Communication Structure Counts:

Network Theory Applied in the Voluntary Contributions Game

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Abstract

Issues of the prisoners' dilemma are commonplace observations in public goods games, with real world applications ranging from environmental regulations to information sharing. This paper, by allowing participants to communicate in several different network structures, demonstrates in a voluntary contributions game that communication links affects contributions to public good. We use empirical data collected through Vanderbilt University subjects to test whether different network structures (positive reinforcement) and the ability to punish (negative reinforcement) have different effects on public investment. We find that players in well-connected symmetrical network structures perform much better than alternative network structures and that punishment systems are less effective in enabling cooperation regardless of the network structure.

Introduction

"There are 4 billion cell phones in use today. Many of them are in the hands of market vendors, rickshaw drivers, and others who've historically lacked access to education and opportunity. Information networks have become a great leveler, and we should use them together to help lift people out of poverty and give them the freedom from want." – Secretary of State Hilary Clinton

Throughout the study of Economics and Political Science we've observed the unequivocal importance of institutions on the success and failure of economies and governments. These institutions and the networks associated with them have shaped societal norms, manipulated supply and demand curves, and influenced individual decision-making. For example, suppose many nations must join in an institutional network to solve an environmental problem. There are strong incentives for each individual nation to free ride and not cooperate in multilateral agreements, but all countries are better off if every nation cooperates, a classic prisoners' dilemma. On a more microeconomic level, a group of hospitals may need to share information securely in order for the healthcare system to function most efficiently. However, there may be external costs and risks to information sharing. How should hospitals be structured within a network to over come these issues and foster greater trust? If we have a better understanding of network theory and the game theory behind it, we can grasp a better understanding of these critical real world issues.

Unfortunately, in classical and even more contemporary models of economics we have assumed that individual decision-making takes place in a vacuum only dependent on reason, preferences, and constraints. Only recently with the rise of Game Theory, Behavioral Economics and Experimental Economics, have those in the field challenged the sufficiency of these assumptions. This paper aims to use experimental data, with Vanderbilt University students as subjects, to better understand how players behave in a network. It questions whether players in some certain network structures perform better than in others or in no network at all in the setting of a public goods game. It also addresses whether positive reinforcement (ability to communicate within a network) or negative reinforcement (the ability to punish) has a more profound effect on investment in public goods.

First, we discuss the existing literature from such fields as economics, computer science, and sociology. Next we outline our experimental design and model our hypothesis. Then we present the results of our data and run robustness tests. Finally, we draw conclusions and report additional information in appendixes.

Literature

In Economics, the majority of recent research on network structure, design, and theory has been heavily influenced by the recent work of Mathew O. Jackson at Stanford, particularly his volume, *Social and Economic Networks* (2012). In Chapter 2 of his work Jackson describes the signature network structures that are used in our experimentation.

See below the fully connected network, the circle network, and the star network, respectively.

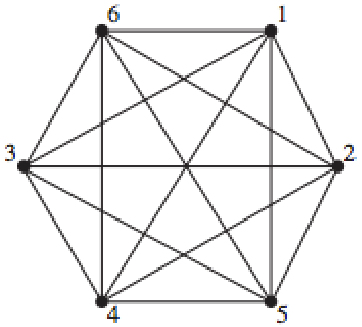
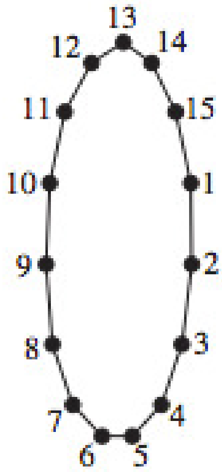


Figure 1: The Fully Connected Network



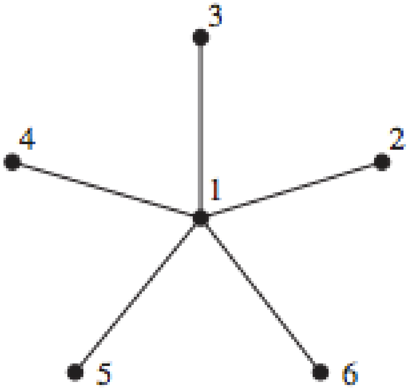


Figure 2: The Circle Network

Figure 3: The Star Network

In Chapter 1 of his work Jackson uses these various network structures to describe many real world applications, from the rise of the DeMedici family over other contenders in Renaissance Florence to the race segregation of certain high schools in the United States. The network structures in Jackson's work and the theories behind them will be central to the aim of this paper.

In terms of research on network structure and its effects on public investment, the field, particularly in experimental economics, is limited. Within the voluntary contributions game specifically many papers have focused on substantially challenging the Nash equilibrium assumption that players will face significant prisoners' dilemma incentives to invest zero in a public good.

Cressman, Song, Zhang, and Tao (2012) cited that experiments in public goods continually have participants contributing between 20-70% of their endowment while the Nash equilibrium strategy is to contribute 0%. They show that both rewards and punishment in institutional design matter in public good game performance, although they do not differential between whether positive or negative reinforcement is more effective. They do, however, find that the mixed institutional design of both reward and punishment is the most effective of all, which is modeled in our own experiment as the fully-connected network with punishment. They do not, however, have different network structures as independent variables.

Fischbacher & Gachter (2001) at the University of Zurich ran experiments by giving a 0.4 ratio payoff for token investment relative to token retention in their total payoff equation. Their results show that half of their 44 participants were "conditional cooperators" willing to break the Nash equilibrium and invest in the public good, a third were free riders, and the remainder exhibited mixed strategies. They conclude that the conditional cooperators begin play as altruists in the public goods game, but the presence of the self-acting free riders eventually drove all participants to converge on zero cooperation as the experiment progressed. This conditional cooperation and devolution to 0 public investment has also been reflected in 4-player reward-punishment games

(Berninghaus, Güth, and Schosser 2013). However, while these papers do investigate coordination games in networks, they do not match our experimental design and do not use different network structures as variables.

The literature continually shows the psychological importance of emotion, reputation, and standing in a network of other nodal actors. Not only do participants donate more based on the contributions of others in the public goods game (Stakova & Ferguson 2010) but personal emotions and emotions of others of others have been found to serve as credible threats in donation decisions (Fehr & Gachter 1999). Milinski, Semmann,& Krambeck (2001) have gone a step further to prove that, if people are given the opportunity for reciprocity in later rounds, reputation helps solve the tragedy of the commons. If, however, people are not connected in a network and the game is not dynamic the public good contribution quickly falls to the Nash equilibrium of 0. This relates to our findings in that the effects of emotion and retribution, especially when communication is allowed, make a significant difference.

In the field of computer science, Judd, Kerns, and Vorobeychik (2010) test the effects of network structure in a digital network coloring game. They find that participants reach consensus in a tightly connected network easier than a loose clique network, but that coloring becomes more difficult as the network becomes better connected. They also find that individual leadership, stubbornness, and influence may have a stronger effect than network structure. However, while they do change network structure, they use a model with several well connected "neighborhood" networks connected loosely together by a smaller proportion ,*q*, of “long distance” vertices as shown in table 4. This does not resemble our symmetrical network structures.

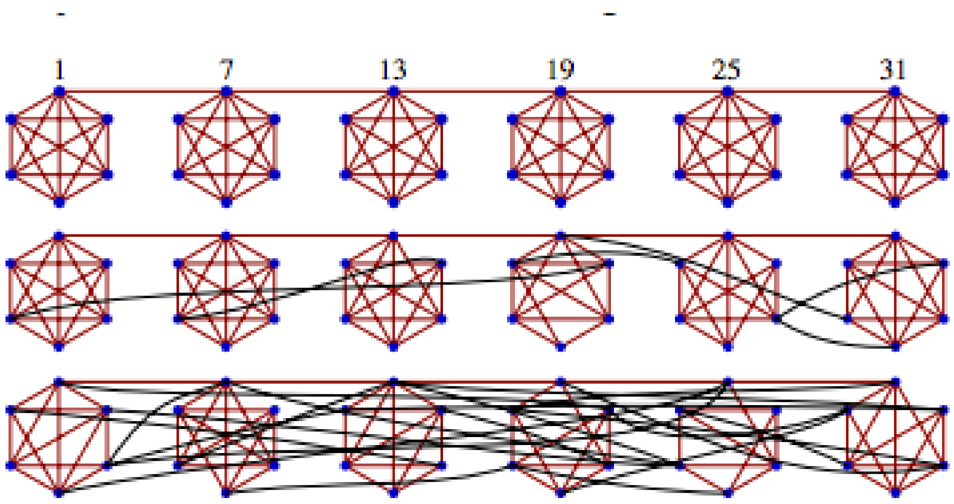


Figure 4: Network Structure used by Judd, Kerns and Vorobeychik (2010)

In relation to network experimentation and the coloring game, McCubbins & Weller (2012) ran a study in which groups of 16 students participated in several trials of a network coordination game with different network structures. Each participant was giving a different “color” identity at start time with the ability to change colors for a small cost. The goal of the experiment was for the entire network to have a unified single color across the network. Each participant was told to cooperate with other players. Although there were costs to changing individual nodal color, players would receive a substantial payoff if coordination was reached. The study found that network structure did have a significant impact on coordination and cooperation. It is substantially different in that, in their coordination game, it is in every player’s interest to fully coordinate; there are no prisoners’ dilemma game aspects, as in our voluntary contributions game.

Eshel, Samuelson, and Shaked in *Altruists, Egoists, and Hooligans in a Local Interaction Model* (1998) find that players in a network are in fact much more altruistic than classical economics would suggest, and these findings grow stronger as network neighborhood size decreases. Alessandra Cassar in *Coordination and Cooperation in Local, Random and Small World Networks: Experimental Evidence* (2005) also found experimental evidence that, especially in local and random networks, cooperation was much easier when communication was allowed. These results were not as strong in the larger and looser "Small World" networks. This is similar to our findings in that experimental, well-structured networks will perform better in the voluntary contributions game than when individuals are unconnected (the empty network) but we do not address the effects of network size.

Not all researchers have found that the outcome of the public goods game is conditional on network structure. Siddharth Surri & Duncan Watts (2011) observe that network structure did not affect players in any one of their multiple network structures. In order to simulate polarizing nodal positions, they introduced artificial players that openly invested zero or all possible tokens; this also did not significantly affect players' investment decisions. That is, players made their decisions completely independently of their network structure and even their network. However, Surri & Watts' experiment used groups of 26 players, a number too large for our purposes. Incentives to corporate in experimental design were far too weak. Their study also remains in contrast with the earlier experiments that did suggest a connection between structure and payoffs.

Experimental Design & Model

In experimental design we chose to have a control group and networked groups. All groups contained five players ($I = \{1,2,3,4,5\}$), but the communication structure within groups differed. Within the networked groups, some nodes could only communicate with adjacent players (player at *i* can only communicate with i+1 & i-1), some could only communicate with a central node (one player star network), and others had full communication with the four other players. All players who had communication abilities had 90 seconds prior to every round to communicate. In the star network the administrator was able send a note to all players. These notes were pre-determined and always encouraged the players to invest more into the public good to reach the goal of $40 per person. Since the platform would not allow one player to act as the central node of the star, the administrator was the next best option and notes encouraging cooperation were seen as simulating what the vast majority of players would have said if in the central node position. Network structure in the Star is non-symmetrical, in that players receive notes from the central node but cannot send them back.

Each study began with an initial payout of $5 to all players and 25 tokens replenished for each round. In each individual round each player has to decide how many of their 25 tokens they would like to invest in the public good. The decision was between retaining coins, receiving $0.10 each, or investing coins in the public good and receiving $0.04 each, while also receiving $0.04 for each token the other four players invest. For example, a player could earn $0.10 if every player did not invest their first coin, but $0.20 if all players invest their first coin; however, the player can earn $0.26 if all players *except* him or her invest their first coin. Therefore, there is mixed incentives in the game- to hold coins and try to see if others will invest or lead an effort to invest and cooperate (a classic prisoners' dilemma problem). In order to make it to the $40 benchmark, an average of 20 coins per round must be invested.

All groups had 2 treatments of 5 rounds each for the experiment. In the second treatment the players were given the ability to distribute punishment points to other players; after each round on investing players are allowed to view who invested what. In almost all cases players punished for lack of cooperation with group investment goals. In rare cases, a "revenge" effect was observed where players punish because they themselves got punished in earlier rounds. In two cases, we observed the revenge effect dismantle the success of the treatment. To avoid this as much as possible, the identity of the punisher is strictly kept anonymous in experimental design.

In terms of structure, each punishment point incrementally reduces the receivers' round payout by 10%. We made it so the first 1-5 punishment points cost the sender \$0.20 each, but sending 6 up to 10 punishment points cost \$0.40 each, so as to discourage total degradation of the game as happened in the pilot study (see appendix A). Although the goal of the study is to measure how network structure affects investment in a public good, we also wanted to attempt to measure whether network structure or ability to punish had a more dramatic *effect* on voluntary investment (since one of the other would have significant economic and political implications). These payouts are described mathematically below:

In the non-punishment rounds:

$P = .10k + \Sigma i (.04i)$

Where P is the total payout, k is the tokens in which you kept, and i are the tokens that were invested in the pool by all players

In the punishment rounds:

When $\rho < 6$:

$P = \eta(.10k + \Sigma i\ (.04i) - .02\rho)$

When $6 < \rho < 11$

$P = \eta(.10k + \Sigma i\ (.04i) - .04\rho)$

Where ρ is the punishment points you send to other players and η is a weight from .9 to 0 such that, $\eta = 1 - .1\Phi$ where Φ is the punishment points you received from others

Total Payout:

$P^* = 5 + \Sigma(1\ to\ 10)\ P$

In the model of the voluntary contributions game, the Nash equilibrium without punishment is to invest 0 tokens, since the players will move to that dominant strategy in the classic prisoners' dilemma game. With punishment there is a trend to invest n + 1 tokens, where n in the amount of tokens that the player who invested the least amount of tokens invested. Thus, you need to invest some to avoid punishment (not be the lowest invested player) but you want to invest just a little bit more than the lowest invested player. However, since 0 investment and 0 punishment remains possible, 0 remains the Nash Equilibrium (Although rarely observed in an empirical setting). Despite this assumed equilibrium, there is literature to show that in multiple treatments the Nash equilibrium is not always constant, especially reliance games when players can be held accountable and reciprocity is possible over multiple rounds. Also, we know that Nash equilibriums do not always hold empirically and we want to see the effects of networks and cooperation on the game.

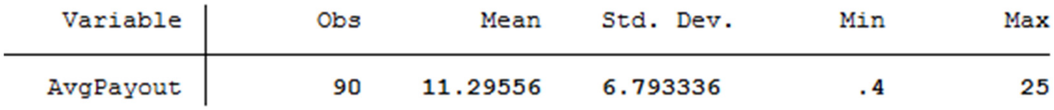
To incentivize participants to join the study we offered gift cards to Starbucks coffee and Chipotle Mexican Grill, with a tier system that allowed us to reward for actual performance in the study. If the participants gained over $40 individually in the study, or had the highest total payout of the all the total contestants, they would get the $10 gift card with all others getting the $5 gift card. This allowed us to maintain the mix incentives of the study by rewarding group investment cooperation while keeping some incentives to not invest and reward individual performance.

After a long delay of trial and error we elected to use vEcon lab over the alternatives such as zTree, Vanderbilt eLab, or an in-person study. vEcon lab had the voluntary contributions game already programmed into the website, it allowed for us to change certain parameters like network structure and punishment options, and it allowed for easy sign-in for the participants and easy monitoring for us as the administrators. vEcon lab also allowed participants to engage in the study from any location with WiFi, which helped us advertise to potential participants and make the study more attractive. Overall, the vEcon user interface was positively received by participants and allowed us easily to collect data on performance on translate it into software programs such as Microsoft Excel and Stata.

The hypothesis of the experiment was that as the networks become more fully connected, average payouts would increase despite the expectations of the Nash equilibrium. Thus, the fully connected network would have the highest average payouts (4 nodal connections for each player), followed by the circle network (2 nodal connections for each player), followed by the star network (1 central nodal connection for each player), and then finally the empty network (no connection) by a wide margin with the least average payouts. We also predicted that communication and cooperation within a small group of 5 will have a larger marginal impact on average payouts than the punishment option, but that it will be may be too statistically close to differentiate.

Data

The data was collected conveniently through the vEcon Lab administrator pages on each participant in each trial group in each and every round and manually entered into Excel, where we ran simple measurements of central location and variance on the data. From Excel the data converted to long form and run through the software program Stata, where the model was crafted and the regression was run. Later Stata was used to also run the robustness tests. The amount of tokens invested into the public good through the experimental process, along with the mean, standard deviation, and range of the data, can be seen in table 1 below.



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    Variable |        Obs        Mean    Std. Dev.       Min        Max
-------------+---------------------------------------------------------
   AvgPayout |         90    11.29556    6.793336         .4         25
```

Table 1: Simple Description of Data

This primitive data shows that on average 45.2% of the tokens available were invested in the public good in the study, which is immediately significant relative to the predicted Nash Equilibrium of 0%. The standard deviation of approximately 6.8 shows high levels of variance within the data set. The range also shows that in at least one round all 5 participants were completely cooperative (all investing the maximum 25 into the public good) while in another hardly anyone invested at all (At least three participants invested 0 tokens).

Continuing the pre-regression analysis on the data, the histogram of player payouts can be seen in figure 5 below:

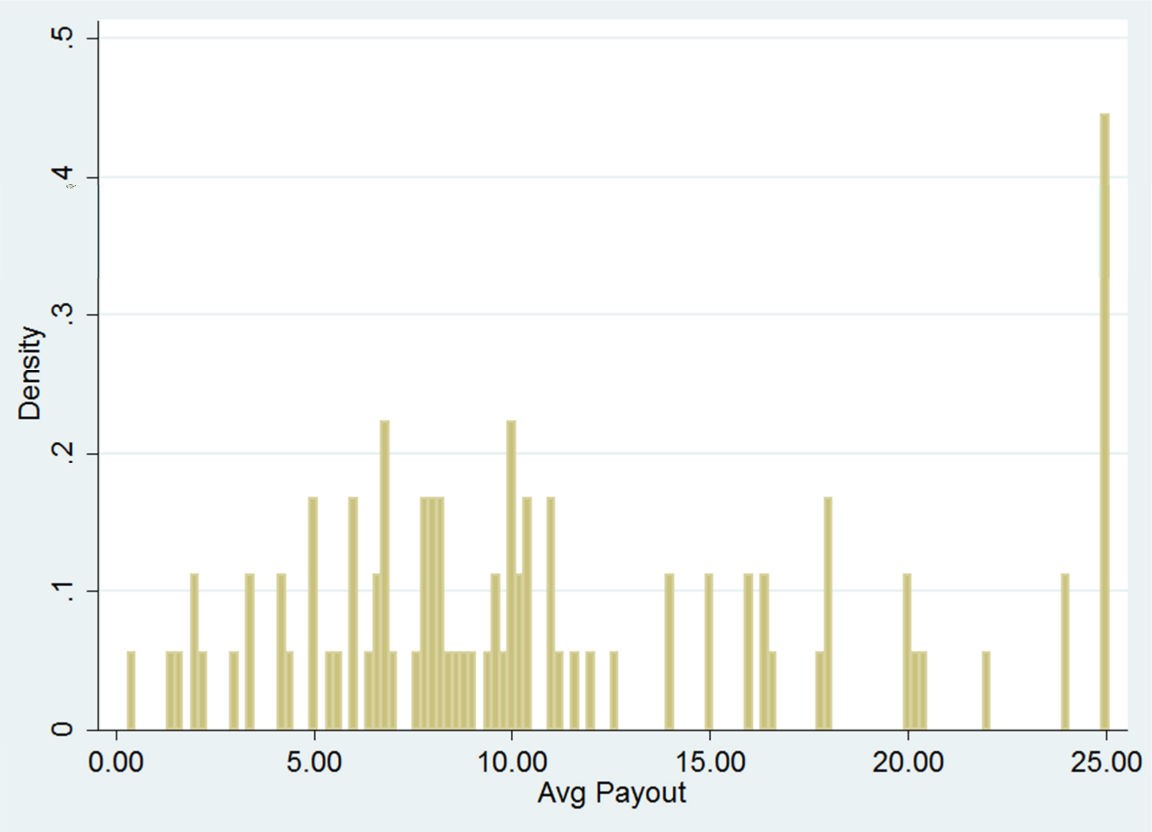
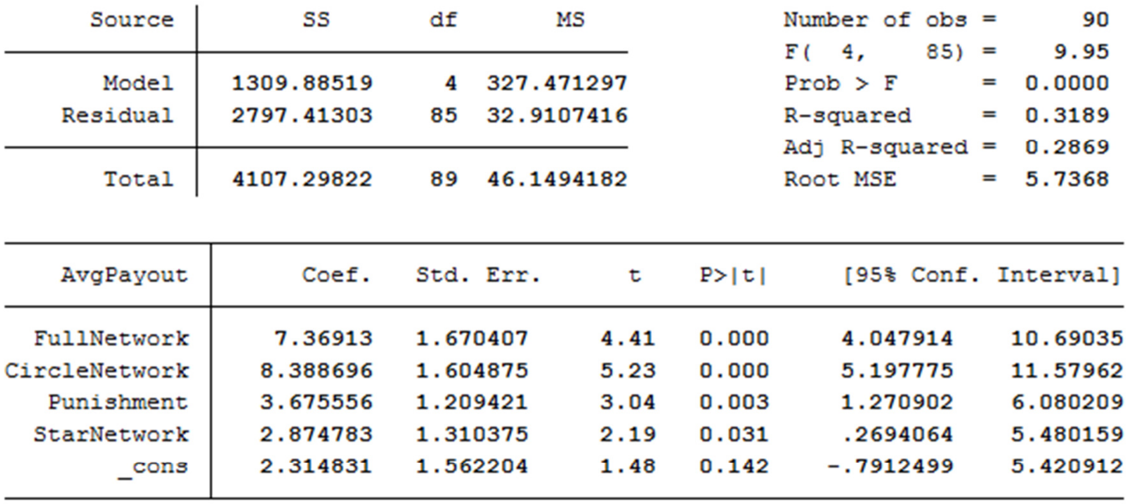


Figure 5: Histogram of Data Frequencies

The Histogram show the data is distributed with a slight positive skew but otherwise remains fairly consistent around the 11.3 mean.

The regression was performed in Stata by converting the experiment parameters into dummy variables and shifting to a binary 0 or 1 value when appropriate. The model included full communication, circle communication, star communication, and punishment as independent variables. Overall, the regression was fairly successful with an r-squared of .319. The results of the regression are displayed in table 2 below:



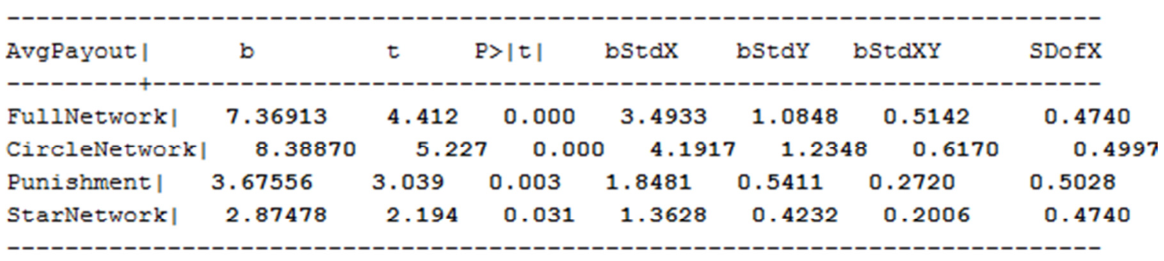
```
      Source |       SS       df       MS              Number of obs =      90
-------------+------------------------------           F(  4,    85) =    9.95
       Model |  1309.88519     4  327.471297           Prob > F      =  0.0000
    Residual |  2797.41303    85  32.9107416           R-squared     =  0.3189
-------------+------------------------------           Adj R-squared =  0.2869
       Total |  4107.29822    89  46.1494182           Root MSE      =  5.7368

------------------------------------------------------------------------------
   AvgPayout |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
 FullNetwork |    7.36913   1.670407     4.41   0.000     4.047914    10.69035
CircleNetwork|   8.388696   1.604875     5.23   0.000     5.197775    11.57962
  Punishment |   3.675556   1.209421     3.04   0.003     1.270902    6.080209
 StarNetwork |   2.874783   1.310375     2.19   0.031     .2694064    5.480159
       _cons |   2.314831   1.562204     1.48   0.142    -.7912499    5.420912
------------------------------------------------------------------------------
```

Table 2: Multivariate Regression Results

The results using the standard t-test show that each independent variable is significant at a 95% significance level. This is reiterated by the low p-values, which, with the exception the Star Network, are all below .01. Communication seems to be highly positively correlated to average payout on a round-to-round basis, increasing average investment by 7.37 in the Full Network and 8.39 in the Circle. These communication variable coefficients were notably higher than the punishment coefficient at 3.68. The addition of the Star Network and the communication between players and the central node (the administrator) seemed to have less significance, with a 95% confidence interval that still encompasses a lower ending of a minuscule effect (0.27) close to 0.

Table 3 below shows the change in the standard deviation of the dependent variable Y (Average Payout) in terms of the change in the standard deviation of the independent variables X (Networks and Punishment).



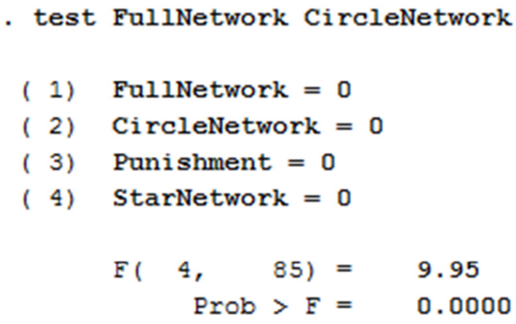
```
-----------------------------------------------------------------------------
AvgPayout|       b         t      P>|t|    bStdX    bStdY   bStdXY      SDofX
---------+-------------------------------------------------------------------
FullNetwork|   7.36913    4.412   0.000   3.4933   1.0848   0.5142     0.4740
CircleNetwork|   8.38870    5.227   0.000   4.1917   1.2348   0.6170     0.4997
Punishment|   3.67556    3.039   0.003   1.8481   0.5411   0.2720     0.5028
StarNetwork|   2.87478    2.194   0.031   1.3628   0.4232   0.2006     0.4740
-----------------------------------------------------------------------------
```

Table 3: Results of Standard Deivations

As seen in *bStdXY* the standard deviation of Average Payout is affected by one standard deviation change in Full Network and Circle Network by about half a standard deviation, Punishment by about a third, and Star Network by only a fifth.

Data Robustness Tests

After collecting the data and running it through the regression we ran several robustness tests in order to identify the strengths and weaknesses of the data. We first ran a simple F-test in Stata to compare the four independent variables in table 4 below.



```
. test FullNetwork CircleNetwork Punishment StarNetwork

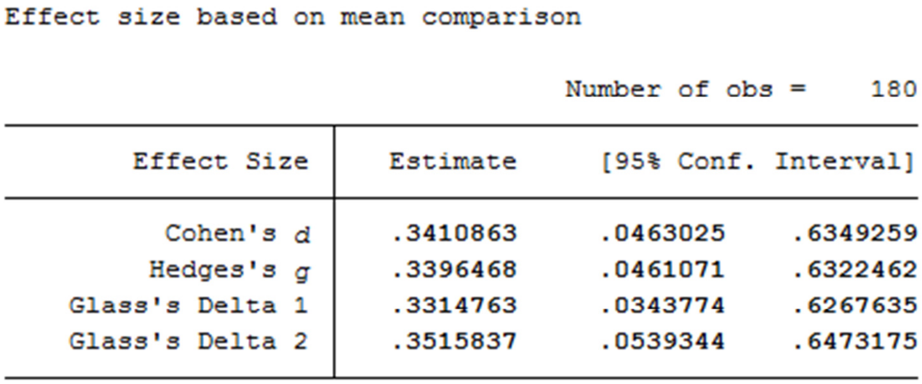
 ( 1)  FullNetwork = 0
 ( 2)  CircleNetwork = 0
 ( 3)  Punishment = 0
 ( 4)  StarNetwork = 0

       F(  4,    85) =    9.95
            Prob > F =    0.0000
```

Table 4: F-Test Results

With an F statistic of 9.95 we concluded that the null hypothesis can be rejected and the variables are in fact independent of each other.

Through Stata again, we test for effect size in relation to the mean. The independent variables are grouped together to determine their effect on the mean using mainly Cohen’s d and Hedge’s g effect metrics. The results are displayed in the table 5 below:



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Effect size based on mean comparison

                               Number of obs =    180

       Effect Size   Estimate    [95% Conf. Interval]

         Cohen's d   .3410863    .0463025    .6349259
        Hedges's g   .3396468    .0461071    .6322462
    Glass's Delta 1  .3314763    .0343774    .6267635
    Glass's Delta 2  .3515837    .0539344    .6473175
```

Table 5: Effect Size Results

We were slightly concerned with the results of our effect test. Statistician Karl Wuensch (2009) has defined .2 as a low effect level with 1% change in variance, .5 as a medium effect level with 6% change in variance, and .8 or higher with a 16% or greater change in variance of the mean. However, we can conclude that our statistics of .34 can be classified as within the medium range, and that due to the wide 95% confidence interval the effect tests are inconclusive to either validating or disproving the data on its effect of mean public good investment.

Further, it has been suggested in game theory experimentation (Wooders 2010) that data with exceptionally low p–values should be spilt into separate distributions and tested for structure and difference. In this situation we use the Kolmogorov-Smirnov (K-S) test to test the distributions of network and punishment against non-network and non-punishment, respectively. The K-S test yields a D statistic that helps show whether a regression variables distribution is normal, and helps to compare whether the distribution of two variables are significantly “different” enough. This helps us view independent variable distributions independently of other distributions. First testing the maximum difference, D, between network and non-network gave us a D-value of 0.5786 with a corresponding p of 0.000. This high D-test statistic and low p-value suggest that it is very unlikely that these distributions are statistically similar. The test found the data set of the non-network rounds slightly more normally distributed than the network rounds. The relationship is shown graphically in figure 6 with non-network as the dotted plot, network as the solid plot, payouts on the X-axis and probability on the Y-axis:

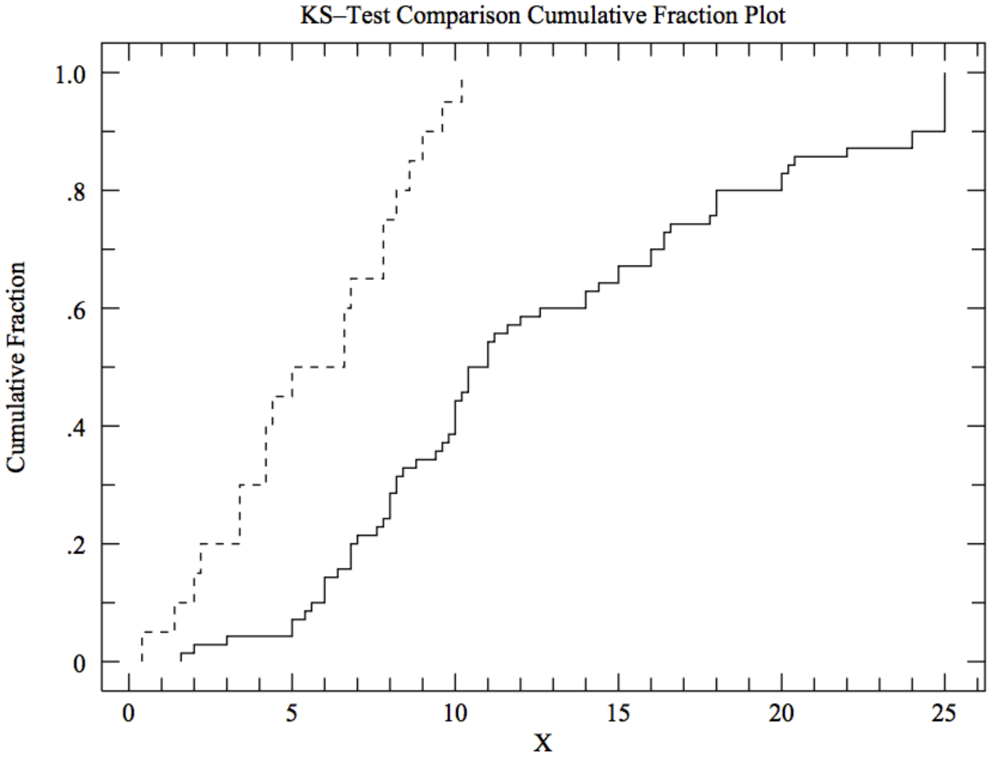


Figure 6: KS Test Network vs. Non Network

Similarly, we perform the same test to compare the distribution of punishment against non-punishment rounds. We find a D-statistic of .2889 with a corresponding p-value of .037; this shows punishment distributions were still significant different at the 5% level, but not significant at the 1% level as the network distributions were. The tests highlights than there isn't enough evidence to conclude that either the punishment or non-punishment rounds have a normal distributions, and the test highlights at least two data outliers according to John Tukey's definition. The second test is again displayed in figure 7 graphically below:

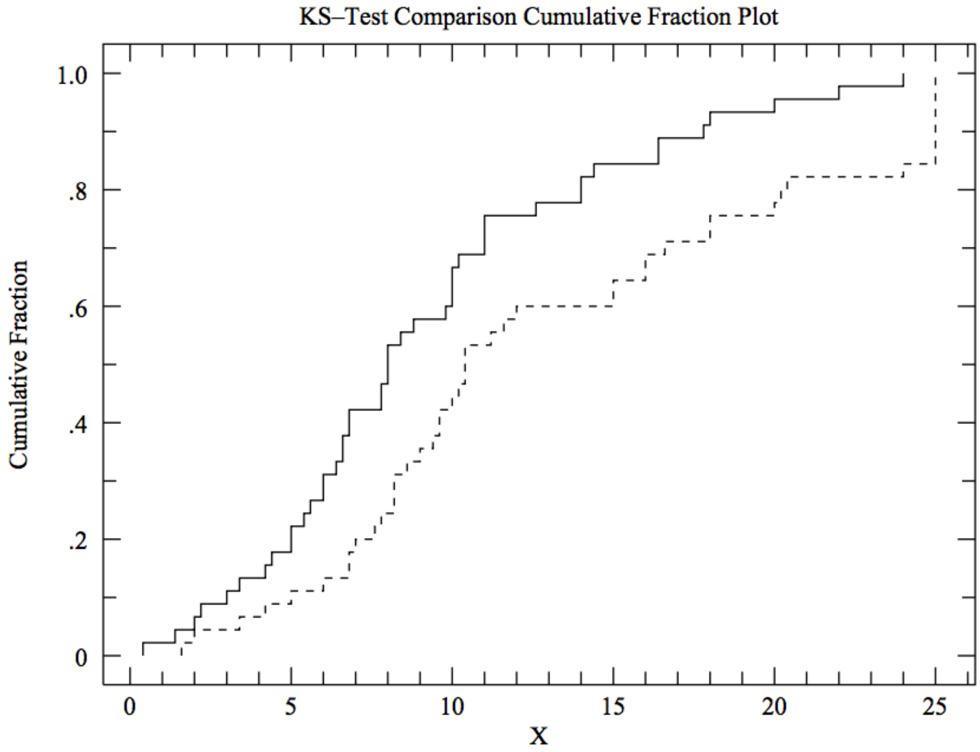


Figure 7: KS Test Punishment vs. Non Punishment

When comparing the full network data to the circle network we found a D-statistic of .0833 and a corresponding p-value of 1.000. This exceptional low D-statics and p-value of 1 leads to the inability for the KS test to differentiate between the full distribution and the circle distribution. This test reinforces the results of the regression coefficients and 95% confidence intervals in confirming that the full and circle networks may be too similar to make definitive conclusions on their similarities or differences in game play results. The test also found that the distribution of circle network data was unlikely normally distributed. The results of the test are displayed in figure 8 graphically below:

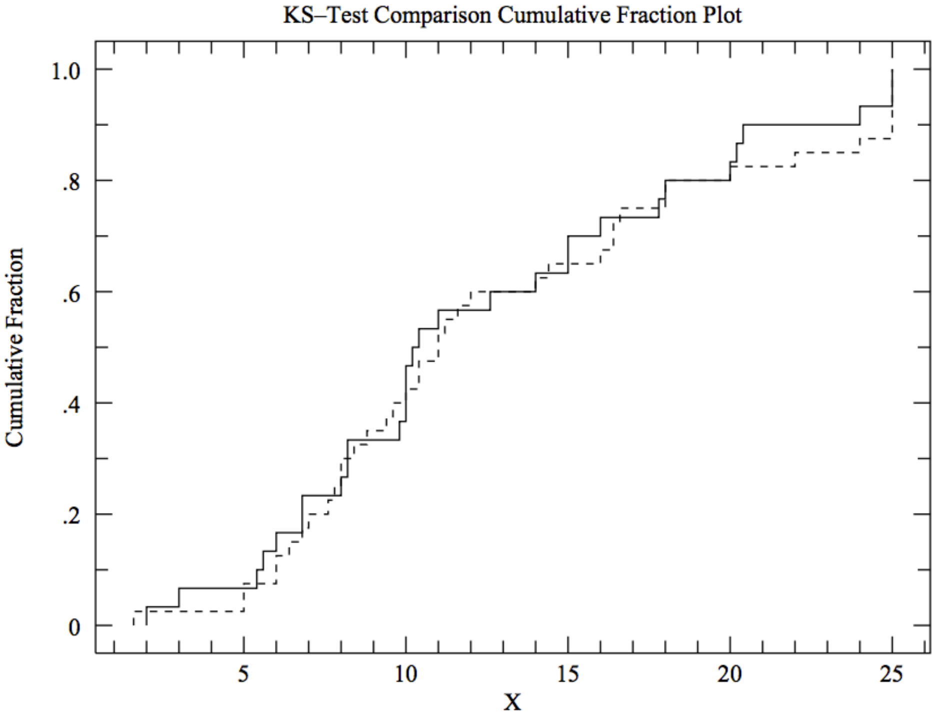
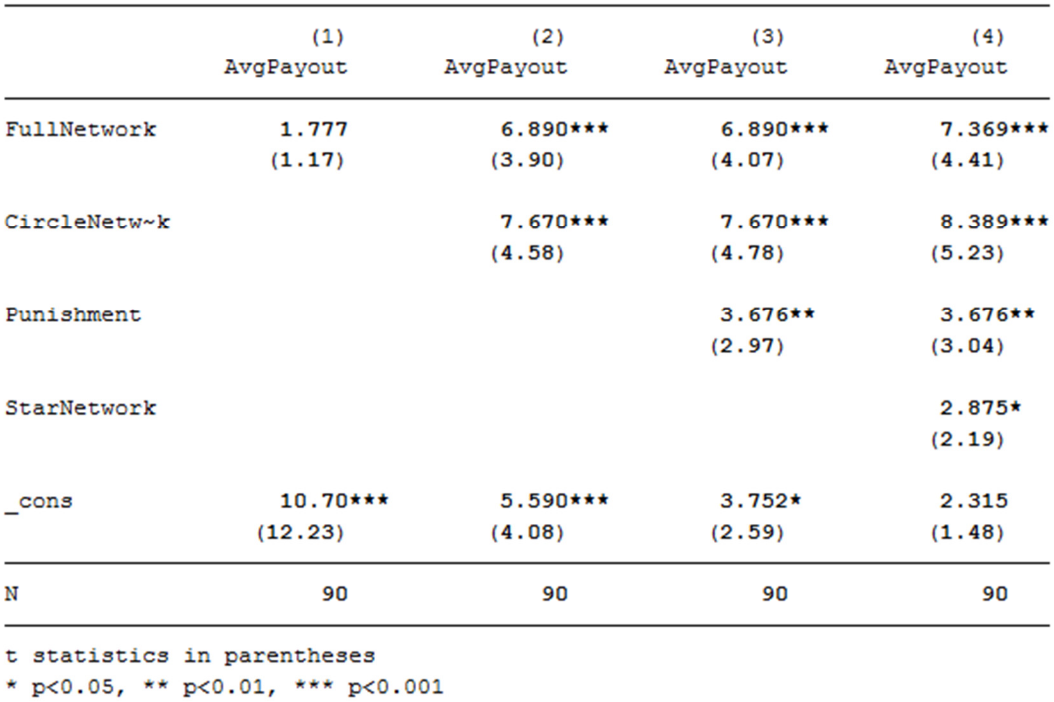


Figure 8: KS Test Full vs. Circle Networks

Finally, we display a specification table using the Esttab in Stata to show the omitted variable bias in early specs and the advancement and improvement of the model over time as more independent variables are added. The results are displayed in table 6 below:

Table 6: Specification Table



	(1) AvgPayout	(2) AvgPayout	(3) AvgPayout	(4) AvgPayout
FullNetwork	1.777	6.890***	6.890***	7.369***
	(1.17)	(3.90)	(4.07)	(4.41)
CircleNetw~k		7.670***	7.670***	8.389***
		(4.58)	(4.78)	(5.23)
Punishment			3.676**	3.676**
			(2.97)	(3.04)
StarNetwork				2.875*
				(2.19)
_cons	10.70***	5.590***	3.752*	2.315
	(12.23)	(4.08)	(2.59)	(1.48)
N	90	90	90	90

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Reduction of the constant term across specs shows the absorbed bias within spec 1 is being explained by added variables in later specs. The two main networks - Full and Circle- are strongly significant (.001) from spec 1 onward (although Full is not significant as a stand-alone in spec 1). Punishment is still significant at the .01 level, and Star at .05 level. Finally, the t-statistics in spec 4 show the validity of the model.

Overall, while there were some deficiencies in the effect tests and the quantity of data collected, the tests show that the presence of both network structure and punishment is significant and the regression holds strong through these robustness tests.

Selection Bias

There's always the possibility while conducting the experiment that the subject pool being sampled does not match the behaviors of the true population in the public goods game. First, we were only able to test 18 control groups (of five participants each) due to limited time and resources. In an ideal situation, and with the multivariate nature of the regression, having at least 30 control groups would have been preferable. Second, the study tended to bias toward Economics majors due to the interest in the topic and the fact the study was advertised to Economics classes (such as 232: Intermediate Macroeconomic Theory). Third, the study certainly had many people that I the experimenter knew since the study was advertised through social media websites and word of mouth. Fourth, the study contained only Vanderbilt undergraduate students – this bias being actually solidified during experimental design due to logistical reasons, internal review board requirements, and to keep the subject pool consistent. Vanderbilt undergraduates might vary in behaviors and opinions from the true population, but probably would model the network of a small group community well – which was the initial goal of the experiment. Although more participants and expansion outside of the Vanderbilt community would have been preferred, the sample pool does not contain enough bias to void the results of the experiment.

If we in fact had more time and resources it would have been interesting to change the group size, with 5 being the lowest and to test larger groups of up to 15 to 20 people if possible so as to challenge the conclusions made in the Suri and Watts paper. This would also allow us the test the theory that in smaller groups the potential for communication to have an effect is significant, but that may not be true for larger groups, and punishment may be more effective.

Conclusions

These results show definitively that beyond the typical predictions made through game theoretic Nash equilibrium the inclusion of networks, and the structure of networks, can have a profound effects on game outcomes that are unpredicted in traditional game models. Overall the players, especially in the rounds without punishment, have strong incentives to free ride and invest nothing in the public good; however, in the fully connected network we observe empirically that this is not the case. Changing the parameters we allowed for the addition of communication networks and the opportunity to punish which over the course of multiple rounds added factors of accountability players could not ignore. We have shown definitively that these adjustments are statistically significant.

We were surprised by the fact that participants in the Circle Network communication structure performed just as well as those in the Fully Connected Network, as confirmed by the KS test run on these two data sets. This did not match our original prediction that a network with greater nodal connections (Full Network) would perform better than one with less (Circle) and that players would lose trust in other players who had their own exclusive connections. However, several factors could account for the similarities of outcomes for the Full and Circle Networks. For the Circle Network treatment, players knew how many participants were in the group and they themselves were connected to other people but did not know communication in the entire network was restricted to only adjacent players (which they did know in the case of the Star notes). Second, players may have trusted that their communications (which usually promoted altruistic public investment behavior) were being relayed across the network by others and believed their notes influenced the entire network. Third, players in the circle network remain in a directed symmetrical position, where each of their actions or potential actions can be weighted equally, and the same thought process might be used.

These possibilities are conducive to results on studies of group consensus and voting behavior in that rational decision making by one individual may be made through observation of previous decisions of unknown individuals within a group (Banerjee 1992). Regardless, the data still shows that the “strongly” connected networks (Full and Circle) perform much better than the isolated network (Star) or especially the control group (Network absence).

The results of this Vanderbilt study and the continued work of network theorists in the field have far reaching implications for economists, policy makers, and institutions. These results show that close-knit fully connected and circle networks have the potential to overcome the pervasive prisoners’ dilemma problem. However, several important questions remain beyond the scope of the data. One of the main questions is that if the assumption is true that public goods are beneficial to everyone in a network but come with extreme free rider problems, can co-operation through communication overcome these coordination costs or is punishment from others or a central authority the only way to bring players to action? This study shows that it in fact is possible for people in small groups to invest in a public good despite free rider reservations if full communication or even circle communication between them is allowed, and that this is as effective, if not more effective, than the ability for players to punish each other.

Second, building off that, is the issue of whether communication in smaller groups is more effective in shifting public investment incentives than communication in larger groups, or even much, much larger groups such a nation or global community. This is a question we cannot definitely answer with our data alone, since, due to limitations on time and resources our group size was fixed at 5; however, we can infer from the data that communication in a small group did have a very strong effect.

Even in a highly advanced society such as the United States, tax evasion, inequality, and poor infrastructure in such things as education and healthcare are rampant. Due to this, institutions such as the IRS, SEC, and FBI are set up through the democratic process to punish people for non-cooperation. Even if a mechanism such as freedom of speech and assembly in the bill of rights *guarantees* the existence of the fully connected network in society, the scope and costs of maintaining that network is massive. Thus, when the numbers of nodal players increases to infinity fully connected networks usually take star form; moreover, in large networks we rely on leaders, mass media, and firms to be the central nodes in our information networks. We've seen in this study that star networks are not as efficient as the ability to punish in increasing public investment in the voluntary contributions game. Therefore, it is not surprising that we have to rely on punishment at the national level to incentive cooperation and order. However, the impact of fully connected and circle networks in local network "neighborhoods" should not be ignored. These networks should be highlighted in today's political climate of non-cooperation as being methods in which we can find real solutions to complex issues, particularly in economics, in the presence of small-group forums.

This paper also raises the importance of self-identity and emotion toward others in individual decision-making, a topic studied extensively in social science and particularly the marketing field. In classical economic models player aim to maximize their personal utility regardless of others, but we've seen in this study and in those previous (c.f., Eshel, Samuelson, & Shaked 1998 and Fehr & Gachter 1999) that this is not that case and actors are much more altruistic. In reality people care deeply about others perception of them, and will consistently make significant economic choices based on the desire to be popular and appear compassionate and just. Although this goes far beyond the data provided here, this experiment does hint at the possibility that even strangers in an experimental setting do consider their own self-image while making decisions, and care about the perception of their own identity.

Appendix A: Pilot Study

Several weeks before the official experiment began we conducted a trial run in Professor Wooders' ECON 235: Strategic Behavior class, mainly to work out any issues with the experiment and to see how comfortable participants were using vEcon lab prior to launch date.

In the voluntary contributions game we ran three groups with the aim of two treatments. Due to the limited number of participants, we were only able to run the experiment with three groups, Group 1 and 2 with five participants, and Group 3 with three participants. To test the network theory hypothesis, Group 1 had no communication, Group 2 had the circle network, and Group 3 had the fully connected network.

In Group 1 with no communication and with a group of 5 individuals we successfully ran the experiment for two treatments- one where the individuals could punish one another for another for disco-operation (Treatment 2) and one where they could not (Treatment 1). The results are displayed in figure 1A below:

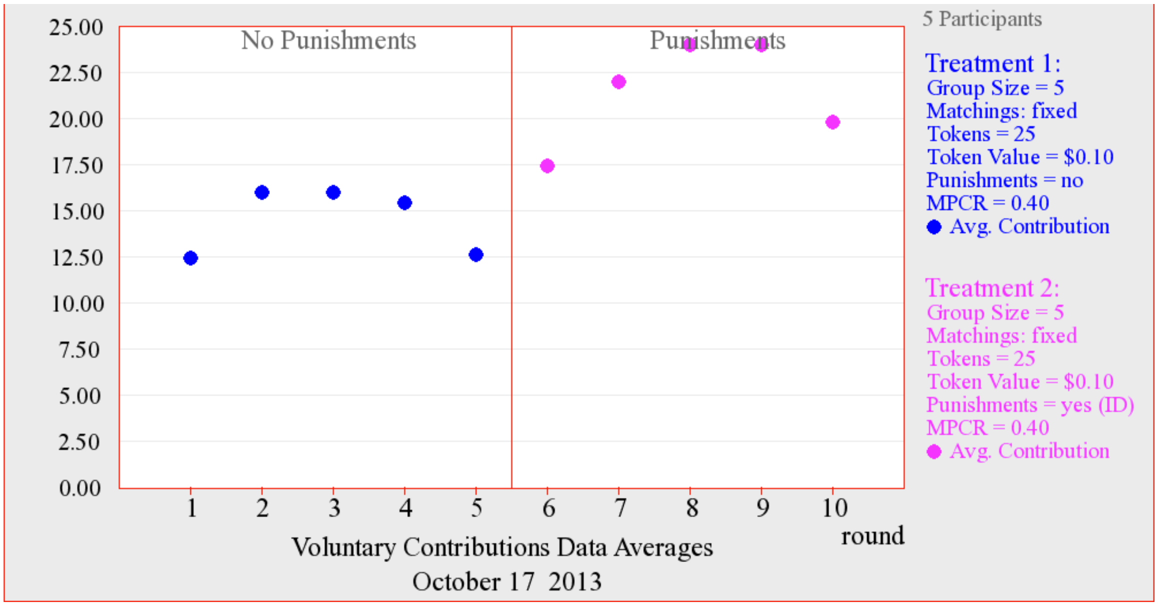


Figure 1A: Pilot Study Results 1

It was clear that the punishment points did affect how much money was raised in the group as a whole. In treatment 1 participants averaged a total payout of just $14.48 across all players, a low across all treatments and all study groups within the pilot study. However, given the ability to punish they quickly raised their total payout averages to $21.44 by punishing players for non-cooperation. This drastic improvement was surprising in a game without communication; however, we were expecting general challenges for these participants in cooperation with communication that we clearly observed from treatment 1.

In treatment 2 we observed some challenges to our experimental design that, while we were pleased that we caught onto early on in the process, was disappointing because of group 2's outstanding performance in round 1, and how they could not continue in round 2. For the official experimental rounds we added the ability for participants who have been booted off the vEcon site to reload back into the experiment;

however, this was an issue for participants in the pilot run following completion of the first treatment. However, the results of treatment 1 are interesting, relevant, and should be analyzed. The second group contained 5 participants. The treatment allowed participants to communicate, but *only* with adjacent players such that p2 could only communicate with p1 and p3 but not p4 and p5, for example. The data shows group 2 doing exceptionally well as shown in figure 2A bellow:

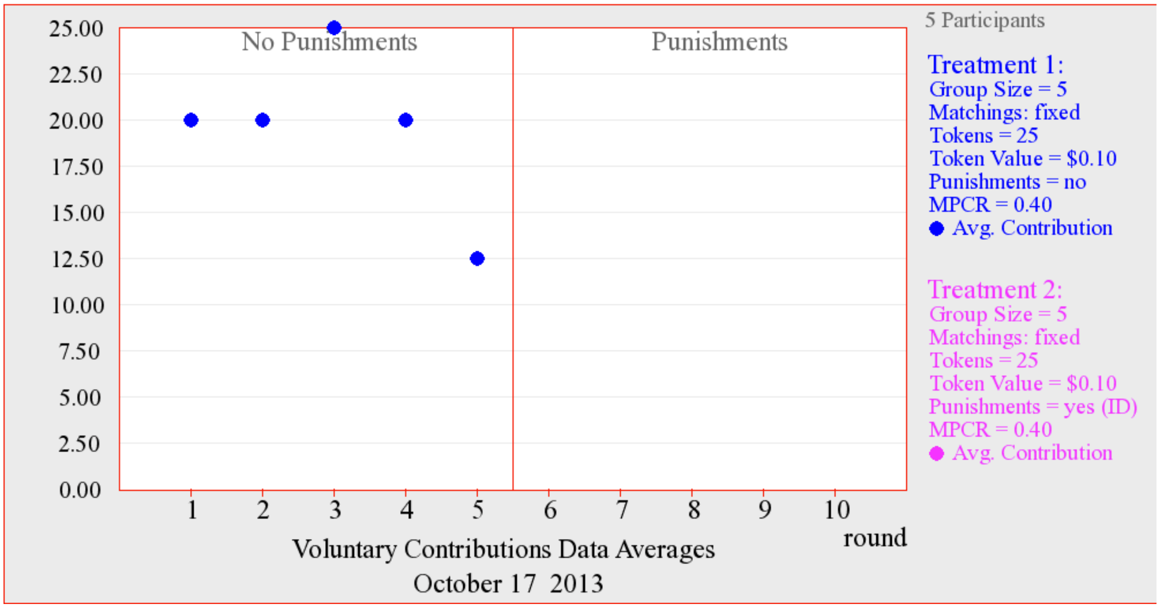


Figure 2A: Pilot Study Results 2

In the first treatment, group 2 had an average payout of $19.50, significantly higher than group 1's (no communication) average of $17.96. In round 3 of treatment 1, group 2 reached an astronomical total payout of $25.00, the maximum payout any group can reach (group 2 was the only group in the pilot study to accomplish this). Looking back at the chat players used the opportunity to communicate to maximize cooperation, even though it was restricted to only adjacent players. This gave us optimism that the thesis hypothesis would hold true in the official study; moreover, that communication in the network would significantly improve total payouts in the public goods game. It would have been very interesting to see players' choices in treatment 2 with the addition of punishment points, unfortunately, due to the technical issues, we could not observe this.

Group 3 was a very peculiar treatment, and the results led us to set certain permanent parameters in the experimental design. Due to poor class attendance on the day of the pilot study, group 3 only contained 3 participants unexpectedly, abet they had the provision of full network communication. There was also no technical issues whatsoever in this study. The data from group 3's pilot run is shown below:

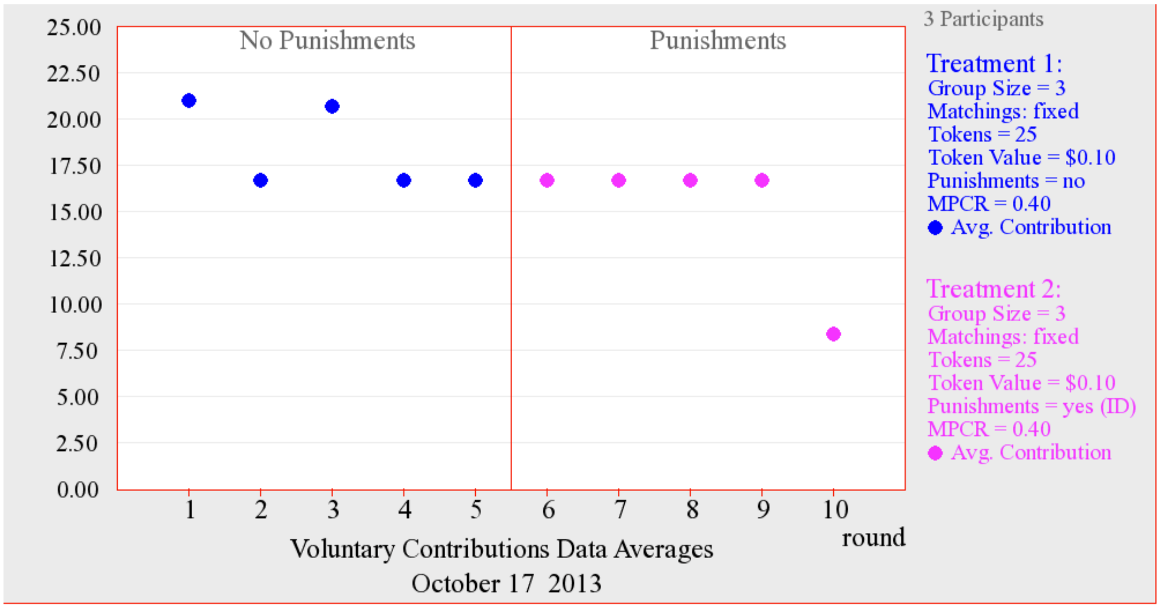


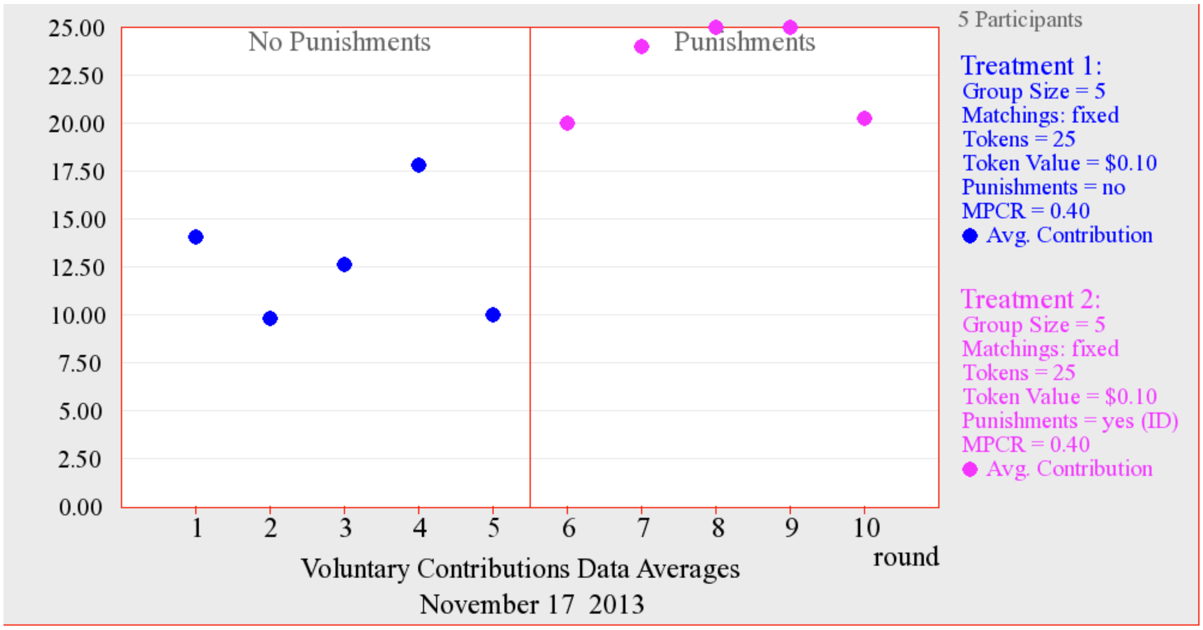
Figure 3A: Pilot Study Results 3

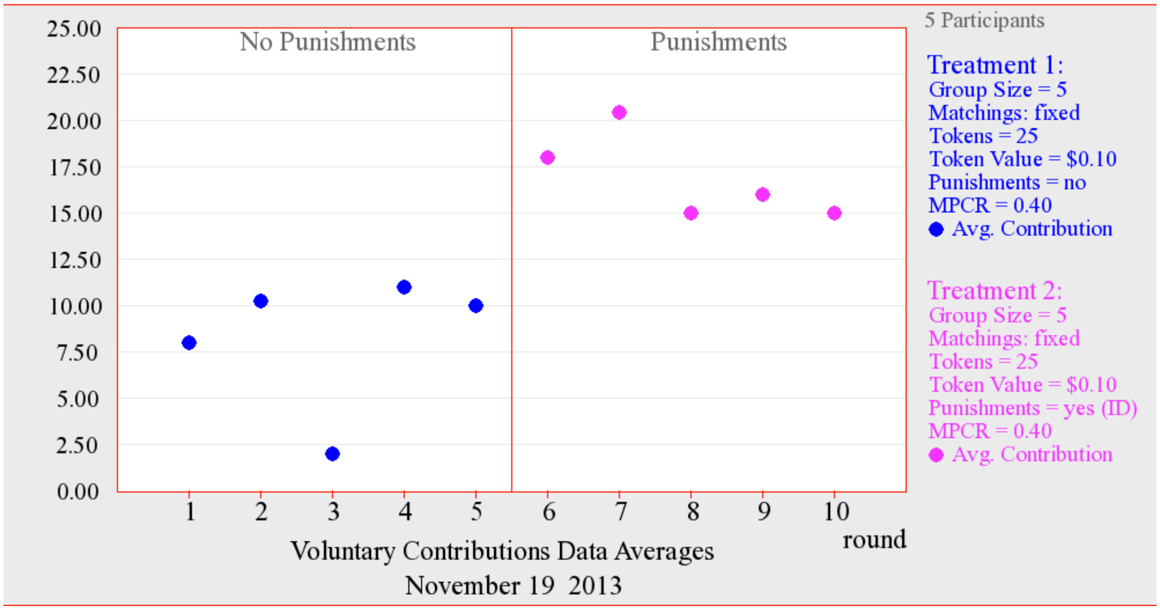
Group 3 performed well in the first round with an average payout of $18.34 with a low standard deviation across rounds of $2.28. Within treatment one communication was strong a players were on pace to beat out Group 1 (no communication) in total payout. However, in treatment 2 when punishment points were added all successes in cooperation broke down. In the entirety of treatment 2 participant 1 and 3 dished out so many punishment points to each other that neither got a positive payout at all, in round 5 of treatment 2 p3 received a -$1.00 payout (the worst performing individual round of any of the pilot study). It seemed as though from the start of treatment 2 p1 was not willing to participate at all, dishing out as many punishment points as they could. Communication turned deceptive, as all players were communicating with the goal of cooperation yet no player actually was willing to fully cooperate, leading group 3 to be unsuccessful in the public goods game

On the surface, the issues that arose in group 3 of the pilot study challenge the assumption in the thesis hypothesis that more connected networks increase success in the voluntary contributions game (as this group participated in a fully-connected network). However, there also can be issues in experimental design that led group 3 to fall. First and foremost, group 3 did not have the 5 participants to was originally planned to have. With 5 participants, the impact of one individual participant would have had smaller effects on the group. Individual deception would have been harder in the fully connected network, especially with the opportunity for the four other players (not just two) to punish the deceiver. Also, the payouts from cooperation would have been higher, up to 100 tokens (for two extra players) as opposed to 50 (25 tokens for each of the two others players). These deficiencies in the smaller group setting have led us to set the group size in all treatments of the official study at 5 participants. The poor result has also led us to question the validity of punishment points in round 2, since the introduction of punishment points correlated with the negative effects in group 3's game. We decided to leave the punishment points in order to compare the effects of communication vs. punishment. An important note on the pilot run is that we were not able to conduct the star network trials, since the administrators (myself and Professor Wooders) had to facilitate the class and answer questions regarding the experimental flow and did not want to be distracted in sending notes to participants. We introduced the star network in the official study.

Appendix B: Data Set[2]

Tables 1,2 & 3 the Fully Connected Network. Table 3 also Star Network predetermined note.





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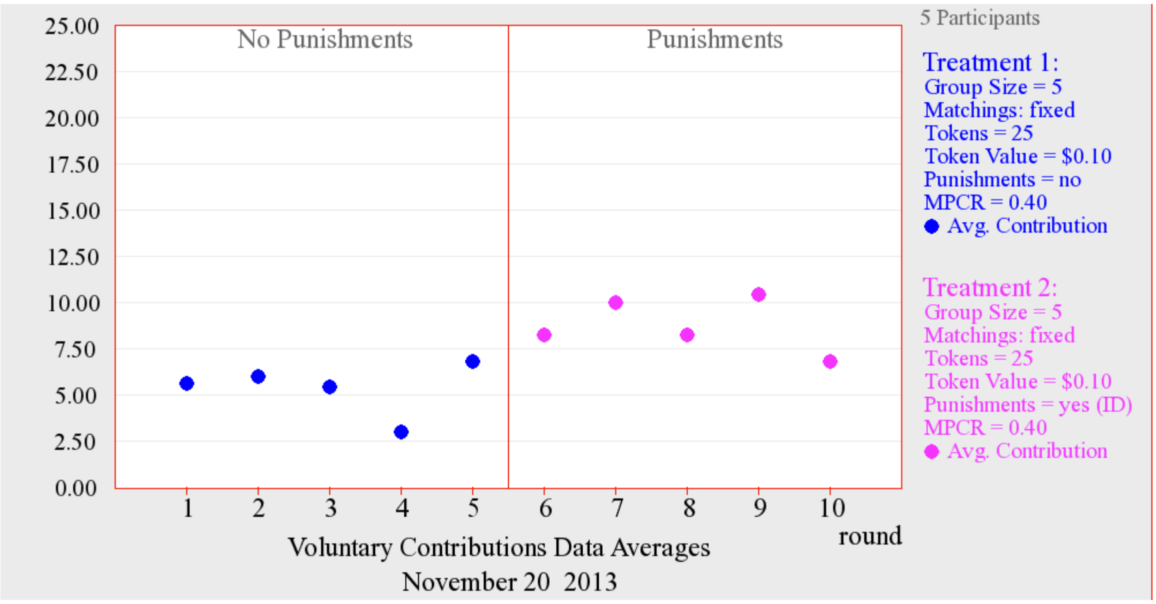
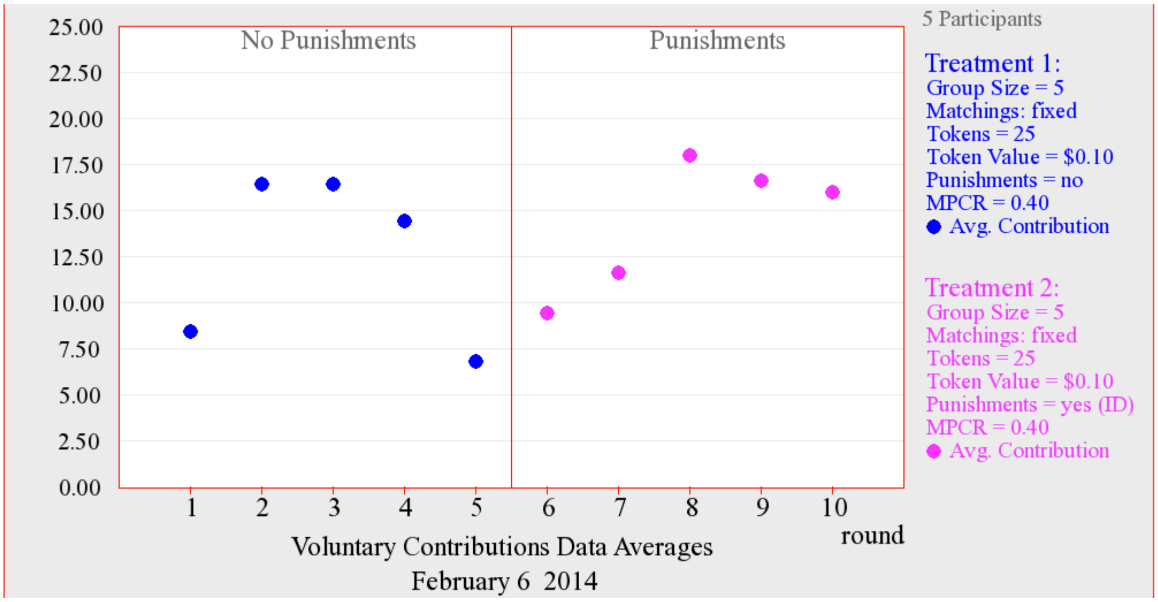
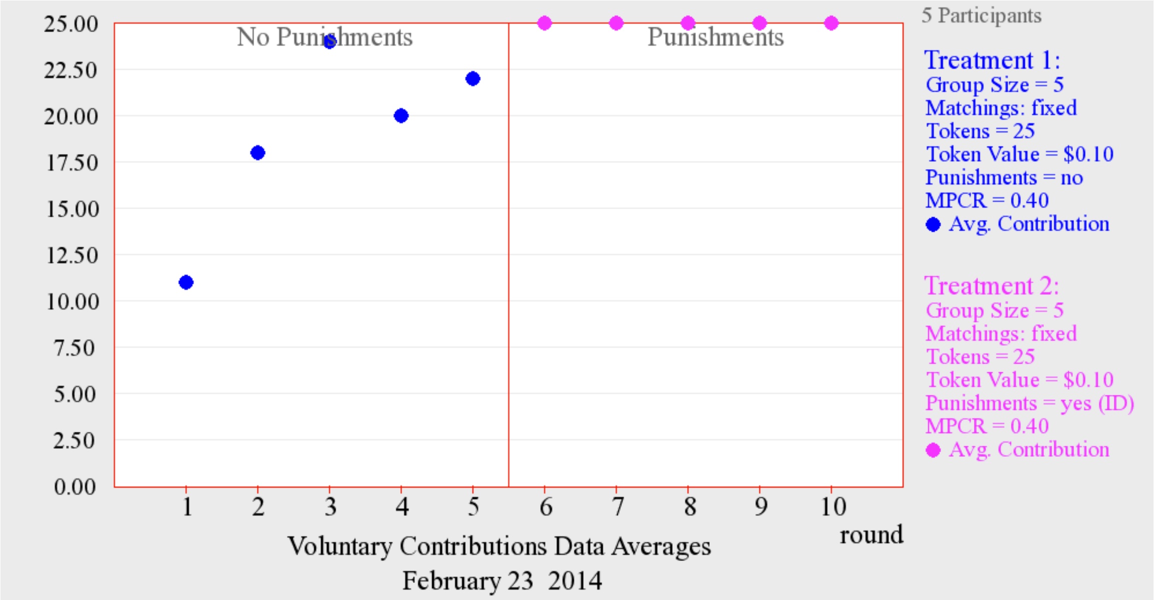
[2] 45 Participants, 90 Rounds



Tables 4, 5, 6 ,7 the Circle Network. Table 5 also Star Network predetermined note.

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round
Voluntary Contributions Data Averages
February 23 2014
5 Participants
Treatment 1:
Group Size = 5
Matchings: fixed
Tokens = 25
Token Value = $0.10
Punishments = no
MPCR = 0.40
● Avg. Contribution
Treatment 2:
Group Size = 5
Matchings: fixed
Tokens = 25
Token Value = $0.10
Punishments = yes (ID)
MPCR = 0.40
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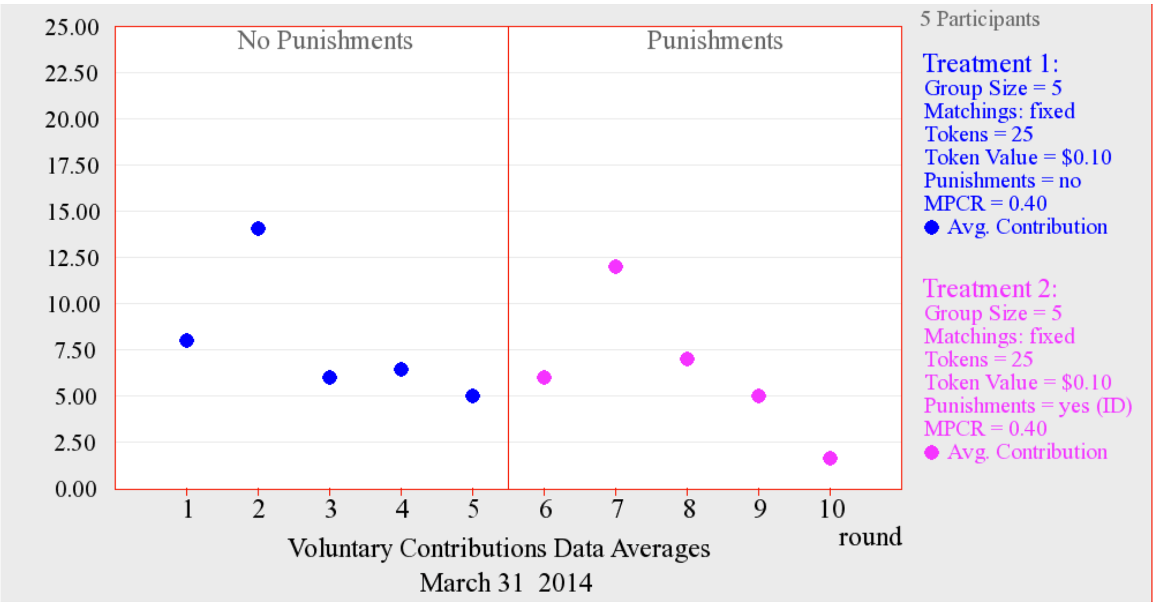
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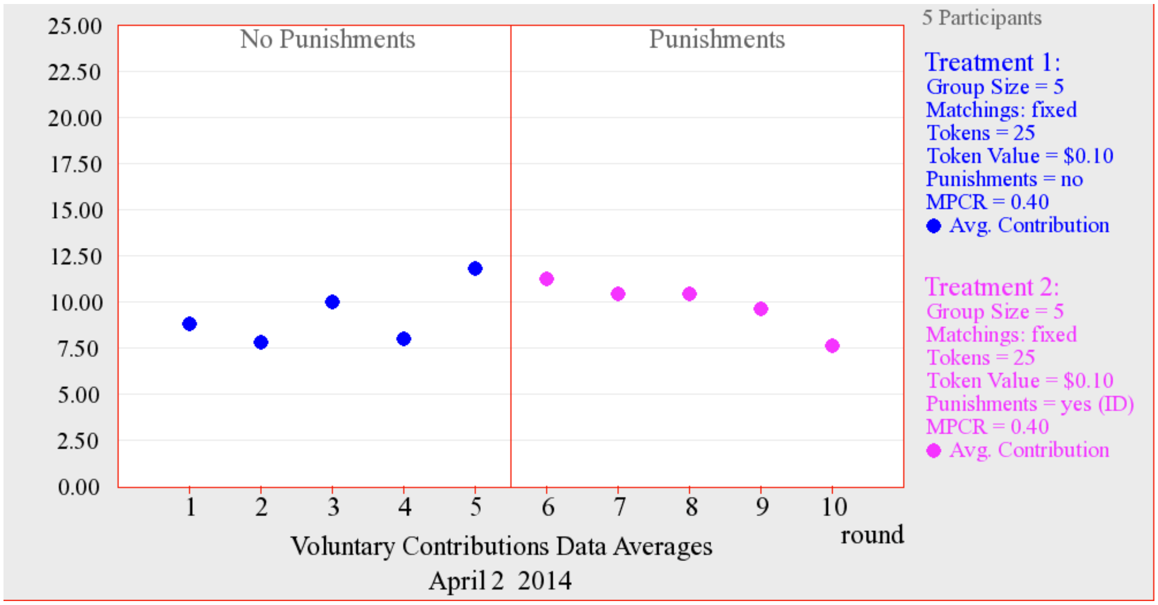
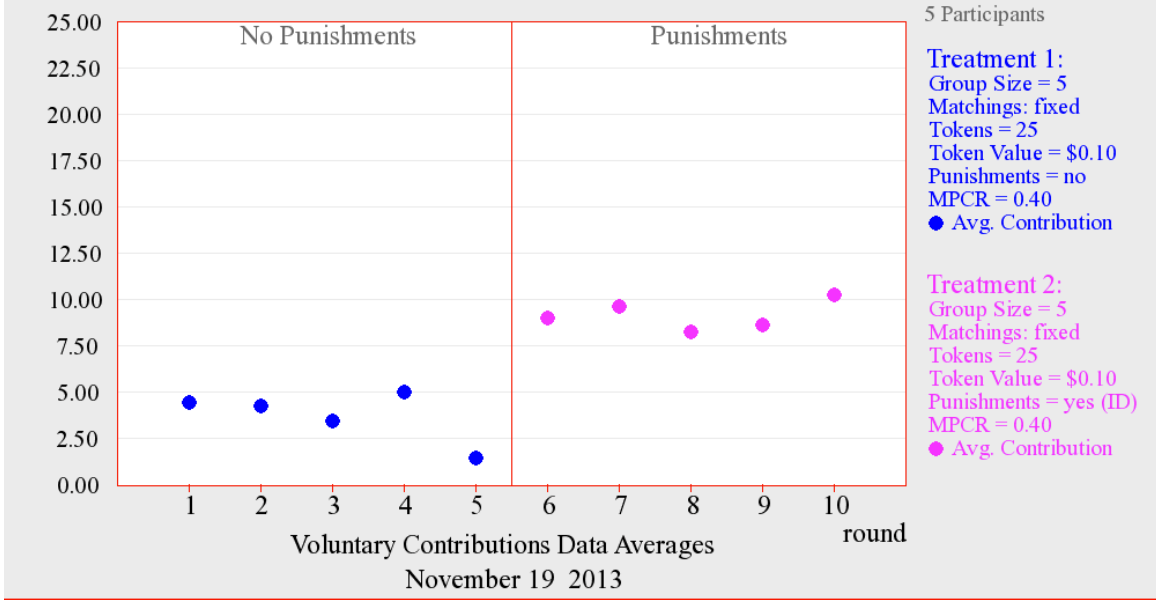
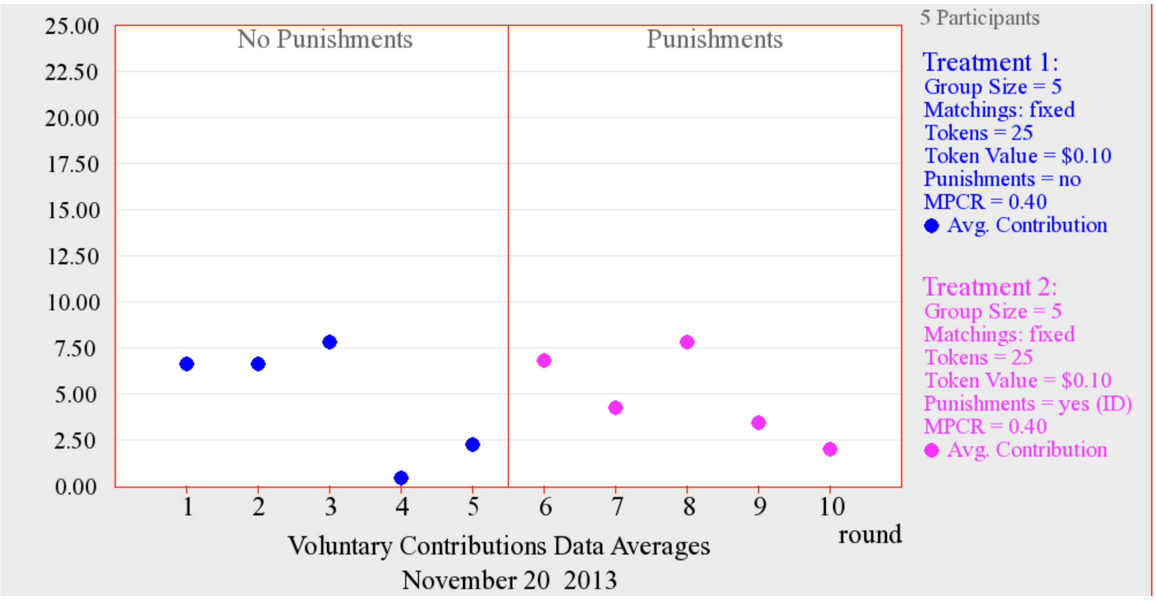
Voluntary Contributions Data Averages
March 31 2014
5 Participants
Treatment 1:
Group Size = 5
Matchings: fixed
Tokens = 25
Token Value = $0.10
Punishments = no
MPCR = 0.40
● Avg. Contribution
Treatment 2:
Group Size = 5
Matchings: fixed
Tokens = 25
Token Value = $0.10
Punishments = yes (ID)
MPCR = 0.40
● Avg. Contribution



Tables 8 and 9, the Empty Network (Control Groups). Table 8 also Star Network predetermined note.

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round
Voluntary Contributions Data Averages
November 20 2013
5 Participants
Treatment 1:
Group Size = 5
Matchings: fixed
Tokens = 25
Token Value = $0.10
Punishments = no
MPCR = 0.40
● Avg. Contribution
Treatment 2:
Group Size = 5
Matchings: fixed
Tokens = 25
Token Value = $0.10
Punishments = yes (ID)
MPCR = 0.40
● Avg. Contribution

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