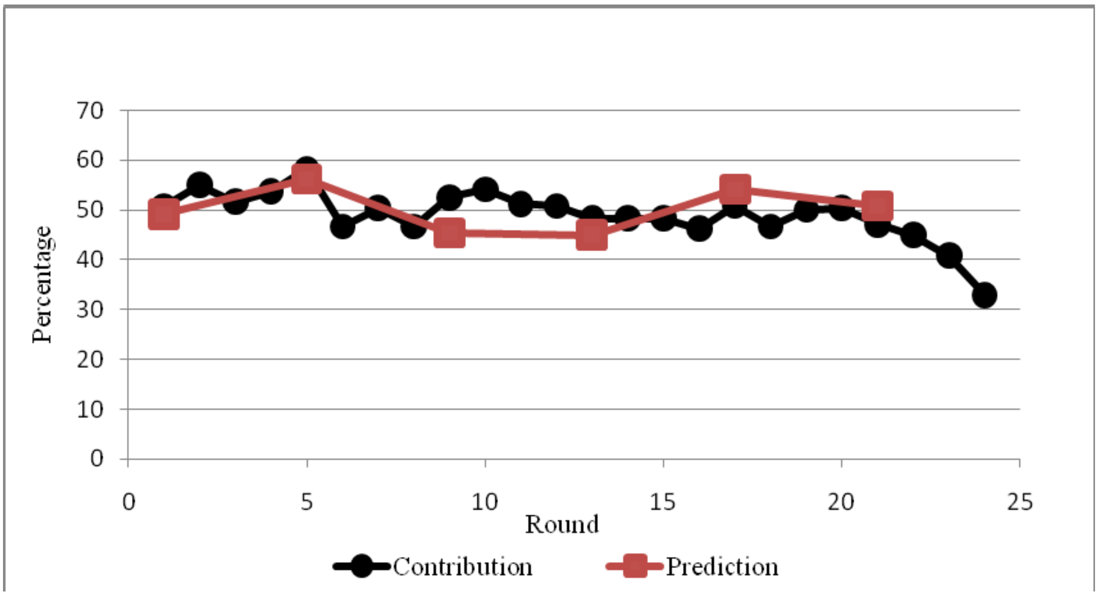


Figure 5 (c): Average predictions and average contributions by the optimists in the RBR24-M treatment

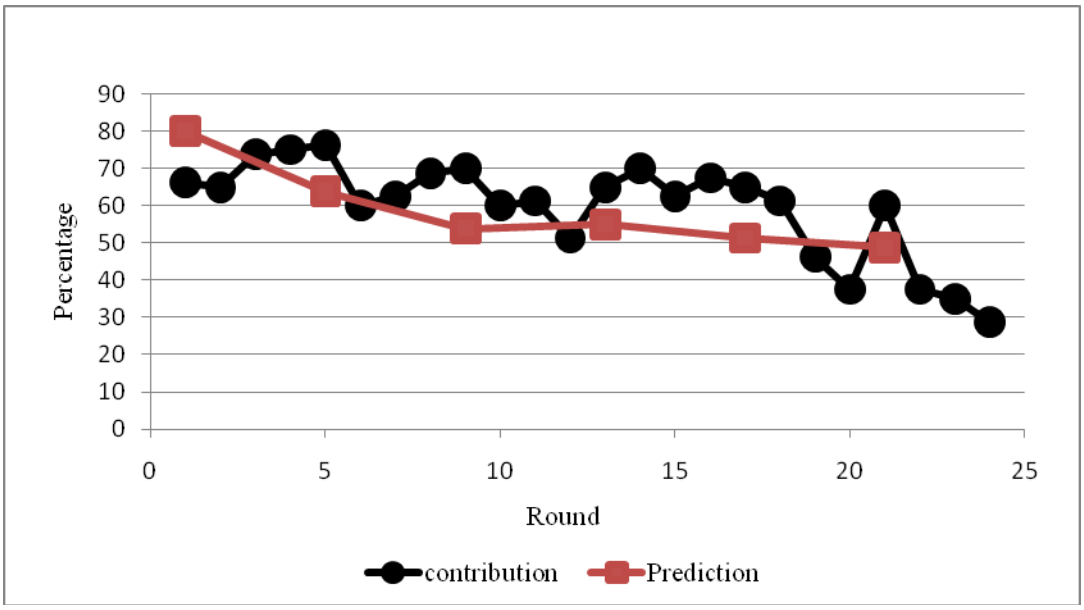


Figure 6 (a): Average predictions and average contributions by the pessimists in the IF24-M treatment

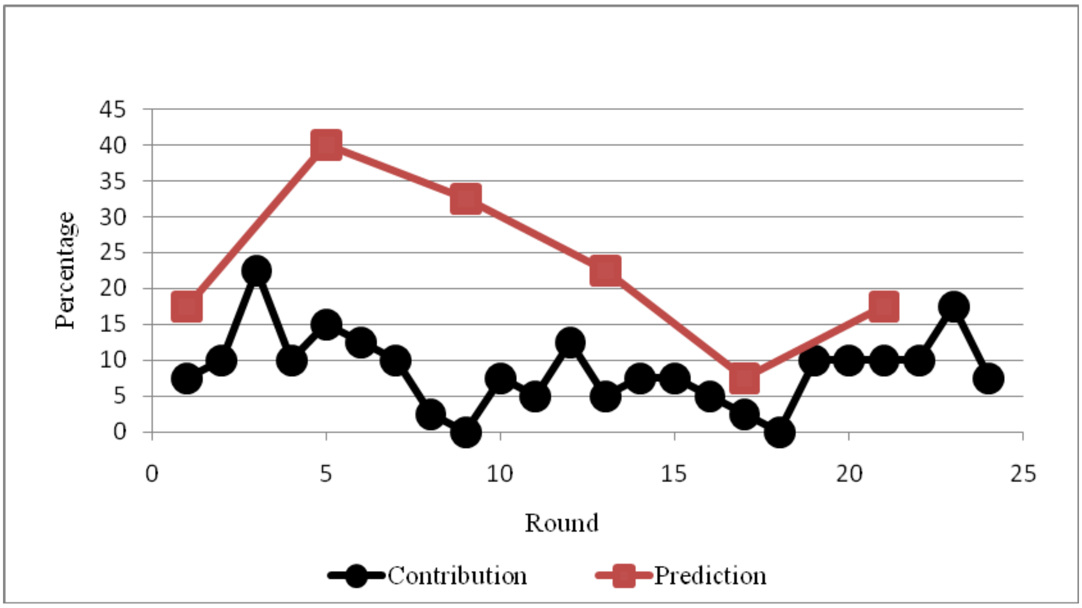


Figure 6 (b): Average predictions and average contributions by the realists in the IF24-M treatment

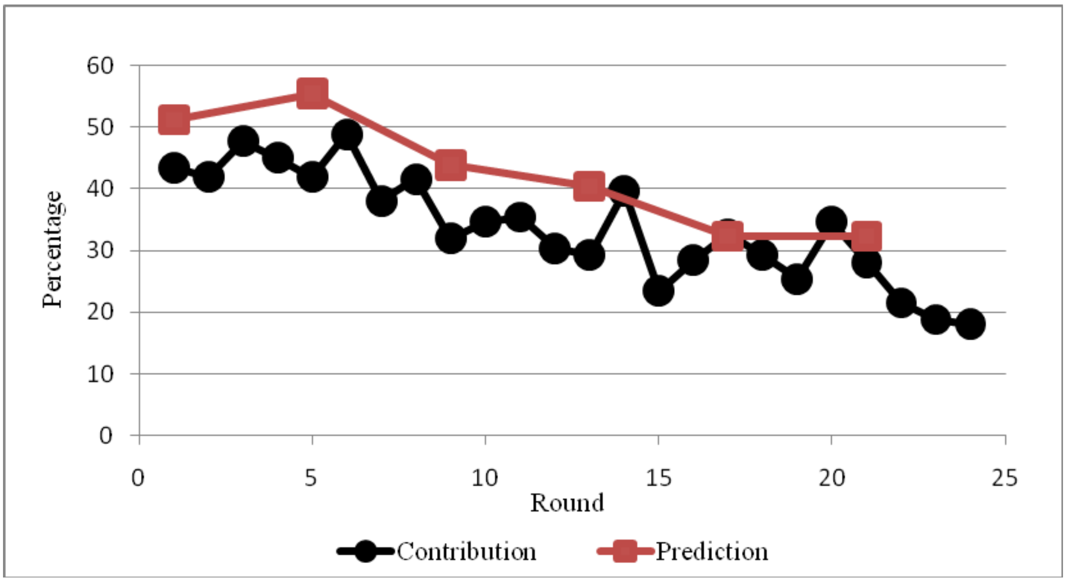


Figure 6 (c): Average predictions and average contributions by the optimists in the IF24-M treatment

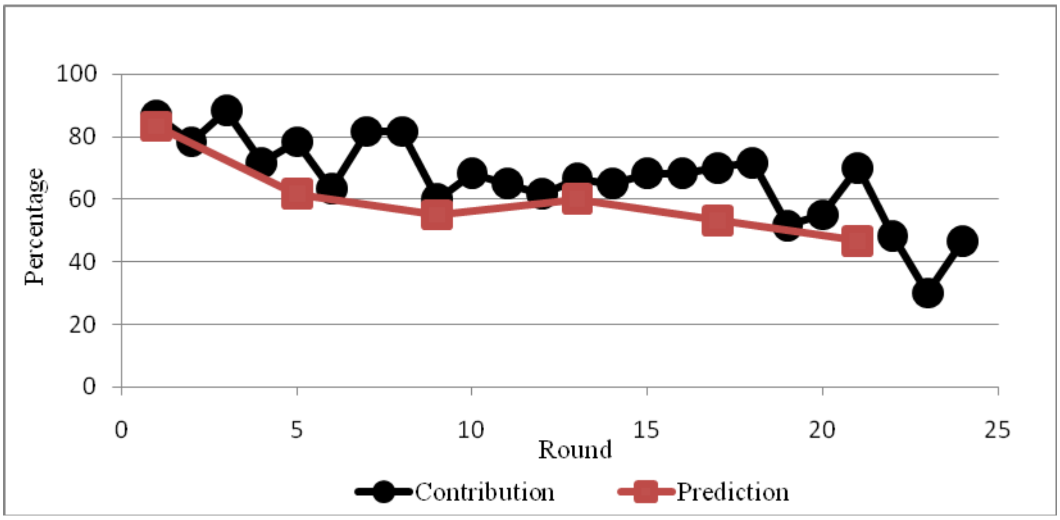
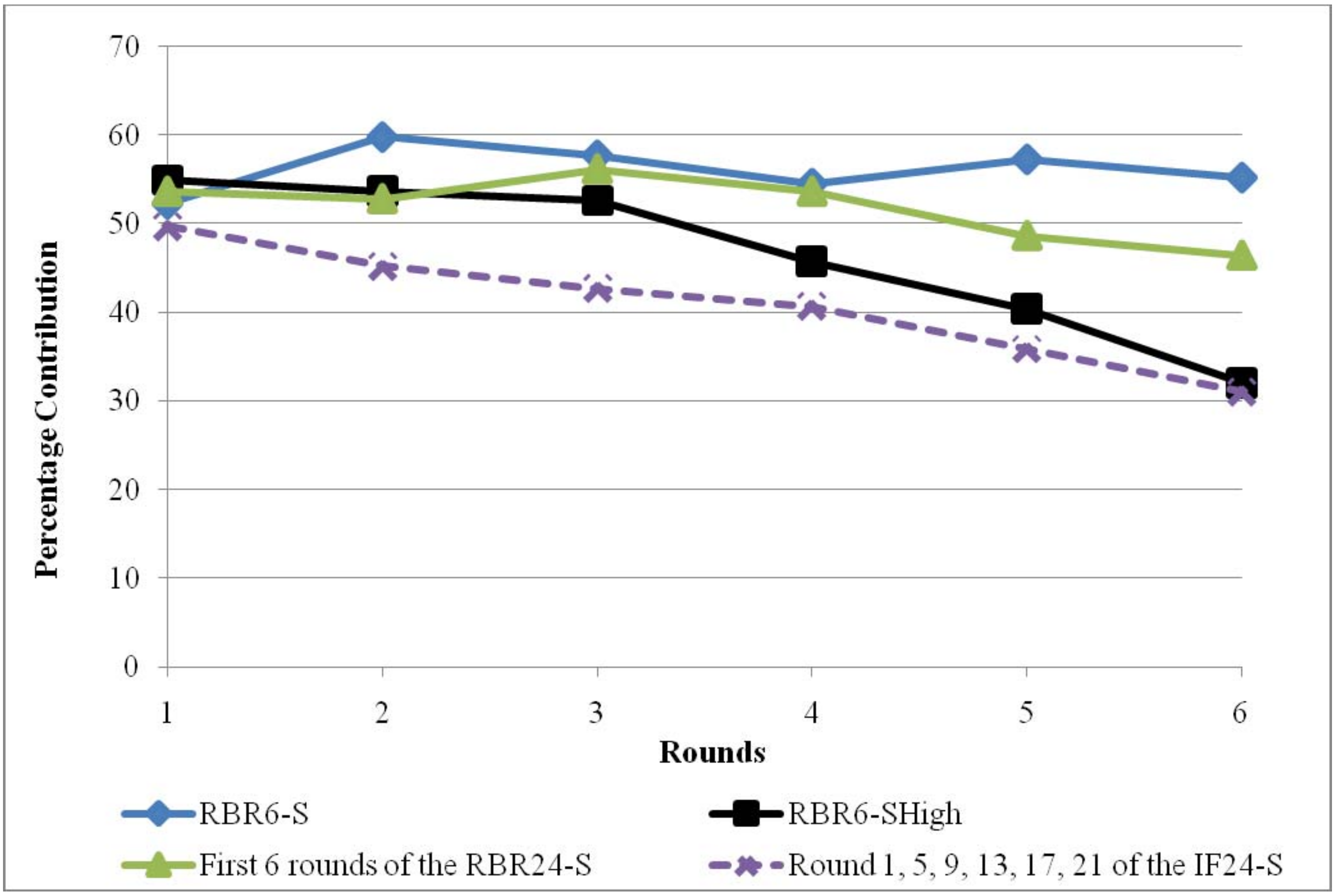


Figure 7: Average contributions in the RBR6-S, the RBR6-S-High, the first six rounds of the RBR24-S and rounds 1, 5, 9, 13, 17, 21 contributions of the IF24-S treatments



Appendix

Instructions for the RBR24-S, IF24-S and NF24-S treatments

This is an experiment in economic decision-making. The University of Auckland has provided the funds to conduct this research. The instructions are simple. If you follow them closely and make appropriate decisions, you may make an appreciable amount of money. This money will be paid to you in cash at the end of the experiment.

You are in a market with 3 other people, i.e. you will be part of a 4 person group. The composition of the group you are in will remain unchanged during the entire session. You will not learn the identity of the other people in your group at any point.

The experiment will consist of a number of rounds. At the beginning of each round each participant will have an endowment of 10 tokens. In each round, each participant will choose – in whole numbers - how many tokens (ranging from 0 to 10) to allocate to a private account and how many tokens (ranging from 0 to 10) to allocate to a public account. For each round, these two numbers should add to 10, the total number of tokens you have for that round. The total number of tokens allocated to the public account will be **doubled** and divided equally among all 4 participants. Your personal earnings for this round will equal the number of tokens you allocated to your private account plus the number of tokens you get back from the public account (the latter may be a fractional amount).

Each new round will proceed in the same way. Tokens allocated to the private account in any round do not carry over to the next round. Every round you start with a fresh endowment of 10 tokens.

The next paragraph differs in the three treatments.

In the round-by-round feedback treatment the next paragraph states:

This experiment will last for 24 rounds. In each round you will decide how to divide your 10 tokens between the private and public accounts. At the end of each round you will get to see the total tokens contributed to the public account (but not the contribution made by individual members of the group) and your own earnings for the round.

In the intermittent feedback treatment the next paragraph states:

This experiment will last for 24 rounds. In each round you will decide how to divide your 10 tokens between the private and public accounts. You will get to see the total tokens contributed to the public account (but not the contribution made by individual members of the group) and your own earnings every four rounds. That is you will make decisions for Rounds 1 through 4 without learning what the total contribution to the public account is or what your earnings are. Then you will get to see this information for all the four rounds at the end of Round 4. Then you will make decisions for Rounds 5 through 8 without learning what the total contribution to the public account is or what your earnings are. Then you will get to see this information for all the four rounds at the end of Round 8. Then you will make decisions for Rounds 9 through 12 without learning what the total contribution to the public account is or what your earnings are. Then you will get to see this information for all the four rounds at the end of Round 12 and so on till Round 24.

In the no feedback treatment the next paragraph states:

This experiment will last for 24 rounds. In each round you will decide how to divide your 10 tokens between the private and public accounts. However you will not get to see any information about the tokens contributed by others to the public account or your earnings per round till the very end of the session. That is you will only learn about the total contributions to the public account and your earnings after all 24 rounds are over.

The rest of the instructions are the same in all three treatments.

At the end of the experiment your total earnings from the 24 decision rounds will be added up and converted into cash at the rate of 5 cents per token.

Once you log in to the computer you will be assigned a subject ID. Please make a note of this and write down this number on the top of each page of your instructions.

Are there any questions?

Please answer the following question before the first round begins.

What is the average contribution to the public account that you expect from the other three members of your group ***in round 1***[19]? Do not include yourself and round to the nearest integer. Please choose one:

____ 0	____ 3	____ 6	_____ 9
____ 1	____ 4	____ 7	____ 10
____ 2	____ 5	____ 8	

You will be paid for this prediction in the following way. Your earnings will be \$1.00 minus the square of the difference of your prediction and the actual average choice.

Suppose you predict that the average choice of the other three group members in Round 1 will be 8. Suppose the actual average turns out to be 4. In this case the absolute difference between the two numbers is 4. The square of this difference is 16. Then you will earn \$1.00 - \$0.16 = \$0.84. On the other hand, suppose you predict that the average choice of the other three group members in Round 1 will be 3. Suppose the actual average turns out to be 9. In this case the absolute difference between the two numbers is 6. The square of this difference is 36. Then you will earn \$1.00 - \$0.36 = \$0.64.

PREDICTION BEFORE ROUND 1

Predicted Average	**Actual Average**	**Difference**	**Square of Difference**	**Earnings (\$1 – Square of Difference)**

[19] We replace this with ***round 5, 9, 13, 17 and 21*** for the prediction of the Round-by-round 6-Beliefs treatment and the Intermittent 6-Beliefs treatment.

RECORD SHEET

Show-up Fee:	**$4.00**
Earnings from Prediction:	__________
Earnings from Experiment:	__________
TOTAL	__________