Conditional Cooperation in Network Public Goods Experiments*

Luke A. Boosey†

Abstract

This study investigates the pattern of contribution decisions in a network public goods game. In this game, each player's payoff depends only on his own contribution and the contributions of his immediate neighbors in a circle network. As in the standard public goods game, we find substantial heterogeneity in behavior across subjects, including both unconditional free-riding and full cooperation, as well as conditional cooperation. We first examine the impact of different information conditions on conditional cooperation. At the aggregate level, we find that players who observe average payoff information about others contribute significantly less than those who observe average contribution information. We then investigate the extent to which conditional cooperators facilitate the spread of cooperation and free-riding behavior across the network. In groups with a single free-rider type, we show that individual contributions decay faster for players who are closer in the network to the free rider. On the other hand, in groups with a single unconditional full contributor type, players do not respond by converging to full cooperation. Instead, we find that proximity to the unconditional full contributor seems only to mitigate (or delay) the typical decline in contributions over time. These contrasting effects are consistent with the widespread claim that conditional cooperation is imperfect, or exhibits a self-serving bias.

Keywords: network public goods game, voluntary contributions, conditional cooperation, self-serving bias
JEL Classification: C9, D03, D83, H41

*I would particularly like to thank John Ledyard for providing financial support and detailed advice on this research. I am also very grateful to Mark Isaac, Sebastian Goerg, the Editor, and two anonymous referees for their helpful comments and suggestions. Previous versions of this paper were greatly improved by comments from Jim Andreoni, Jean-Laurent Rosenthal, Leeat Yariv, Federico Echenique, Salvatore Nunnari, and Cary Frydman. Special thanks also go to Chris Crabbe for programming the Caltech experiments in Multistage. Funding for the experiments conducted at Florida State University were generously provided by the College of Social Sciences and Public Policy.

†Department of Economics, Florida State University, Tallahassee FL, 32306-2180, USA. Email: `lboosey@fsu.edu`

1 Introduction

In many different settings, public goods are provided using the voluntary contributions mechanism. For example, local school boards often solicit contributions from families within their district to help finance ongoing programs or new facilities. Economists have long sought to understand why individuals contribute in these environments, despite facing the incentive to free ride. In repeated settings, experimental studies have consistently shown that average contributions are significant, although they decline over time (see, e.g., Isaac et al. (1984) and Isaac et al. (1985)).[1]

A number of these experimental studies have demonstrated that a substantial fraction of individuals are *conditional cooperators* who contribute more when they expect others to do the same (see, e.g., Keser and Van Winden (2000), Fischbacher et al. (2001), Brandts and Schram (2001), Croson et al. (2005), Croson (2007), Fischbacher and Gächter (2010), Kocher et al. (2008)). This result is often coupled with evidence to support the claim that conditional cooperators exhibit a downward or self-serving bias, and thus only attempt to partially match the increased contributions they expect from others (Fischbacher et al. (2001), Fischbacher and Gächter (2010), and Ambrus and Pathak (2011)).[2] At the same time, there is also a growing literature on the importance of network structure for the decisions of agents whose interactions are governed by an underlying network.[3] In this paper, we examine the spread of cooperative behavior through conditional cooperation in a network public goods game (NPGG) where each player's payoff depends only on his own contribution and the contributions of his immediate neighbors in a circle network.

The circle network environment provides a particularly interesting setting for examining the issue of conditional cooperation, for at least two reasons. First, although the decisions made by players from outside my neighborhood are not directly payoff relevant, they may be important if they influence the decisions made by my immediate neighbors (as may be the case if players are conditional cooperators).[4] In turn, one might conjecture that the kind of information provided to players about others from outside their neighborhood influences behavior. For instance, observing the average payoff earned by my neighbors might convey more information than observing their average contribution, since the former reveals something about the contribution decisions made by my neighbors' other neighbors. If players are conditional cooperators, then providing different kinds of information feedback upon which to condition decisions may generate different dynamic patterns of contributions in a repeated network public goods game. Indeed, a recent study by Hartig et al. (2015) shows that using individual rather than average information can have a strong impact on conditional cooperation.

Second, the overlap between players' neighborhoods on the circle allows us to look at the

[1]Several alternative theories have been proposed to explain this puzzle, including other-regarding preferences (Andreoni (1990), Fehr and Schmidt (1999), Bolton and Ockenfels (2000), Cox et al. (2007), Cox et al. (2008)), reciprocity (Rabin (1993), Dufwenberg and Kirchsteiger (2004), Charness and Rabin (2002), Falk and Fischbacher (2006)), confusion (Andreoni (1995), Andreoni and Croson (2008)), learning (Andreoni (1988), Anderson et al. (1998)), and strategic behavior (Andreoni (1988), Ambrus and Pathak (2011)).

[2]For a full discussion of the literature, see the surveys by Ledyard (1995) and Chaudhuri (2011).

[3]These include a comprehensive treatment by Galeotti et al. (2010), and several more targeted studies such as Bramoullé and Kranton (2007), Fatas et al. (2010), Rand et al. (2011), Carpenter et al. (2012), Boosey and Isaac (2016), Charness et al. (2014), and Leibbrandt et al. (2015).

[4]This intuition is similar to the idea that cooperation cascades in social networks, as shown by Fowler and Christakis (2010), although the nature of cascades in their setting refers more to the transfer of behavior from one interaction to another, rather than to the evolution of behavior in a repeated setting.

extent to which conditional cooperators can spread cooperative or free-riding behavior across the network. In the standard environment, a number of studies have demonstrated that group composition is an important factor for sustaining cooperation (Fischbacher and Gächter (2010), Gächter and Thöni (2005), Burlando and Guala (2005), and de Oliveira et al. (2015)). For example,de Oliveira et al. (2015) show that the presence of a single free-rider type, or the colloquial 'bad apple', can significantly harm cooperation in groups.[5] Their result emphasizes the second-order effect of the free-rider type on the behavior of conditional cooperators in the group. In the network environment, we can study an additional dimension of this effect. Specifically, if conditional cooperators respond to the decay in average contributions within their neighborhood, cooperation should break down more quickly for those who are closer to the 'bad apple' in the network. Moreover, while de Oliveira et al. (2015) focus on the effect of free-rider types, we consider a similar conjecture regarding the effect of an unconditional full contributor type (whom we might refer to as a colloquial 'good egg'). That is, can a single unconditional full contributor induce others to increase their contributions, starting with his immediate neighbors and spreading across the network?

We designed an experiment to examine the pattern of contributions in the repeated network public goods game under different information treatment conditions. In all games, after each period, the subjects observed the total contributions made in their neighborhood. In addition, we varied whether subjects were shown average contributions or average payoffs, and whether the relevant average was reported for their neighborhood or for the entire group. Previous research has suggested that contributions are sensitive to the type of feedback provided, particularly given the prevalence of conditionally cooperative behavior. For example, Bigoni and Suetens (2012) find that average contributions are lower when players are provided with feedback about the individual earnings of others, in addition to information about individual contributions. Similarly, in a public goods game with costly punishment, Nikiforakis (2010) shows that the efficacy of punishment is sensitive to the feedback format. In both cases, the effect of feedback format seems to rest on the saliency of different features of the social dilemma environment. While feedback about contributions tends to invite cooperative comparisons, feedback about payoffs tends to make the benefits of free riding more salient.

We add to this existing work on feedback format by examining how both the type of feedback and the reference group about whom feedback is provided affects contribution decisions in the network public goods game. Our initial conjecture is that the broader reference group (providing feedback about the whole network rather than just the player's immediate neighborhood) may further facilitate the decay in cooperation. Consistent with Bigoni and Suetens (2012), we find that average contributions are lower in treatment conditions where payoff feedback is provided to the subjects between periods. In contrast, we find no evidence that providing information about the player's neighborhood versus information about the whole network has any effect on contributions.

In addition, the experimental data provide some interesting patterns regarding the spread of behavior across the network. Since these patterns are similar across the different information treatments, we pool together the data and concentrate our analysis on the pattern of contribution decisions across the network. Consistent with previous studies, we find considerable heterogeneity in the behavioral types of players. There are a number of pure free-rider types

[5]The notion that one bad apple can spoil the bunch has also been studied by others, including Myatt and Wallace (2008) in the context of collective action problems, and researchers in psychology, sociology, and organizational behavior. See Felps et al. (2006) for a review of the psychology and organizational behavior literatures.

who contribute nothing towards the public good. In addition, we find a small number of unconditional full contributor types who always contribute close to their entire endowment. One limitation of our design is that the cooperative types were not elicited separately, as has become popular since the work of Fischbacher et al. (2001). Instead, we rely on a set of criteria applied to the subjects' decisions in the repeated network public goods game to provide a conservative measure of players' cooperative types.

After exploring the classification of subjects into behavioral types, we investigate the extent to which conditional cooperators facilitate the spread of cooperation and free-riding across the network. First, we find that in groups with conditional cooperators and a single free-rider type, the decline in contributions spreads gradually across the network. Players who are close to the free-rider decay faster and earlier than those who are positioned further away. This finding complements the 'bad apple' result reported in the non-network environment by de Oliveira et al. (2015) and suggests that in a simple network environment, the effect spreads gradually across the network.

On the other hand, in groups without any free-rider types, the presence of an unconditional full contributor does not induce a comparable increase in average contributions by the conditional cooperators. Rather, it seems that unconditional full contributors can only mitigate (and in some cases only delay) the familiar decline in contributions over time. That is, a so called 'good egg' can help to stay the breakdown in cooperation, but convergence towards full contribution does not spread across the network. This result also echoes a recent finding by Hartig et al. (2015), which suggests that conditional cooperators are more responsive to the bad example of a low contributor than the good example of a high contributor. In addition, as in the groups with only a free-rider type, we find that proximity to the unconditional full contributor is important. Players who are positioned next to the unconditional full contributor maintain average contributions at a relatively high level, although they do not increase their contributions. However, for players positioned further away, average contributions are lower and exhibit the familiar pattern of decay over time.

Our findings are especially consistent with the argument that conditional cooperators exhibit a downward or self-serving bias (see, e.g., Fischbacher and Gächter (2010)). This argument would help to explain why the unconditional full contributor types appear to be less influential than the free-rider types, since the bias would tend to work against the former while complementing the latter. On the other hand, the asymmetric response to different kinds of unconditional behavior may also be partially conflated with the classification procedure used to categorize subjects into behavioral types. For instance, our classification procedure cannot perfectly identify free rider types who behave strategically in the repeated game setting. In light of this limitation, future research may benefit from using a separate elicitation procedure and a more systematic assignment of types to groups.

The rest of the paper is organized as follows. In Section 2, we introduce the experimental environment, first by describing the network public goods game used in our experiments, then by outlining the treatments and experimental procedures. Section 3 presents the key experimental findings regarding the information treatments and the spread of behavior across the network. Section 4 concludes.

2 Experimental design and procedures

2.1 The network public goods game

The network public goods game (NPGG) is a natural extension of the standard linear public goods game with voluntary contributions. The game consists of n players, each with an endowment of 100 tokens that may be allocated between a public good and private consumption. Public good consumption for a given player is determined only by the total level of contributions in his neighborhood, which is comprised of himself and the players with whom he is connected in the network. This feature is based on the model originally introduced by Bramoullé and Kranton (2007) for the private provision of public goods on networks.

In our experiment, the game consists of $n = 6$ players connected within a circle network. Thus, player i's payoff is given by

$$\pi_i = 100 - g_i + A \cdot \left(g_i + \sum_{j \in N_i} g_j \right) \tag{1}$$

where g_j is player j's public good contribution, A is the marginal per capita return (MPCR) to the public good, and N_i is the set of player i's direct neighbors in the network. In the circle network, each player is connected to two other players. In every game, the MPCR was set to $A = 0.6$, which induces the classical social dilemma, since each individual's incentive to free ride conflicts with the socially efficient outcome where everyone contributes their full endowment.

2.2 Treatments

In each session of the experiment, subjects participated in four separate matches. Each match consisted of 15 periods of the network public goods game in fixed groups. We implemented four treatment conditions in which we varied the information provided to subjects between periods along two dimensions. In all treatments, subjects observed the total contributions made in their own neighborhood and their own payoff from the previous period. The treatments differed with respect to the additional information provided between periods. First, we varied whether subjects were shown information about the payoffs received by others or about the contributions made by others. Second, we varied whether they were shown the average payoff (respectively contribution) for their neighborhood or for the entire group of six players in the network. The resulting treatment conditions are described as follows. In *C-N*, subjects were shown the average contribution made in their own neighborhood; in *C-G*, subjects were shown the average contribution made in the whole group of six players; in *P-N*, subjects were shown the average payoff received in their own neighborhood; and in *P-G*, subjects were shown the average payoff earned in the whole group of six players.[6]

2.3 Procedures

We conducted two sets of experiments. The first set consisted of six sessions (with a total of 72 subjects) conducted in 2011 in the Social Science Experimental Laboratory (SSEL) at the California Institute of Technology (Caltech). The second set consisted of four sessions (with a

[6]Note that the *C-N* treatment condition is always implicitly available to the subjects, since it can be deduced from total contributions in their neighborhood.

Table 1: Experimental design: Sessions & treatments

Session	Match 1	2	3	4	No. of subjects	Matching clusters	Experiment location
1	*P-N*	*P-G*	*C-N*	*C-G*	12	1	Caltech
2	*C-N*	*C-G*	*P-N*	*P-G*	12	1	Caltech
3	*C-G*	*C-N*	*P-G*	*P-N*	12	1	Caltech
4	*P-N*	*P-G*	*C-N*	*C-G*	12	1	Caltech
5	*C-N*	*C-G*	*P-N*	*P-G*	12	1	Caltech
6	*P-N*	*P-G*	*C-N*	*C-G*	12	1	Caltech
7	*C-N*	*C-G*	*P-N*	*P-G*	24	2	FSU
8	*P-N*	*P-G*	*C-N*	*C-G*	24	2	FSU
9	*C-G*	*C-N*	*P-G*	*P-N*	24	2	FSU
10	*P-G*	*P-N*	*C-G*	*C-N*	24	2	FSU

total of 96 subjects) conducted in 2016 in the XS/FS Laboratory at Florida State University (FSU).[7] All procedures and instructions were carefully replicated to ensure that conditions were the same in both sets of experiments. While the first set of experiments were programmed and run using the open source software, Multistage, the experiment was reprogrammed and conducted using zTree (Fischbacher, 2007) for the second set of sessions.

At the beginning of the experiment, instructions were distributed and read aloud to the subjects.[8] After the instructions, subjects participated in an unpaid practice match to familiarize themselves with the experiment and the interface. In the first set of sessions, we recruited 12 subjects who then formed a single matching cluster. In the second set of sessions, we recruited 24 subjects who were then divided randomly into two independent matching clusters with 12 subjects. Matching clusters were fixed for the entire session. Then, before each match in a session, subjects in each matching cluster were randomly divided into two groups of six players and randomly reassigned to a position in the circle network.

In each session, subjects participated once in each of the four treatments. Specifically, we assigned a different treatment condition to each of the four matches in a session. We varied the order of the treatments across sessions as described in Table 1. Subjects were randomly regrouped (within their matching cluster) between matches. The first set of sessions lasted approximately 1 hour and subjects earned an average payoff of $25.00 (including a $10 show-up fee). On the other hand, the second set of sessions lasted approximately 1 hour and 15 minutes and subjects earned an average payoff of $15.98 (including a $7 show-up fee).

[7] All subjects were undergraduate students at the respective institutions.

[8] Sample instructions are included in the Appendix.

3 Results

The results are organized as follows. First, we test for differences between the two subject pools. Second, we compare contributions across the four treatment conditions to evaluate aggregate treatment effects. Third, we use the individual level data to classify players into three behavioral types, labeled *free riders* (F), *unconditional full contributors* (U), and *conditional cooperators* (C). Any players who we are unable to classify according to one of the three behavioral types are classified as *others* (O). We focus our individual analysis on the behavior of the conditional cooperators, although partly also on those classified as others. In particular, we investigate the effects of (i) the player's neighbors' classifications, and (ii) the player's proximity to a free rider (or unconditional full contributor) in the network on behavior over time. Finally, in order to explore the spread of behavior across the network more closely, we examine a particular subset of the possible group compositions, where the group includes either a 'bad apple' or a 'good egg'.

3.1 Differences between subject pools

We begin the analysis by comparing average contributions between the two subject pools. Figure 1 demonstrates that there is significantly more cooperation (on average) in our subsample using Caltech undergraduate students than in the subsample using FSU undergraduate students. The differences are substantial in all four treatments (see Figures A.1 - A.4 in the Appendix). Furthermore, using the average contribution calculated over all rounds for each matching cluster as the unit of observation, we find that the differences between subject pools are highly significant using the Mann-Whitney U-test ($p = 0.014$).[9]

In Section 3.3, we compare the distribution of classifications between subject pools and show that the main difference between subject pools is that there are substantially more players classified as unconditional full contributors in the Caltech subsample compared to the FSU subsample, where there are almost none. We would expect this difference to be one of the driving factors leading to higher average contributions in the Caltech subsample, both for the unconditional full contributors' direct influence on the average and for their indirect influence on the contributions of conditional cooperators. We summarize these findings with the following result.

Result 1 *Average contributions are (economically and statistically) significantly higher in the Caltech subsample than in the FSU subsample.*

3.2 Aggregate treatment effects

Figure 2 shows that at the aggregate level, average contributions in all of the treatments exhibit the familiar pattern of decay with repeated play. Note that the observations from both subject pools are pooled to produce Figure 2. However, the pattern of average contributions over time is similar in each of the subsamples, as shown in Figures A.5 and A.6. Although the differences are small, there is some visual evidence to suggest that average contributions are lower in the 'payoff' treatment conditions (*P-N* and *P-G*) than in the 'contribution' treatment conditions (*C-N* and

[9] The differences are also significant for each treatment; *P-N* ($p = 0.028$), *P-G* ($p = 0.039$), *C-N* ($p = 0.005$), and *C-G* ($p = 0.007$).

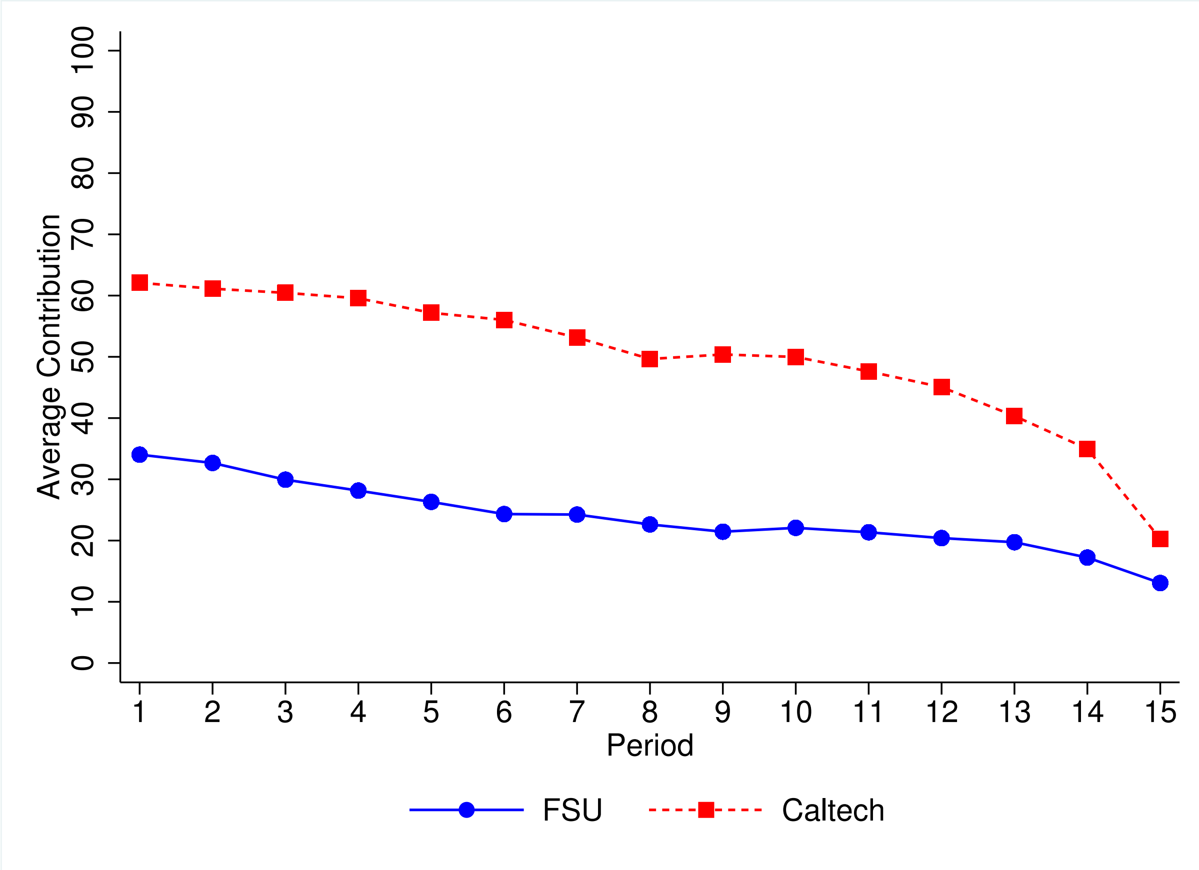

Figure 1: Average contributions over time by subject pool

C-G). To provide more convincing evidence of these differences, we turn to the nonparametric Wilcoxon signed-ranks test using matched pairs.

Given the within-subjects design in each session, we generated 14 independent observations for each treatment by computing the average contribution over all players and all rounds for each independent matching cluster. Then we conducted a series of Wilcoxon signed-ranks tests to compare between each pair of treatment conditions. With this approach, the level differences between subject pools should not matter for the purposes of testing the treatment effects. First, we find that there are no differences between *P-N* and *P-G* ($p = 0.221$) or between *C-N* and *C-G* ($p = 0.198$). Thus, the reference group for whom the average (payoff or contribution) is reported does not significantly affect behavior. However, consistent with Figure 2, we do find significant differences between the payoff and contribution conditions, both between *P-N* and *C-N* ($p = 0.016$) and between *P-G* and *C-G* ($p = 0.064$).[10] We summarize these findings as follows.

Result 2 *Whether subjects are shown the average in their neighborhood or in the whole group, average contributions are lower when the information shown reports average payoff than when it reports average contribution.*

[10]In addition, there is a significant difference between *P-G* and *C-N* ($p = 0.013$), while we are unable to reject the null hypothesis of no difference between *P-N* and *C-G* ($p = 0.433$).

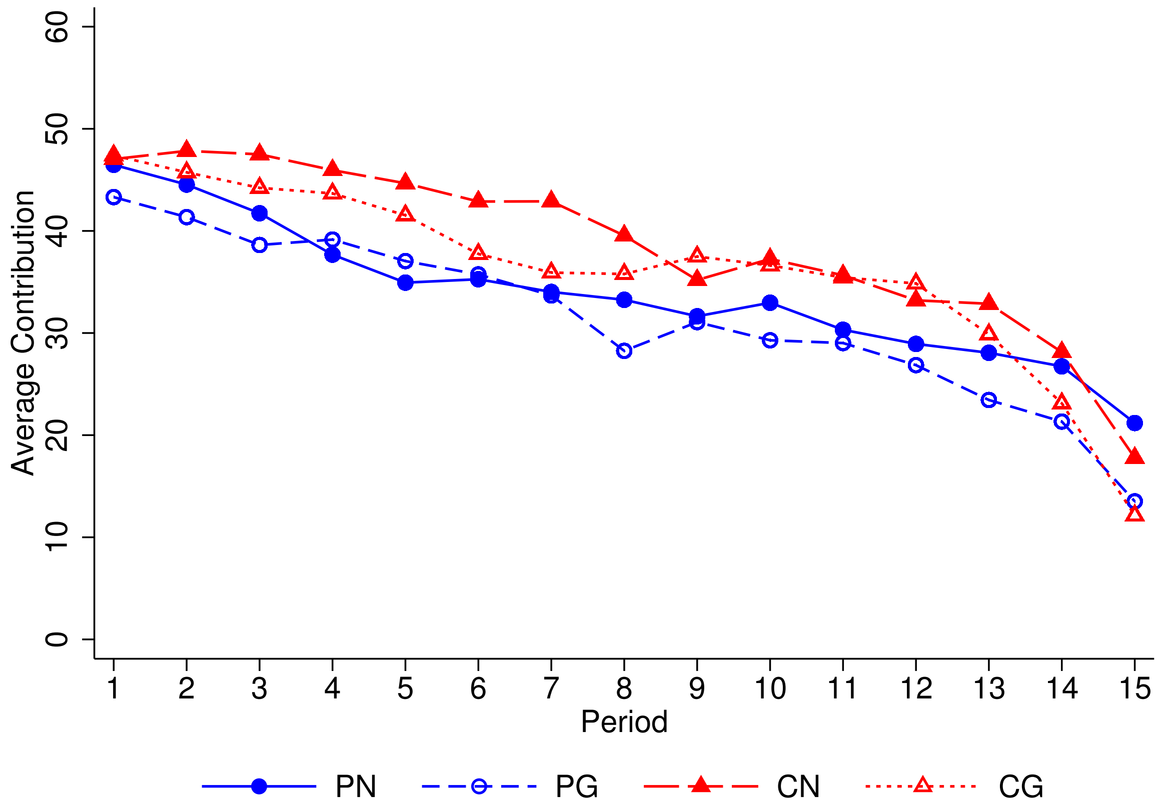

Figure 2: Average contribution by treatment

This result is consistent with previous work that examines the effect of different forms of feedback on cooperation. Bigoni and Suetens (2012) show that providing earnings information on top of contributions feedback makes the benefit to free riding more salient and leads to significantly lower average contributions than when only contributions feedback is provided. Other studies to demonstrate the importance of feedback include Nikiforakis (2010), who shows that the efficacy of punishment depends critically on feedback format, and earlier work by Sell and Wilson (1991), who show that providing feedback at the individual level increases contributions compared to the case where feedback is aggregated.

3.3 Individual level results

At the individual-level, we first try to classify the subjects into two unconditional types; *free-riders* and *unconditional full contributors*. One limitation of our study is that we do not use a separate elicitation mechanism, such as the variant of the strategy method procedure introduced by Fischbacher et al. (2001).[11] As such, we take a conservative approach to classifying subjects as *free riders* and *unconditional full contributors*. Specifically, each subject in a given match is

[11] As another example, Kurzban and Houser (2005) apply a statistical method to classifying subjects' decisions. Alternatively, see the classification of types by first-period contributions only in Gunnthorsdottir et al. (2007).

Table 2: Subject Classifications

Classification	Treatment			
	P-N	*P-G*	*C-N*	*C-G*
Unconditional Full Contributors (U)	**16**	**6**	**16**	**14**
Caltech	(16)	(5)	(16)	(13)
FSU	(0)	(1)	(0)	(1)
Free-Riders (F)	**18**	**24**	**17**	**22**
Caltech	(7)	(8)	(6)	(9)
FSU	(11)	(16)	(11)	(13)
Conditional Cooperators (C)	**50**	**65**	**70**	**61**
Caltech	(24)	(37)	(31)	(27)
FSU	(26)	(28)	(39)	(34)
Other (O)	**84**	**73**	**65**	**71**
Caltech	(25)	(22)	(19)	(23)
FSU	(59)	(51)	(46)	(48)
Total	**168**	**168**	**168**	**168**

classified as a *free-rider* (F) if in all but one of the first 14 periods, the subject contributed 10 tokens or less. On the other hand, a subject in a given match is classified as an *unconditional full-contributor* (U) if in all but one of the first 14 periods, the subject contributed 90 tokens or more.[12] Note that we discard the final period from each match to eliminate endgame effects and introduce a tolerance for a deviation from the prescribed behavior in one period.

Next, we look for evidence of conditional cooperation among the remaining subjects (those who are not classified as a (U) or (F) type). To do so, we first calculate the Spearman rank correlation coefficient between the subject's contribution and the lagged average contribution in their neighborhood. In a one-sided significance test with $p = 0.05$ and a sample size of 14, the critical value for this correlation coefficient is 0.538. Comparing the calculated correlation coefficient with the critical value, we find substantial evidence in favor of conditional cooperation by the individuals in each of the treatments. Those subjects whose correlation coefficients are significant are classified as *conditional cooperators* (C), while any remaining unclassified subjects are classified as *others* (O). The number of subjects classified as each behavioral type are reported in Table 2 with the breakdown by subject pool shown below the totals from pooling both sets of experiments.

Consistent with previous studies, a cursory examination of subjects' behavior indicates a significant amount of conditional cooperation and several unconditional free-rider types. In addition, there are some players who we classify as unconditional full contributor types, although the percentage of these types is small in all treatments. Moreover, the distribution of behavioral types is significantly different between our two subject pools (Fisher's exact test, $p = 0.000$), with a much higher percentage of *others* and only two players classified as *unconditional full*

[12] The most restrictive criteria would be to require a contribution of 0 in every period for a player to be classified as a free-rider and to require a contribution of 100 in every period for a player to be classified as an unconditional full contributor. However, using these criteria, there are in total just 31 players classified as (F) types, and just 18 players classified as (U) types. Thus, compared with the more relaxed criteria we use for our analysis, the restrictive criteria decreases the number of classified free-riders and unconditional full contributors. Under these classifications, the number of groups with the specific compositions studied in Section 3.4 are also different. However, the main findings reported there are all qualitatively robust to the more stringent classification criteria.

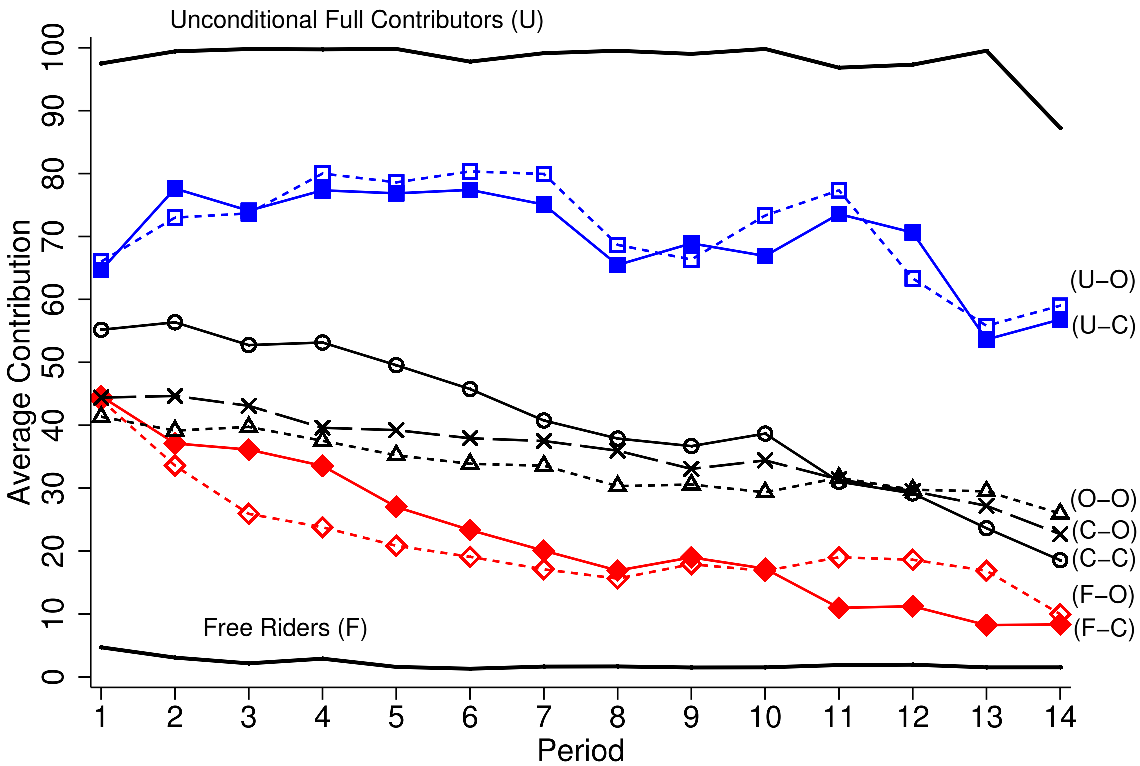

Figure 3: Average Contributions over time for Conditional Cooperators based on their immediate neighbors' classifications. The labels in the figure – e.g. (U-C), (C-C), (F-C) – indicate the classifications of the two neighbors for the (conditional cooperator) players included in the subclass.

contributors in the FSU subsample.[13] As discussed in Section 3.1, these differences are consistent with the difference in overall average contributions between subject pools.

We turn next to a deeper analysis of conditional cooperation in our data. Figure 3 plots the average contribution over time for our classified (C) and (O) types, further sub-classified by the classifications of their two direct neighbors. We note that this figure does not account for the full composition of behavioral types in the group. Rather, it only controls for the local composition of types in a player's immediate neighborhood. Nevertheless, the differences in behavior based only on subjects' immediate neighborhood composition are quite salient.

Consider the players who have one free-rider (F) neighbor and one neighbor who is either a (C) or (O). On average, the contributions of these players converge much faster towards free-riding than the contributions of those who do not have a free-rider type in their immediate neighborhood. A natural conjecture is that unconditional full contributors will have a comparable, opposing effect, eliciting a gradual increase in average contributions from players in their

[13]The distributions are also significantly different for each treatment condition, with $p < 0.001$ for Fisher's exact test in each case.

neighborhood. However, this does not appear to be the case. Instead, the average contributions of the players who have one unconditional full contributor (U) neighbor and one (C) or (O) neighbor are essentially level, perhaps even with a slight decline in the last few periods.[14] It is also noteworthy that the average contribution made by conditional cooperators whose neighbors are either (C) or (O) types also exhibit the same pattern of decay over time observed at the aggregate level.

To check for differences in the levels and slopes for the different subclasses of (C) and (O) types, we report the results of a panel regression on contributions against sub-classification and the interaction between period and sub-classification (immediate neighbors' classifications). The results are reported in Table 3. First, there are significant level effects, relative to the omitted sub-classification (F-F), for all sub-classifications except (F-O). Moreover, using a series of pairwise Wald tests for coefficients, we find significantly higher coefficients for (U-U), (U-C) and (U-O) than for all other sub-classifications except (U-F), and significantly higher coefficients for (C-C), (C-O), and (O-O) than for (F-C) or (F-O). That is, there is a significant level effect generated by the presence of an unconditional type (free-rider or unconditional full contributor) in a player's immediate neighborhood.

Second, the effect of the period is not significant for the omitted category (F-F). Calculating the overall effect of period for the other sub-classifications and testing for significance, we find that period has a significant negative effect for all other sub-classifications. Moreover, Wald tests for differences between coefficients indicate significantly larger (negative) slope coefficients for the (F-C) and (F-O) sub-classes (which are not different from each other) than for (U-C) or (U-O) sub-classes (also not different from each other) or for (C-O) or (O-O) sub-classes. In addition, although the slopes are similar for (F-C), (F-O), and (C-C) sub-classes, there is a significant level effect on the latter relative to the two former, consistent with Figure 3. Nevertheless, as noted earlier, these results may be confounded by the presence of free-rider types outside the player's immediate neighborhood. Specifically, if conditionally cooperative behavior can spread across the network, we need to consider the entire group composition.

To that end, we extend the analysis by exploring the effect of proximity to one of the unconditional types in the network. For each player, we calculate the distance of the shortest path connecting the player to a free-rider type in the network. With $n = 6$ in our circle network, the maximal distance is 3. Then, for each independent matching cluster, we calculate the average contribution over all rounds and over all (C) and (O) players, by distance to the closest (F) player. This generates 14 independent observations each for the average contribution by players who are 1 step from a free-rider, 2 steps from a free-rider, and 3 steps from a free-rider. Using a Wilcoxon sign rank test on these 14 observations, we find that average contributions are significantly different for players at each level of proximity to a free rider. That is, players who are 1 step away from a free-rider contribute significantly less than players who are 2 steps away ($p = 0.002$) and players who are 3 steps away ($p = 0.003$). Likewise, players who are 2 steps away contribute significantly less than players who are 3 steps away ($p = 0.028$).

We follow a similar approach to generate 14 independent observations each for the average contribution by players who are, respectively, 1 step, 2 steps, and 3 steps, from an unconditional full contributor (U). Again, using the Wilcoxon sign rank test reveals that players who are 1 step away from a (U) type contribute significantly more than players who are 2 steps away

[14] Figure 3 also shows that there is virtually no difference between the pattern of contributions for players with (U-C) neighbors versus those with (U-O) neighbors, and similarly no difference between the pattern for those with (F-C) neighbors versus those with (F-O) neighbors.

Table 3: Panel Regression on Contributions against Period & Neighbors' Classifications

Dependent variable = contribution	Coefficient	S.E.
FSU	-14.69***	(4.669)
(U-C)	52.63***	(7.358)
(U-O)	56.73***	(11.834)
(C-O)	27.95***	(8.847)
(C-C)	38.96***	(8.249)
(O-O)	23.03***	(8.446)
(F-C)	20.41**	(10.379)
(F-O)	12.82	(7.977)
(U-U)	72.10***	(6.641)
(U-F)	52.77***	(11.969)
Period	-1.558	(1.133)
Period × (U-C)	-0.347	(1.121)
Period × (U-O)	-0.692	(1.282)
Period × (C-O)	-0.259	(1.154)
Period × (C-C)	-1.440	(1.170)
Period × (O-O)	-0.436	(1.162)
Period × (F-C)	-1.007	(1.343)
Period × (F-O)	-0.045	(1.036)
Period × (U-U)	0.558	(1.133)
Period × (U-F)	-2.329	(1.630)
Constant	30.567***	(6.641)
Observations	8085	

The omitted sub-classification is (F-F). Standard errors are clustered by matching cluster.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

($p = 0.018$) and players who are 3 steps away ($p = 0.043$). Likewise, players who are 2 steps away contribute less than players who are 3 steps away, although only at the 10% level of significance ($p = 0.0796$).

While these results provide strong supporting evidence for the idea that free-riding and cooperation spread gradually across the network, they still do not completely take into account the effect of the overall group composition on behavior. For instance, there may be groups with both multiple free-riders distributed throughout the network or groups with both a free rider and an unconditional full contributor. In these cases, our simple measure of proximity to a free-rider or to an unconditional full contributor will not be ideal. Thus, to extend the analysis further, we explore behavior in a particular subset of the possible group compositions - those with a single free rider (a 'bad apple') and five players who are either conditional cooperators or others; and those with either one or two adjacent unconditional full contributors (a 'good egg') together with a mix of players who are either conditional cooperators or others.

3.4 The effect of group composition

3.4.1 Groups with a single free rider

Consider first the spread of free-riding in groups that consist of a single free-rider type, along with a mixture of classified conditional cooperator (C) and other (O) types. Given the structure of the circle network, conditional cooperation in these groups would not only suggest that contributions decay over time, it would also imply different rates of decay for players located closer to or further from the free-rider in the network.

Figure 4 illustrates that precisely this pattern emerges for the groups with a single free-rider in our experiments. There were 10 such groups spread across the four treatments in the first set of sessions, and 25 such groups across the four treatments in the second set of sessions. Figure 4 shows the average contribution in the first period and in each 4-period block from period 3 to 14, for the free-rider; for the two players who are direct neighbors of the free-rider, collectively labeled (F + 1), the two players who are located two steps away from the free-rider (F + 2); and for the player who is located three steps away from the free-rider (F + 3). In each of the 4-period blocks, (F + 1) players are closest to free-riding, while the (F + 3) player is furthest from free-riding. The effect of proximity to the free-rider shown in Figure 4 is also robust across subject pools, as shown by Figures A.7 and A.8, and across treatments, as shown by Figures A.9 - A.12 in the Appendix.

Table 4, reports the results for an OLS regression of contribution on proximity to the free rider in groups with a single (F) type. We report the estimates for one specification using all periods and two separate specifications to capture the first seven periods and the penultimate seven periods.[15] The slope coefficients on period in the regression are negative and significant for all three locations relative to the free-rider. This is consistent with the downward or self-serving bias usually attributed to conditional cooperators. Using just the first 7 periods, the slopes are not significantly different from one another. Using the penultimate 7 periods, the slope is less pronounced for players who are directly connected to the free rider, but more pronounced for the players who are two or three steps away from the free rider. This suggests that the decay in average contributions made by players who are farther away from the free rider speeds up over time after the players who are closer have already converged towards free riding.

These findings suggest that the result obtained in de Oliveira et al. (2015) also extends to the network public goods game. Moreover, as we might expect if conditional cooperation is driving behavior, the convergence towards free riding is faster for players who are closer to the free-rider type in the group.

[15] We drop the last period to eliminate endgame effects.

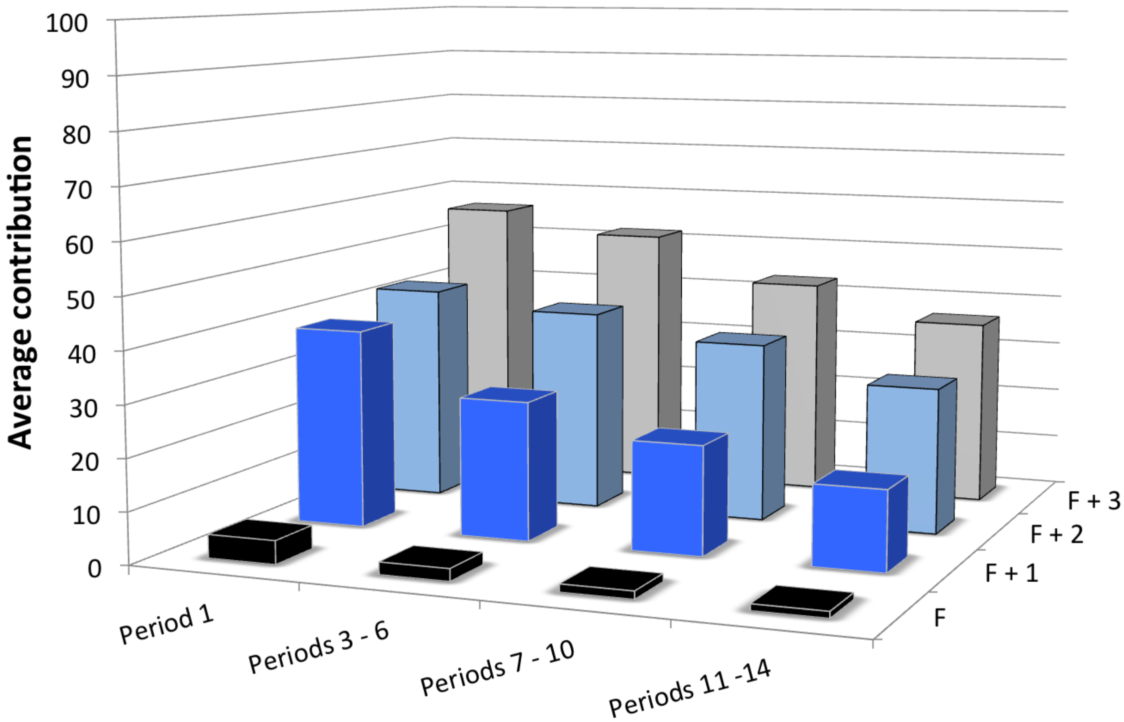

Figure 4: Average contributions in groups with 1 free-rider. F indicates the free-rider; $F + 1$ denotes the two players located one step from the free-rider; $F + 2$ denotes the two players who are two steps from the free-rider; $F + 3$ denotes the player located three steps from the free-rider.

3.4.2 Groups with one or two (adjacent) unconditional full contributors

In addition, we also examine the impact of the colloquial 'good eggs'. For this, we consider the groups in which there are no free-rider (F) types, and either 1 unconditional full contributor (U) type or 2 (U) types right next to each other. Across all treatments, there are 5 groups with a single (U) and 4 groups with two (U) types located next to each other.[16]

In Figure 5, we show the average contribution by player proximity to the (U) player(s) over the same period blocks used in Figure 4. Compared to the free-rider types, the unconditional full contributor types have a substantially weaker influence on their neighbors. In fact, players who are three steps away from the unconditional full contributor (U + 3) exhibit significant decay, comparable to the pattern of contributions for players who are three steps away from a free-rider (F + 3) in Figure 4. On the other hand, players closer to the unconditional full contributor increase their average contributions at first, and display a considerably weaker tendency to decay over time. This also is consistent with the notion that conditional cooperation exhibits a selfish bias, such that the cooperative behavior of an unconditional full contributor type only serves to mitigate the decline of contributions over time.

[16]Since there are relatively fewer groups of this composition than for the case with a single free rider, we do not break down Figure 5 by treatment.

Table 4: The effects of proximity to a free rider

Dependent variable = contribution	(1) All periods	(2) Periods 1 - 7	(3) Periods 8 - 14
$F+2$	12.026***	8.803**	18.248***
	(3.045)	(3.023)	(3.929)
$F+3$	26.184***	23.891***	24.055**
	(7.446)	(7.290)	(9.281)
Period	-1.634***	-2.042***	-1.389***
	(0.291)	(0.628)	(0.270)
Period $\times$ $F+2$	0.023	0.767	-0.456
	(0.201)	(0.611)	(0.379)
Period $\times$ $F+3$	-0.588	-0.081	-0.252
	(0.487)	(0.967)	(0.906)
Constant	35.402***	36.931***	32.832***
	(3.650)	(3.561)	(4.751)
# of observations	2595	1211	1211
R^2	0.1467	0.1061	0.1006

The omitted category is for $F+1$, which consists of the players who are direct neighbors to the free-rider in the group. Standard errors shown in parentheses are clustered by matching cluster.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The effects of proximity to an unconditional full contributor

Dependent variable = contribution	(1) All periods	(2) Periods 1 - 7	(3) Periods 8 - 14
$U+2$	-21.144*	-18.127*	-14.413
	(8.284)	(7.712)	(15.642)
$U+3$	-20.549	-3.565	-41.342**
	(14.649)	(15.590)	(10.023)
Period	-1.692***	1.619*	-0.466
	(0.338)	(0.562)	(1.595)
Period $\times$ $U+2$	0.181	-0.815	-0.325
	(0.263)	(1.207)	(0.960)
Period $\times$ $U+3$	-2.042	-6.269**	-0.405
	(1.612)	(1.569)	(0.461)
Constant	80.444***	67.937***	69.470***
	(7.405)	(8.346)	(10.009)
# of observations	615	287	287
R^2	0.1917	0.1508	0.1726

The omitted category is for $U+1$, which consists of the players who are direct neighbors to the unconditional full contributor(s) in the group. Standard errors shown in parentheses are clustered by matching cluster.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

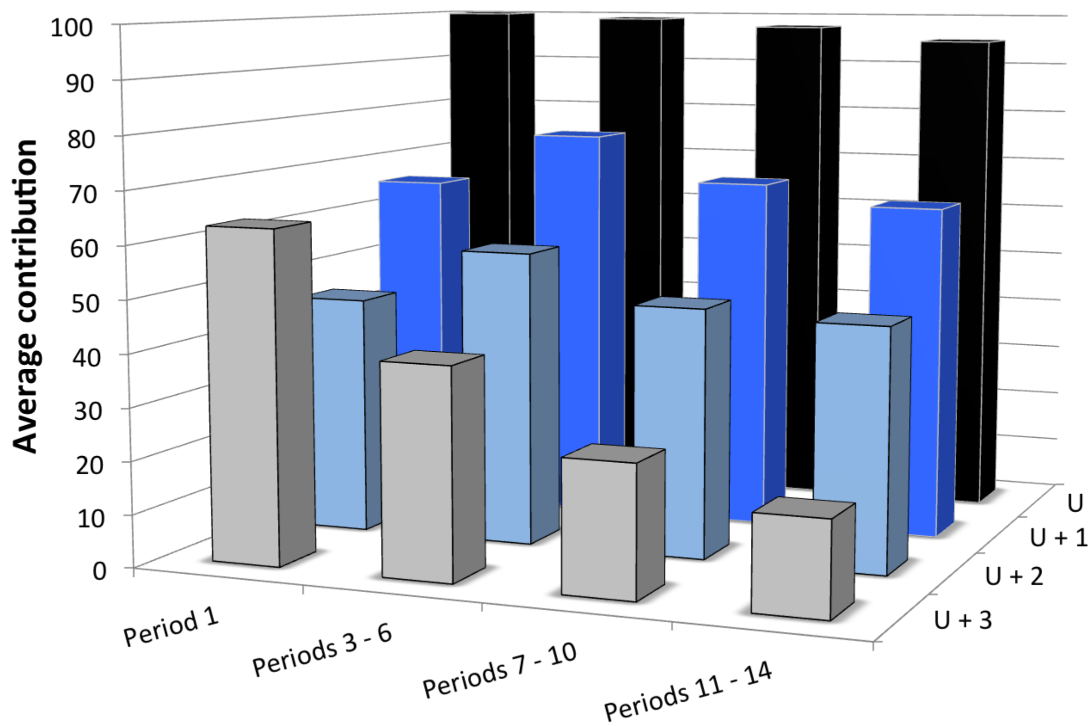

Figure 5: Average contributions in groups with 1 or 2 (adjacent) unconditional full contributors. U indicates the unconditional full contributor; $U + 1$ denotes the two players located one step from a U; $U + 2$ denotes the two players who are two steps from a U; and $U + 3$ denotes the player located three steps from a U (when applicable).

Table 5 reports the results for an OLS regression of contribution on proximity to the unconditional full contributor in groups with either a single (U) type or two adjacent (U) types, over all periods, over the first seven periods, and the penultimate seven periods. The reported slope coefficients on period in model (2) suggest a significant, positive slope for (U + 1), statistically insignificant (positive) slope for (U + 2), and a large, significant negative slope for (U + 3). Using the last 7 periods, we get slightly negative (but statistically insignificant) slope coefficients for all three levels of proximity, (U + 1), (U + 2), and (U + 3).

Thus, to some extent, an unconditional full contributor is able to arrest the decline in contributions for his immediate neighbors. Over time, the effect spreads to players who are further away, but is not strong enough to prevent the typically observed decline in average contributions.

4 Conclusion

The findings reported in this paper illustrate that the dynamics of conditional cooperation can be particularly salient in network public goods games. Consistent with previous work, we find that conditional cooperation leads to lower contributions when subjects are provided with feedback about payoffs rather than only about contributions. On the other hand, varying whether feedback relates to a player's neighborhood alone, or extends to the entire network, does not appear to have a significant influence on behavior.

In addition, we find that unconditional full contributors and free-riders can affect the dynamics of cooperation across the network through their conditional cooperator neighbors. The effects of these two unconditional types on behavior appear to be asymmetric. In groups with a single free-rider type, the conditional cooperators exhibit the usual pattern of declining contributions. Moreover, we show that the effect depends on a player's proximity to the free-rider in the network. On the other hand, in groups with an unconditional full contributor (and no free-rider types), conditionally cooperative players do not converge towards higher contribution levels. Nevertheless, the unconditional full contributor can partially delay the decline in average contributions, at least for players who are located in close proximity to the unconditional full contributor. The asymmetry we observe in the impact of the two different unconditional types is consistent with the widespread argument that conditional cooperators exhibit a downward or self-serving bias when they condition on the expected contributions of others. Finally, the results on the gradual spread of behavior are consistent between our two different subject pools, one of which is significantly more cooperative (on average) than the other, which suggests that our results are robust to groups that are both relatively more cooperative and those that are relatively less cooperative.

Although we do not report or discuss them here, other group compositions, where both unconditional types are present (or where neither are present), also exhibit the gradual process of decay, consistent with the hypothesis of imperfect or partial conditional cooperation. For instance, although there are very few observations, average contributions by conditional cooperators in groups with one free-rider and one unconditional full contributor also appear to decay over time, though with limited decay for players who are closer to the unconditional full contributor and stronger decay for players who are closer to the free rider in the group. A more systematic analysis of the precise contribution patterns in these kinds of groups is left for future research.

One of the main limitations of our experimental design is that we do not use a separate procedure to elicit and classify contributor types. In addition, although the differences are small, it is puzzling that we found a smaller percentage of unconditional full contributors in our *P-G* treatment than in the other three treatments. One possibility is that the randomization of types across treatments failed in our relatively small sample. A separate elicitation procedure would allow for a more balanced assignment of types across treatments, in addition to being more robust than the procedure used for this paper. Thus, in future work, a more systematic approach to examining the role of group composition in the NPGG would benefit from a more controlled design in which behavioral types are elicited separately and group composition is more tightly controlled. Our design could also be improved by implementing the different treatments between subjects, rather than within subjects. Nevertheless, the evidence of contagion in the circle NPGG environment studied here is encouraging for future research into the effects of network structure on contribution decisions, and particularly in relation to the dynamics of conditional cooperation.

References

Ambrus, A. and P. A. Pathak (2011). Cooperation over finite horizons: a theory and experiments. *Journal of Public Economics 95*(7), 500–512.

Anderson, S. P., J. K. Goeree, and C. A. Holt (1998). A theoretical analysis of altruism and decision error in public goods games. *Journal of Public Economics 70*(2), 297–323.

Andreoni, J. (1988). Why free ride? strategies and learning in public goods experiments. *Journal of Public Economics 37*(3), 291–304.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. *Economic Journal 100*(401), pp. 464–477.

Andreoni, J. (1995). Cooperation in public-goods experiments: Kindness or confusion? *American Economic Review 85*(4), pp. 891–904.

Andreoni, J. and R. Croson (2008). Partners versus strangers: Random rematching in public goods experiments. *Handbook of Experimental Economics Results 1*, 776–783.

Bigoni, M. and S. Suetens (2012). Feedback and dynamics in public good experiments. *Journal of Economic Behavior & Organization 82*(1), 86–95.

Bolton, G. E. and A. Ockenfels (2000). Erc: A theory of equity, reciprocity, and competition. *American Economic Review 90*(1), pp. 166–193.

Boosey, L. and R. M. Isaac (2016). Asymmetric network monitoring and punishment in public goods experiments. *Journal of Economic Behavior & Organization 132, Part A*, 26–41.

Bramoullé, Y. and R. Kranton (2007). Public goods in networks. *Journal of Economic Theory 135*(1), 478–494.

Brandts, J. and A. Schram (2001). Cooperation and noise in public goods experiments: applying the contribution function approach. *Journal of Public Economics 79*(2), 399–427.

Burlando, R. and F. Guala (2005). Heterogeneous agents in public goods experiments. *Experimental Economics 8*(1), 35–54.

Carpenter, J., S. Kariv, and A. Schotter (2012). Network architecture, cooperation and punishment in public good experiments. *Review of Economic Design 16*(2-3), 93–118.

Charness, G., F. Feri, M. A. Meléndez-Jiménez, and M. Sutter (2014). Experimental games on networks: Underpinnings of behavior and equilibrium selection. *Econometrica 82*(5), 1615–1670.

Charness, G. and M. Rabin (2002). Understanding social preferences with simple tests. *Quarterly Journal of Economics 117*(3), pp. 817–869.

Chaudhuri, A. (2011). Sustaining cooperation in laboratory public goods experiments: a selective survey of the literature. *Experimental Economics 14*(1), 47–83.

Cox, J. C., D. Friedman, and S. Gjerstad (2007). A tractable model of reciprocity and fairness. *Games and Economic Behavior 59*(1), 17–45.

Cox, J. C., D. Friedman, and V. Sadiraj (2008). Revealed altruism. *Econometrica 76*(1), 31–69.

Croson, R., E. Fatas, and T. Neugebauer (2005). Reciprocity, matching and conditional cooperation in two public goods games. *Economics Letters 87*(1), 95 – 101.

Croson, R. T. (2007). Theories of commitment, altruism and reciprocity: Evidence from linear public goods games. *Economic Inquiry 45*(2), 199–216.

de Oliveira, A. C., R. T. Croson, and C. Eckel (2015). One bad apple? heterogeneity and information in public good provision. *Experimental Economics 18*(1), 116–135.

Dufwenberg, M. and G. Kirchsteiger (2004). A theory of sequential reciprocity. *Games and Economic Behavior 47*(2), 268–298.

Falk, A. and U. Fischbacher (2006). A theory of reciprocity. *Games and Economic Behavior 54*(2), 293–315.

Fatas, E., M. A. Meléndez-Jiménez, and H. Solaz (2010). An experimental analysis of team production in networks. *Experimental Economics 13*(4), 399–411.

Fehr, E. and K. M. Schmidt (1999). A theory of fairness, competition, and cooperation. *Quarterly Journal of Economics 114*(3), pp. 817–868.

Felps, W., T. Mitchell, and E. Byington (2006). How, when, and why bad apples spoil the barrel: Negative group members and dysfunctional groups. In B. Staw (Ed.), *Research in Organizational Behavior*, Volume 27, pp. 181–230. Amsterdam: Elsevier.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics 10*(2), 171–178.

Fischbacher, U. and S. Gächter (2010). Social preferences, beliefs, and the dynamics of free riding in public goods experiments. *American Economic Review 100*(1), 541–556.

Fischbacher, U., S. Gachter, and E. Fehr (2001). Are people conditionally cooperative? evidence from a public goods experiment. *Economics Letters 71*(3), 397–404.

Fowler, J. H. and N. A. Christakis (2010). Cooperative behavior cascades in human social networks. *Proceedings of the National Academy of Sciences 107*(12), 5334–5338.

Gächter, S. and C. Thöni (2005). Social learning and voluntary cooperation among like-minded people. *Journal of the European Economic Association 3*(2-3), 303–314.

Galeotti, A., S. Goyal, M. O. Jackson, F. Vega-Redondo, and L. Yariv (2010). Network games. *Review of Economic Studies 77*(1), 218–244.

Gunnthorsdottir, A., D. Houser, and K. McCabe (2007). Disposition, history and contributions in public goods experiments. *Journal of Economic Behavior & Organization 62*(2), 304 – 315.

Hartig, B., B. Irlenbusch, and F. Kölle (2015). Conditioning on what? heterogeneous contributions and conditional cooperation. *Journal of Behavioral and Experimental Economics 55*, 48 – 64.

Isaac, R. M., K. F. McCue, and C. R. Plott (1985). Public goods provision in an experimental environment. *Journal of Public Economics 26*(1), 51 – 74.

Isaac, R. M., J. M. Walker, and S. H. Thomas (1984). Divergent evidence on free riding: An experimental examination of possible explanations. *Public Choice 43*(2), pp. 113–149.

Keser, C. and F. Van Winden (2000). Conditional cooperation and voluntary contributions to public goods. *The Scandinavian Journal of Economics 102*(1), 23–39.

Kocher, M. G., T. Cherry, S. Kroll, R. J. Netzer, and M. Sutter (2008). Conditional cooperation on three continents. *Economics Letters 101*(3), 175–178.

Kurzban, R. and D. Houser (2005). Experiments investigating cooperative types in humans: A complement to evolutionary theory and simulations. *Proceedings of the National Academy of Sciences of the United States of America 102*(5), 1803–1807.

Ledyard, J. O. (1995). Public goods: A survey of experimental research. In J. Kagel and A. Roth (Eds.), *Handbook of Experimental Economics*, Chapter 2. Princeton University Press.

Leibbrandt, A., A. Ramalingam, L. Sääksvuori, and J. Walker (2015). Incomplete punishment networks in public goods games: experimental evidence. *Experimental Economics 18*(1), 15–37.

Myatt, D. P. and C. Wallace (2008). When does one bad apple spoil the barrel? an evolutionary analysis of collective action. *Review of Economic Studies 75*, 499 – 527.

Nikiforakis, N. (2010). Feedback, punishment and cooperation in public good experiments. *Games and Economic Behavior 68*(2), 689–702.

Rabin, M. (1993). Incorporating fairness into game theory and economics. *American Economic Review 83*(5), pp. 1281–1302.

Rand, D. G., S. Arbesman, and N. A. Christakis (2011). Dynamic social networks promote cooperation in experiments with humans. *Proceedings of the National Academy of Sciences 108*(48), 19193–19198.

Sell, J. and R. K. Wilson (1991). Levels of information and contributions to public goods. *Social Forces 70*(1), 107–124.

Appendix

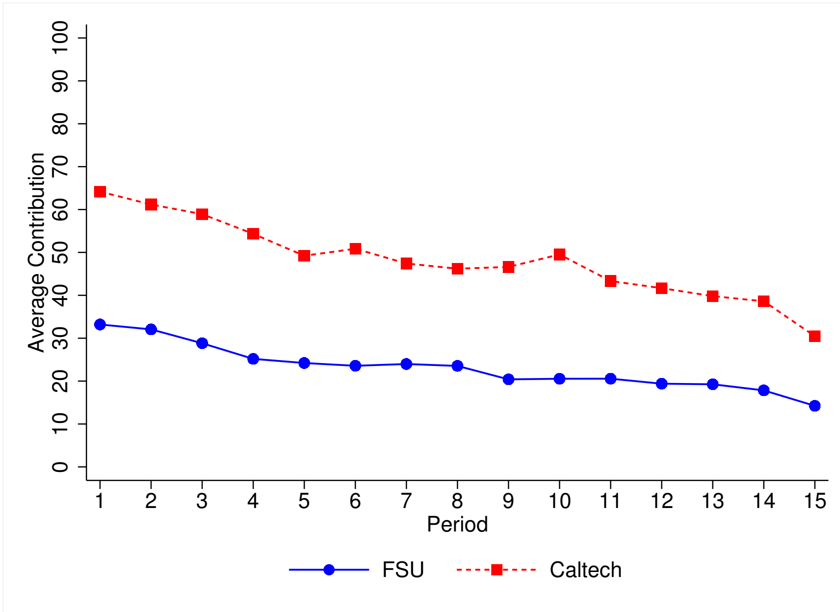

Figure A.1: Average contributions in P-N by subject pool

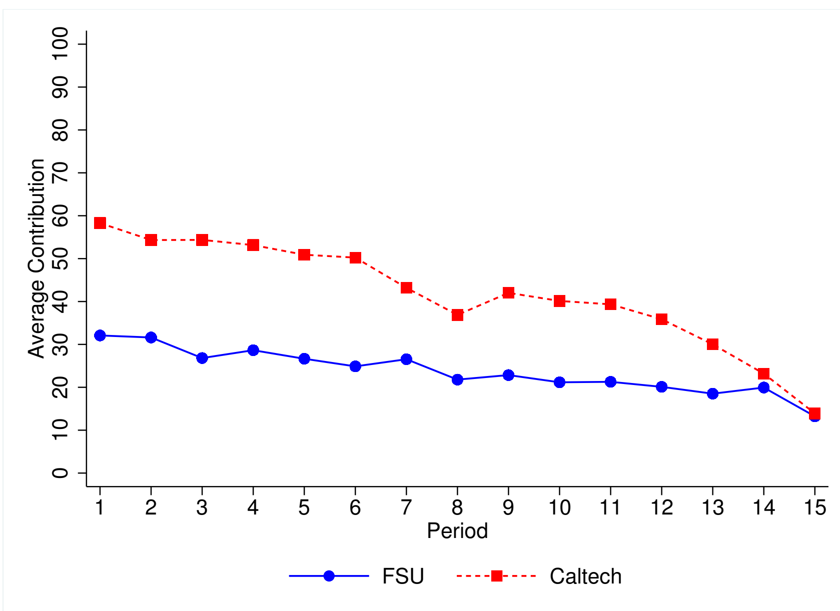

Figure A.2: Average contributions in P-G by subject pool

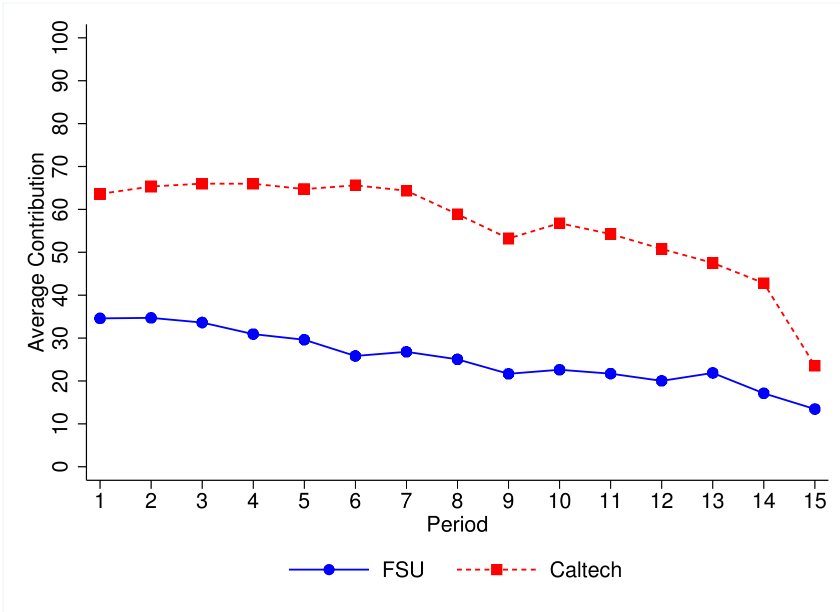

Figure A.3: Average contributions in C-N by subject pool

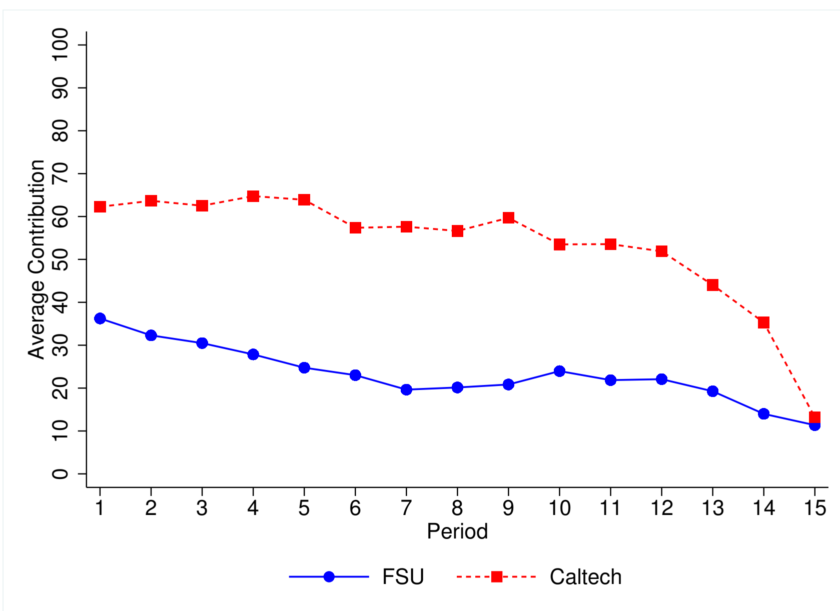

Figure A.4: Average contributions in C-G by subject pool

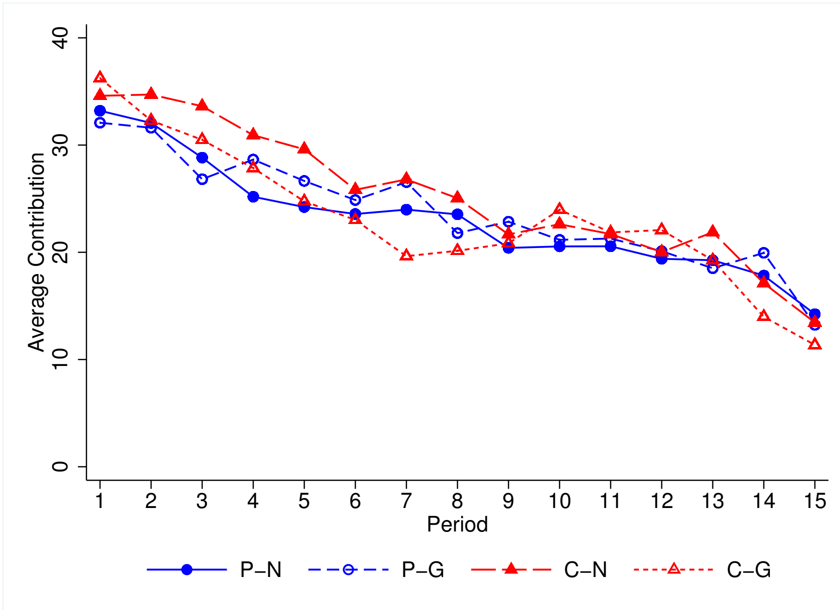

Figure A.5: Average contributions by treatment for FSU subject pool

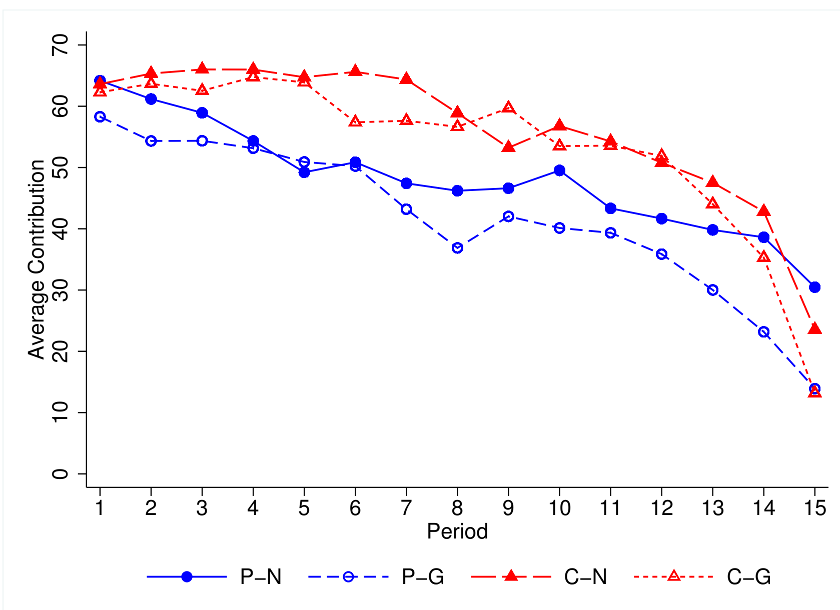

Figure A.6: Average contributions by treatment for Caltech subject pool

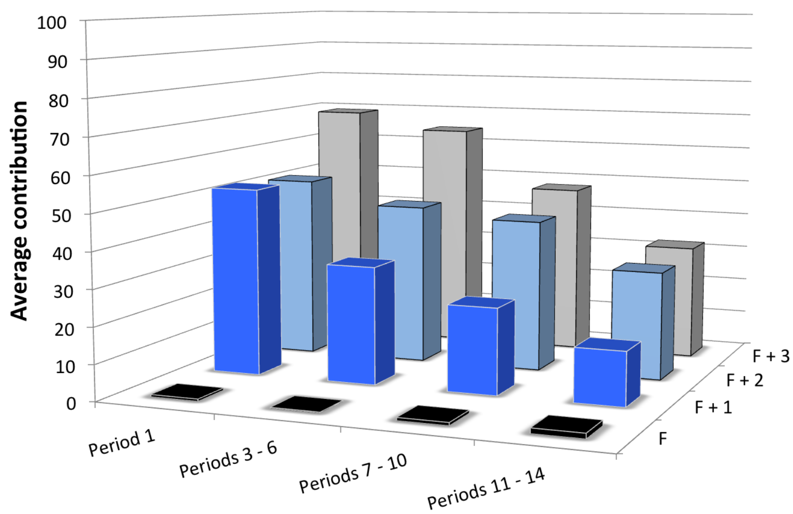

Figure A.7: Average contributions in groups with 1 free-rider for Caltech subject pool

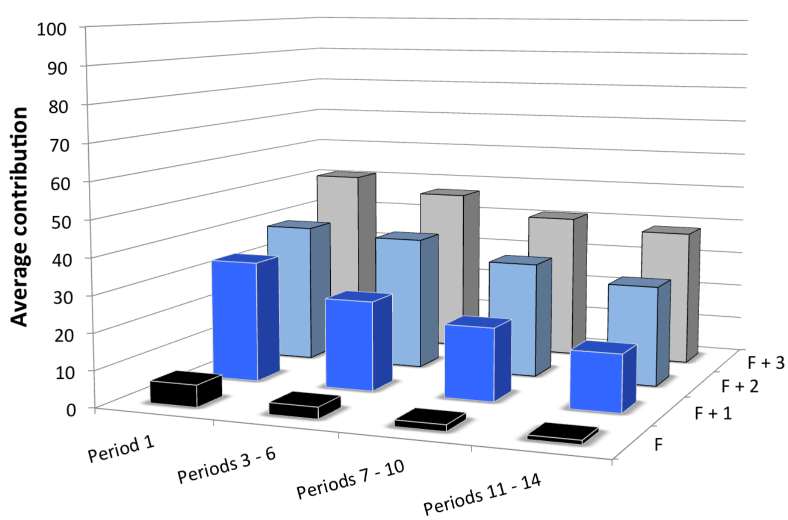

Figure A.8: Average contributions in groups with 1 free-rider for FSU subject pool

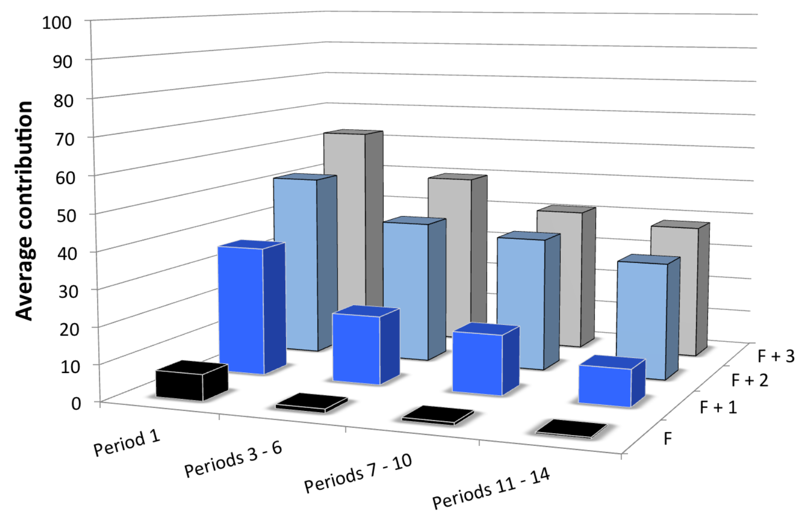

Figure A.9: Average contributions in groups with 1 free-rider: Treatment P-N

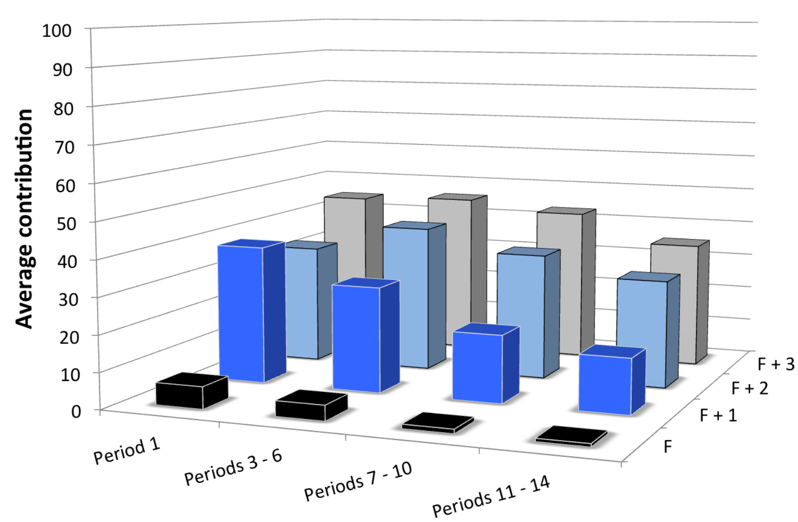

Figure A.10: Average contributions in groups with 1 free-rider: Treatment P-G

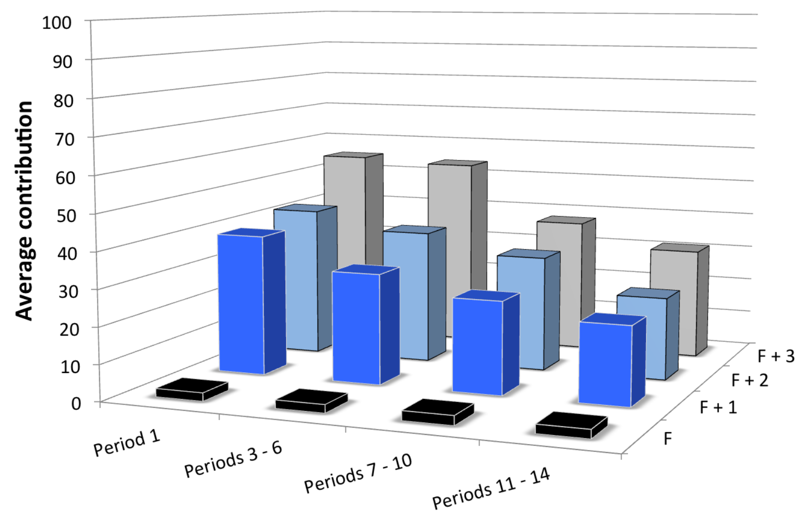

Figure A.11: Average contributions in groups with 1 free-rider: Treatment C-N

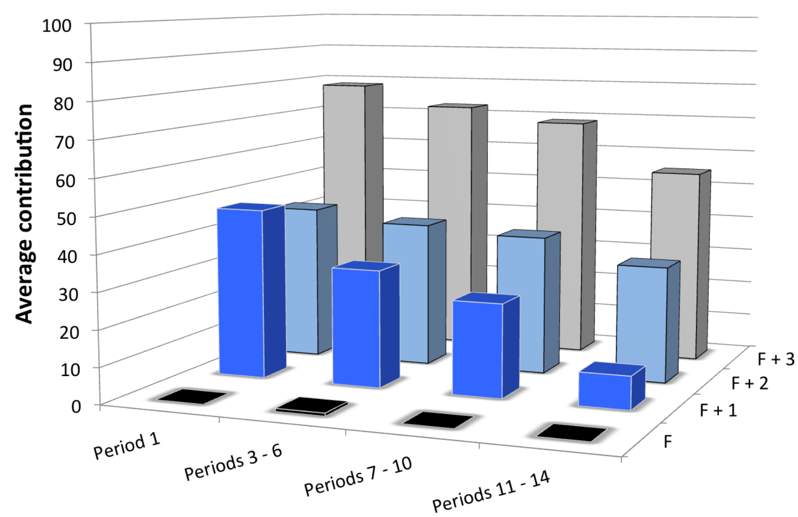

Figure A.12: Average contributions in groups with 1 free-rider: Treatment C-G

Experiment Instructions

Thank you for agreeing to participate in this experiment. During the experiment, please give us your full attention and follow the instructions carefully. Please turn off your cell phones, and refrain from chatting with other subjects, opening other applications on your computer, or engaging in other activities. At the end of the experiment, you will be paid discreetly by check, based on the payoffs you earn. What you earn depends partly on your own decisions, and partly on the decisions of others. Do not talk or try to communicate with other participants during the experiment.

Following these instructions, there will be a practice session with four periods. In the experiment, your earnings will be denominated in **tokens**. At the end, these earnings will be converted to US dollars at the rate of **800 tokens** to **1 US Dollar**.

This experiment consists of four matches. In each match, there will be 15 rounds. For each match, you will be divided into groups of SIX members each. You will be randomly assigned to exactly one of these groups and you will not know who out of the other participants is in your group. You will remain in this group for the entire first match. For each other match, you will be randomly rematched into different groups of SIX members each. Thus, your group will be fixed during a given match, but may be different across matches. Other than the set of players in each group, the parameters and the features of the match will be the same for all groups.

Each match will proceed as follows. At the start of the match, you will be randomly assigned to a position (node) in the network depicted in Figure A.13. The other 5 members of your group will be assigned to the other positions, so that only one member is at any position, and all positions are filled.

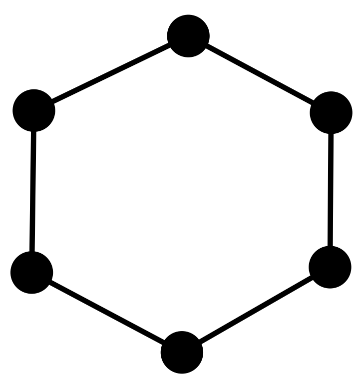

Figure A.13: Circle network with 6 agents

The match will consist of 15 rounds. During the match, your position will be identified by a node labeled "You" and a player number. Your player number and your location will remain fixed throughout each round of the match. Likewise, your group members, and their locations will be fixed throughout each round of the match. If your node is connected to another node, then that node will be displayed in red to indicate the connection. The players located at the red nodes are your **direct neighbors** in the network.

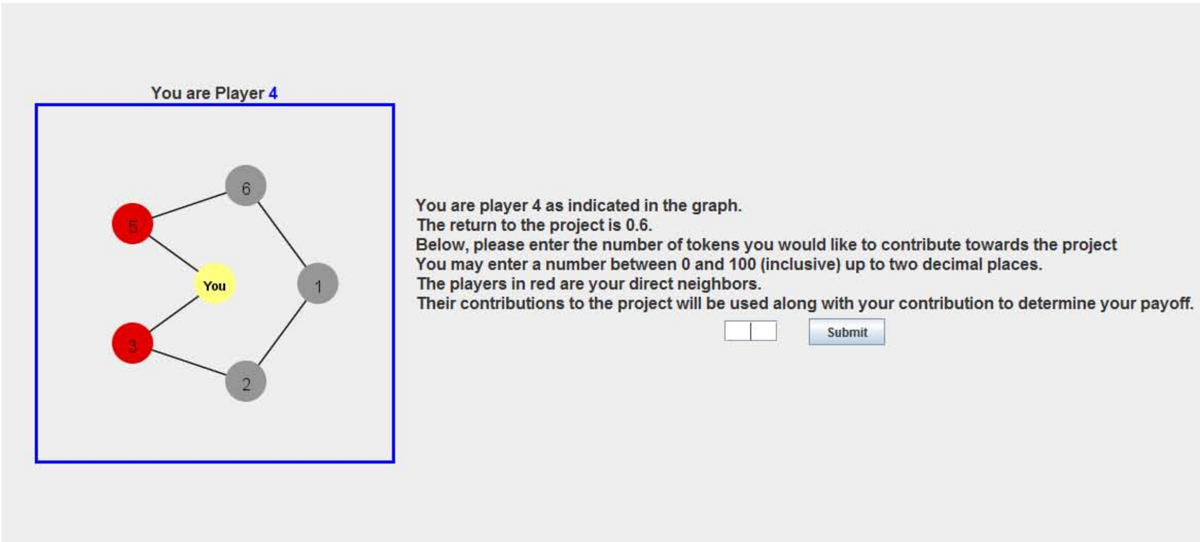

Figure A.14: The decision screen for a match

In each round, you will face exactly the same decision problem. At the start of every round, you will be given an endowment of 100 **tokens**. You must decide how much of this endowment to contribute to a given project, and how much to keep for yourself. You cannot contribute a negative amount nor can you contribute more than **100 tokens** towards the project. You may choose any number up to two decimal places within that range. In a given round, your earnings from the project depend on your allocation to the project in that round and the allocations made by your **direct neighbors** in that round. Specifically, your earnings from the project are calculated by adding your contribution and the contributions of your **direct neighbors**, then multiplying the total by the return factor, which is 0.6. Your earnings from the project will then be added to whatever number of tokens you keep (which will be 100 minus your contribution) to give your overall payoff from the round.

For example, suppose you allocate 40 **tokens** to the project and keep 60 **tokens** for yourself, and the sum of the allocations made by your **direct neighbors** to the project is 80. Then your earnings from the project will be

$$0.6 \cdot (40 + 80) = 72,$$

while your earnings from the tokens you keep will be 60. Thus, your total earnings would be $Earnings = 72 + 60 = 132$.

To summarize, your earnings in a given round will be equal to

$$\text{Earnings } = 100 - \text{ your contribution } + 0.6 \times (\text{ total contributions by you and your neighbors }).$$

Each round is a separate decision problem, so your earnings in any round will depend only on the decisions made by you and your **direct neighbors** in that round. After each round, you

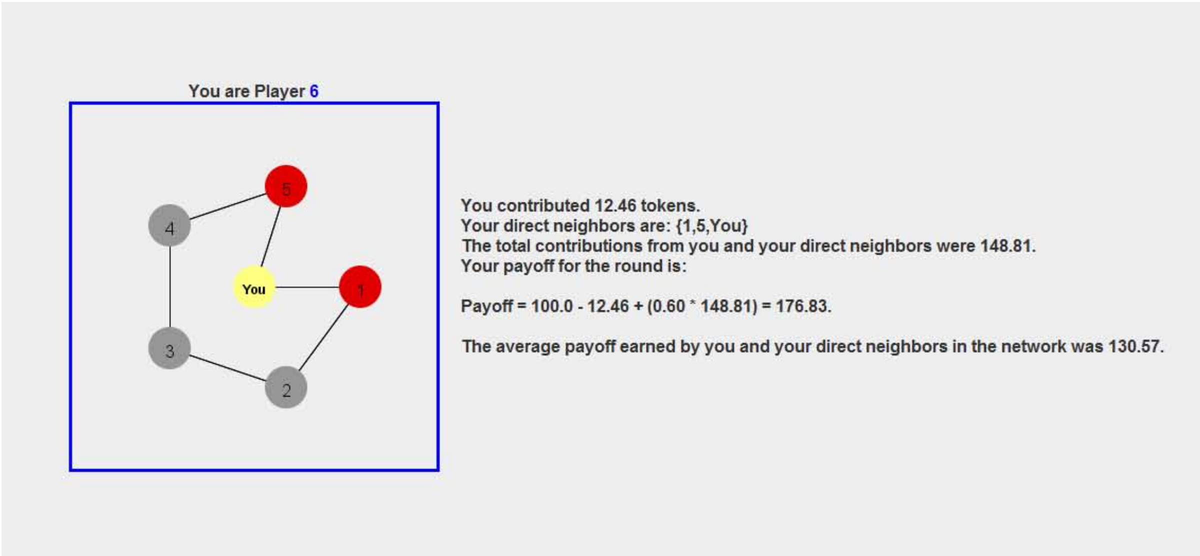

Figure A.15: The round summary screen for a match

will see certain information about what happened. This information will be different for each match, as will be described below and before the match. At the end of the match, all of your round payoffs will be added together to give your match payoffs. At the end of the last match, your match payoffs will be summed and converted into US dollars according to the exchange rate above.

After each round, you will see the following information in all matches.

- The amount that you contributed to the project
- The total contributions to the project from **you AND your direct neighbors**
- Your payoff from the round

In addition, match specific information will be provided as specified before each match.

Match 1
The average payoff received by **you and your direct neighbors**

Match 2
The average payoff received by **all SIX players in your group**

Match 3
The average contribution made by **you and your direct neighbors**

Match 4
The average contribution made by **all SIX players in your group**

Now we will run through a practice match with 4 rounds, so that you can familiarize yourself with the software. If you have any questions, please raise your hand. You will not be paid for this practice session. As a reminder, please do not communicate with the other subjects in any way.