AN EXPERIMENTAL ANALYSIS OF TEAM PRODUCTION IN NETWORKS[1]

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ABSTRACT

Experimental and empirical evidence emphasize the role of networks on social outcomes. In this paper we test the properties of exogenously fixed networks in team production. In all our treatments, information flows along an exogenously determined informational structure. Subjects make the very same decisions in a team-work environment under four different organizational networks: the line, the circle, the star, and the complete network. In every network, links make information available to neighbors. This design allows us to analyze decisions across networks and a variety of subjects' types in a common setting: a standard linear team production game. Our results suggest that the organizational structure matters. Contributions significantly differ across networks, being the star the most efficient incomplete one. We are able to replicate our experimental data using a simple behavioral model based on the erosion of conditional cooperation due to network incompleteness.

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1. Introduction

During the past decades the efficient design of teams has become a mainstay for the organization of work. Many firms use teams or have implemented team-type incentive systems for a wide variety of productive activities. For example, Lazear (1998) argues that forming teams is economically desirable when they make possible gains from complementarities in production among workers, facilitate gains from specialization by allowing each worker to accumulate task-specific human capital, or encourage gains from knowledge transfer of idiosyncratic information that may be valuable to other team members. If communication is available and fluid within teams, workers do not need to acquire all the knowledge necessary to produce. Instead, they may acquire only the most relevant knowledge and, when confronted with a problem they cannot solve, ask someone else.

The analysis of teams in the economics literature, pioneered by Alchian and Demsetz (1972), has focused on the free-rider problem, which arises when the actions taken by the team members are not perfectly observable. Modern work organizations commonly evaluate and reward teams according to the joint performance of team members. Yet, under standard economic assumptions these group incentives would have no effects to motivate workers (Holmstrom 1982). In many economic situations there is a conflict between the collective and individual interests. Team members may shirk on other team member's efforts, individuals may free ride on other's contributions to a public good and some firms may not invest as much as they promised in joint-ventures. The list of examples where team production fails to achieve optimal outcomes is so large that incentives to free ride seem to be an almost unbeatable force. Public good games are a natural way to model these social interactions: individuals have incentives to free-ride on other's contributions to a group account and allocate all their resources on their own private account. The socially preferred outcome where everybody exerts their maximum individual effort level is rarely achieved.

The analysis of public good games has been a mainstream topic in the field of experimental economics (Ledyard (1995) is the classical survey). In the last decades, there has been a huge body of experiments that analyze how the amounts contributed for the production of public goods react to changes in several features of the problem at hand.[3] There is, however, one aspect that is particularly relevant for the analysis of teams that has not been addressed in the literature: the

[3] Zelmer (2003) provides a recent meta analysis of public goods experiments.

structure of the team. In real life organizations, it is rarely the case that all team members directly interact with each other. There is however a huge variety of possible structures, represented by the set of networks that can be formed (identifying the set of nodes with the team of agents). It is reasonable to assume that an agent is only able to observe the behavior of those members of the team with whom he directly interacts. This idea leads us to wonder whether different observational structures within a team may lead to different outcomes. If this is the case, it would be of interest for the designer of a team, e.g. the organization, to know which kind of network structure provides the most efficient outcome.

The aim of this paper can now be advanced. Succinctly expressed, it is to study whether the behavior in a team production game changes when we vary the observational structure. Moreover, we aim to identify which networks features enhance contribution levels. In order to make our results comparable with previous experimental literature, we consider teams of four players. Our participants repeatedly play a public good game based on the Voluntary Contribution Mechanism (VCM). In this game they are asked to allocate their endowment between a group and a private account. The returns from each account are designed so that group earnings are maximized when participants contribute all their endowment in the public account. However, each individual has an incentive to keep his endowment for himself. The observational structure is determined by an exogenous and fixed network, which is defined over the team members. After each round, each subject is informed about the contribution that each of his neighbors (i.e., the players linked to him) made. However, a subject is not informed about the behavior of those team members to whom she is not directly linked.

We focus our analysis on four stylized connected networks:[4] the complete network, the circle, the star and the line. A key variable in our analysis shall be the connectivity (number of links) of each player. The complete and the circle network are symmetric. Since we consider four agents, in the complete network, all players have three links and, in the circle, all players have two links. The star and the line are asymmetric. In the star, all players have one link but the central player, who has three. In the line, two players have two links and two players have only one. The choice of these four stylized networks allows us to compare the behavior of players with the same connectivity in symmetric versus asymmetric networks: For instance, players with three links in the complete network vs. the star and players with two links in the circle vs. the line. It also allows us to compare the behavior of

[4] A network is connected if there is a path of links between each pair of agents.

players with one link across the two asymmetric networks. Note also that all these networks are well defined for any group size.[5]

We present experimental results dealing both with contributions to team production. Our results support that it is the network structure, rather than the absolute amount of information available at the group level what becomes the major determinant of behavior. The star network, with only 3 links per group, gets the maximum average contribution, even when the difference with the complete networks is never statistically significant. A formal analysis of contributions by types suggests that the existence of a central subject being able to observe all individual contributions in the group make a clear difference.

We are able to capture the behavioral nature of these differences across networks and types by a stylized (dynamic) model based on very simple behavioral hypotheses. Our model considers that players are conditional cooperators and inherits its main ingredient, the presence of decay, from some influential models of network formation like, e.g., Jackson and Wolinsky's (1996) connections model or Bala and Goyal (2000). In these models, the decay represents *frictions* that determine the value of the externalities generated by individual links. In our setup of a repeated VCM played within a fixed network structure, the decay measures how much a conditional cooperator discounts (or weights) the contribution of a direct (and therefore observed) neighbor in order to predict the contribution made by a subject that she does not observe. Analogously to the aforementioned models, the decay is positively related to the distance (number of links) between the two subjects in the network.[6]

Some simulations based on our model capture most of the regularities observed in the experimental data. It is far from our purpose to describe with our model the precise behavioral rules that define subjects' behavior in the lab. Rather than that, we provide an analytical basis for the deterioration of information in networks. The incompleteness of the network erodes conditional cooperation by making more difficult for subjects to get accurate information about the decisions of the other group members.

[5] The choices of these networks can also be motivated by the fact that they are prominent structures in some models of network formation. See for instance Jackson and Wolinsky's (1996) connections model, Bala and Goyal (2000) and Galeotti and Meléndez-Jiménez (2004).
[6] A decay factor is applied *per* link that separates the two players.

Interestingly, the simulations of the model offer a good approximation to the evolution of (group) average contributions in the lab in different networks, relative to the complete one. Moreover, they also capture differences in behavior across types.

The rest of the paper is organized as follows: Section 2 discusses the related literature. Section 3 explains the experimental design and procedures. Section 4 reports on the experimental results. Section 5 introduces a simple behavioral model that reproduces our results. Section 6 concludes.

2. Related literature

In the context of social dilemmas played in the lab, the role of information was first analyzed by Fox and Guyer (1978). They studied an n-person prisoners' dilemma and showed that to inform each subject about the choices of the other subjects after each round increases cooperation rates relative to a scenario where they are just informed about the number of cooperators. More recently, Cason and Khan (1999), in a public goods experiment, showed that the provision of continuous information fosters higher levels of contributions, compared to the provision of information at regular intervals. Eckel et al. (2008) supports the idea that the perceived quality of information matters. In a public good experiment, becoming the commonly observed agent depends on the score subjects got in a pre-experimental questionnaire. Significant differences are observed in followers' decisions when the best scorer becomes the central player (relative to the case where it is the worst scorer who plays the central role). Andreoni and Petrie (2004) concluded that letting subjects to visually identify the other group member and their past level of contributions has a positive effect on contributions.[7]

Croson and Marks (1998) analyze a more complex environment, with multiple equilibria in which the public good is provided. They show that to inform subjects about the vector of contributions (randomly ordered every round) does not improve efficiency as compared to a baseline scenario where subjects receive just aggregate information. However, when information is traceable, contribution levels significantly raise. Fatas et al. (2007) draw a similar conclusion in a standard public

[7] Gächter et al. (1996) also analyze the impact of information and anonymity, being the identities public only at the end of the experiment. Their results suggest that giving information ex-post has a very limited effect (there are no significant differences).

good game and in a coordination game (the minimum game). In both games, when information can be traced, contribution levels increase over 50%.

In our experiment, subjects receive information after each round and such information can be traced back in all treatments. Differently, we vary the observational structure (network), i.e., agents are informed about the contribution levels of a subset of the other member of the groups. It was not until very recently that some experiments on networks emerged in economics.[8] Kirchkamp and Nagel (2001), Cassar (2002), and Riedl and Ule (2002) have conducted some experiments on cooperation in prisoners' dilemma, considering the role of networks on cooperation. Some other recent economic experiments have studied network formation, for instance, Deck and Johnson (2002), Callander and Plott (2003), and Falk and Kosfeld (2003).[9]

To the best of our knowledge, the only two papers that indirectly address the network structure issue are Carpenter (2007) and Choi, Gale and Kariv (2005). In the former, punishment behavior depends both on the sanctioning structure of the game and the group size. In the latter, different network structures are implemented to study observational learning in the lab[10]. They consider three agents and three directed-network structures: the star, the (directed) circle and the complete network. The network architecture has a significant influence on subjects' behavior. In our view, our experiment is the first systematic study of undirected, connected networks in a team production environment. The next section presents our design in detail.

3. Experimental Design and Procedures

We consider groups of 4 agents N = {1, 2, 3, 4}. Our experiment consists of four treatments, with twenty periods each. Each treatment corresponds to a network defined on N that determines an organizational structure. These networks are depicted in Table 1: the complete network (N1), the circle (N2), the line (N3) and the star (N4). In Table 1, an edge between two agents represents a link. We assume that the networks are undirected, i.e., if an agent is linked to another, the

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[8] This contrasts with the large theoretical background on economic networks. See the surveys by Jackson (2005) and Goyal (2005).

[9] See Kosfeld (2004) for a survey on the emergent literature on network experiments.

[10] In a companion paper, Fatas et al. (2008), we analyze sanctioning behaviour under different network structures.

later is also linked to the former.[11] Formally, N1 is such that all the players are linked; N2 is a connected network (cf. footnote 2) such that all players have exactly two links; N3 is a connected network such that two players have one link and the remaining ones have two; and N4 is such that one player (the center) is linked to all players and the remaining ones are only linked to the center. In all four networks we follow a partner matching, that is, the same group of 4 subjects plays twenty periods. Moreover, each subject's position within a network is randomly determined at the beginning of the experiment and fixed throughout the 20 rounds.

[Table 1 around here]

Along the experiment subjects play the Voluntary Contribution Mechanism (VCM) game. In this game links involve the information about contribution. Thus, after each round, each subject is able to observe only the contribution levels made by the other group members they are linked with.

We classify the subjects according to their number of links, i.e., the number of players whose behavior they can observe. We have type 3 players (T3), i.e., those who observe the behavior of all the other members of the group; type 2 players (T2), i.e., those who observe the behavior of two subjects; and type 1 players (T1), i.e., those who only observe the behavior of one subject.[12]

The game proceeds as follows. At the beginning of each period $t \in \{1,\ldots,20\}$, each subject is endowed with 50 Experimental Currency Units (ECUs). Each subject (simultaneously) chooses the portion of her endowment to contribute to a group account, $c_i(t)$. Subjects make their contribution decision by typing on their computer keyboard. Each ECU contributed to the group account yields a payoff of 0.5 ECU to each of the four members of the group. Each ECU not contributed by the subject is credited to the subject's private account. Therefore, the earnings, in ECU, of individual i in period t is given by:

$$\pi_i(c_i(t), \Sigma_{j \in N \setminus \{i\}} c_j(t)) = 50 - c_i(t) + 0.5 \cdot \Sigma_{j \in N} c_j(t)$$

It is easily seen from that individual i's earnings at period t are maximized at $c_i(t) = 0$. At the end of each period subjects are informed of the contribution levels of each member of the network they are linked to. If the game is played once, to contribute

[11] In our setup, if two players interact, it is reasonable to assume that each of them is able to observe the behavior of the other.

[12] N1 has three T3 players, N2 has three T2 players, N3 has two T2 players and two T1 players, and N4 has a T3 player (the center) and three T1 players.

zero is a dominant strategy. If the game is finitely repeated, there is a unique subgame perfect equilibrium: all players contribute zero in all periods.

At the end of each period, in all networks, the computer displays the subject's own initial endowment, the contribution of the other team member’s who are linked to them, and their earnings from both accounts. The computer program then continues to the next period.

All sessions were conducted at LINEEX (Laboratory for Research in Experimental Economics), at the University of Valencia. Subjects were recruited from undergraduate courses in business and economics. Some of the subjects had participated in previous experiments, but all of them were inexperienced in this particular type of experiment (public good games experiments). No subject participated in more than one session of the study. On average, a session lasted around 50 minutes, including initial instructions and payment of subjects, and the average payment was around 14 €. The experiment was computerized using ZTREE (Fischbacher, 2007).

4. Experimental Results

We divide this section in two subsections. In the first one we analyze how the different informational networks affect contribution levels in our game. We will see that different organizational structures drive to different contribution levels, being the star the best non-complete network. In the second subsection we study where these differences come from, focusing on the behavior of the different players’ types.

4.1 Analysis of Contribution across Networks.

[Figure 1 around here]

Figure 1 shows the temporal paths of the average contribution to the public good in all four networks in blocks of five rounds. By pure inspection, contribution levels in N1 and N4 are higher than in the other two networks. In Figure 1, we also observe the significant decline of the contribution levels over time in all four networks. N4 seems to follow a flatter path and has the highest contribution levels in the last periods.

To examine the statistical validity of the impressions obtained from Figure 1, Table 2 shows a more sophisticated formal analysis. We analyze how different independent variables (network and period) affect contribution levels. Given the nature of the dependent variable, panel data model with random effects at the individual level are used in all regressions.[13]

[Table 2 around here]

In models 1 and 2 we analyze how time and the different network structures affect contribution levels. To this aim, we introduce as independent variables *period* (from 1 to 20) and four treatment dummies (N1, N2, N3 and N4) which take value 1 in case the observation comes from the corresponding network, and zero otherwise. For example, N1 takes value equal to 1 if the observation comes from a subject allocated in N1. To check if there are significant differences on contribution levels between networks we also compare dummies coefficient using a t-test, which computes point estimates, standard errors, and p-values for linear combinations of dependent variables, in this case networks.

As it has been found in many other PGG experiments (see for instance Fatas et al. 2007) there is a significant decrease in contributions over time. But what is salient is that N1 and N4 outperform N3. This is a partially expected result, mainly because in N1 the number of links doubles the links in N3, so subjects are able to perfectly monitor the other team members. But N4 has the same number of links than N3. The only difference between these two structures is that in N4 there exists one member of the team that can perfectly monitor all other member's contributions. In a sense, we can think of N4 as the most hierarchical structure, given the presence of this "coordinator", even when the public good keeps being fully horizontal. We do not find significant differences between N1 and N2 networks. This is related to the equivalence of both networks in informational terms.[14]

4.2 Analysis of Contribution by Types.

Given the significant differences in contribution observed across some networks, in this subsection we study where these differences come from.

[13] We therefore correct the standard errors using a relatively conservative clustering approach to correct for repeated observations, due to Liang and Zeger (1986). Each group is treated as a separate cluster. This is appropriate for these regressions since observations from players in the same group are not independent.

[14] In N2 is easy to compute the individual contribution of the group member subjects do not observe. Each subject gets information about two other group member's contribution and earnings coming from the public good, so just a little calculation is needed to get the last piece of information.

[Table 3 around here]

In Table 3 we calculate the average contribution levels both, by player's type and by network. By inspection, across types we see that contribution levels are related to the type. While T1 players contribute almost exactly the average contribution level, T2 players contribute around 13% less than the average contribution, and T3 players contribute around 17% above the average. Focusing on the heterogeneous networks (N3 and N4), in which there are two types of players, we observe no mayor differences between types. Across networks, T1 players contribute 40% more in N4 than in N3, T2 players contribute around 20% less in N3 than in N2, and T3 players contribute around 7% more in N4 than in N1.

[Table 4 around here]

In Tables 4 and 5 we present a formal analysis on the effect of the subjects' type on contributions. Analogously to Table 3, we use panel data model with random effects at the individual level (cf. footnote 13). In Table 5 we analyze differences on contribution levels between types separately in the two heterogeneous networks (N3 and N4). The independent variables in these models are period and three dummies (T1, T2 and T3) which again take value 1 or 0 depending on the type of the player (T1=1 if the observation comes from a T1 player, and so on). Table 4 suggests that there are no significant differences between types of players within any heterogeneous network.

[Table 5 around here]

In Table 5, we check whether same type players act in a different way in different organizational structures. In models 5, 6 and 7 we analyze if there are significant differences on contribution levels within each type, across the different networks, using the network dummies described above.

We do not find significant differences in the contribution levels of T2 players between N2 and N3. On the contrary, T1 and T3 players do change their contributions depending on the organizational structure. T1 players contribute significantly more in N4 than in N3, which confirm the impression we obtained from Table 4. Moreover, even if the differences in contributions of T3 players across N4 and N1 (given by Table 4) are small, Table 6 shows that they contribute significantly more in N4. This result suggests that, even when the information is the same for T3 in N3 and N4, full observation reinforces contribution in the star network.

5. A Simple Behavioral Model

Given the significant differences described in the previous section, a natural objective is to generate a consistent theoretical explanation. In this section we present a model in which a decay factor tries to capture the accuracy losses associated to the network incompleteness. Incompleteness make more difficult for conditional cooperators to find their natural reference point: the behavior of others.[15]

5.1 The dynamic model: Behavioral assumptions

For concreteness and, in analogy to the experimental design, we will focus on the case of four players, N = {1, 2, 3, 4}, and our four network structures, G = {N1, N2, N3, N4}.[16] Given $g \in G$, the distance between two agents $i,j \in N$, denoted by $d(i,j)$ is the (minimum) number of links that separates them. For each $i \in N$, we denote by $N_i(g)$ the set of i's neighbors in $g \in G$. Time is considered to be discrete $t \in \{1, \ldots, 20\}$. At each period t, each $i \in N$ (simultaneously) decides a contribution to a public good, $c_i(t) \in [0,50]$. Previously to this choice, i learns $c_j(t\text{-}1)$ for each $j \in N_i(g)$. The payoff to player i at period t is determined by

$$\pi_i(c_i(t), \Sigma_{j\in N\backslash\{i\}}\, c_j(t)) = 50 - c_i(t) + 0.5\cdot\Sigma_{j\in N}\, c_j(t).$$

We propose a dynamics where all agents are conditional cooperators, *i.e.*, they substantially contribute as long as they observe that the other agents also contribute significantly.[17] Specifically, in order to define precisely this behavior, we assume that each player would like to contribute exactly the average contribution of the other members of the group at the current period. Since all the players

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[15] In all our treatments subjects get specific information about earnings coming from both the private and the group account. So, it is not impossible for them to compute, even in an approximate way, the average behavior of the other players. Following the literature surveyed in section 2, our model tries to construct a very simple analytical framework to explain why the quality of information (i.e. the network incompleteness) might have a significant effect on decisions.

[16] The model can be perfectly defined for all possible connected networks of any size.

[17] In a population of selfish (game theoretical) players, all players contribute 0 at every period. However, several experiments (e.g. Fischbacher et al. 2001) strongly suggest that a significant proportion of subjects are conditional cooperators. In our simple model, we abstract from the presence of selfish players and show that a population of conditional cooperators can reproduce some of the regularities observed in the lab.

decide their contributions simultaneously, we need an additional assumption: we assume that each agent behaves "*à la* Cournot", that is to say, she considers that, at each period, the other members of the group will continue to make the same contribution that they made in the previous period.[18] In this sense, our model considers bounded-rational players since they do not anticipate that others, like themselves, update their contributions based in what they observe. We introduce our first assumption:

Assumption 1 (A1): Agents are conditional cooperators *à la* Cournot.

Put in other words, H1 states that, at each $t > 1$, each player aims to contribute the mean contribution of the remaining players at t-1. In the complete network, all agents can directly apply the rule. However, in the incomplete networks there are players that need to predict the past contribution of other members of the group.

We assume that an agent, say i, predicts the contribution of a player (j) that he does not directly observe using as a *proxi* a weighted average between the Nash equilibrium prediction (zero) and the contribution of that of her neighbors (say $k \in N_i(g)$) that is closest to j in the network.[19] The weights depend on the distance between k and j. We assume that i perceives k's contribution as more informative about j's behavior the closer k is to j. Therefore, in order to predict j's behavior, i applies a decay factor to k's contribution *per* link that separated k from j. Hence, if k and j are very close, i's prediction on j's behavior is close to k's contribution whereas if they are far away, i's prediction is close to zero. This idea is formalized as follows.

Assumption 2 (A2)*:* The prediction of i on j's contribution at period t is:

$$\hat{c}_{i,j}(t) = \delta^{d(i,j)-1} \cdot \frac{\sum_{k \in N_{i,j}} c_k(t)}{\left| N_{i,j} \right|}, \tag{1}$$

where $\delta \in (0,1)$ and $N_{i,j} = \arg\min_{k \in Ni(g)} d(k,j)$.[20]

Hence, given (A1), the dynamics is governed by the following system of difference equations:

[18] In a Cournot adjustment process, agents best-respond to the previous period pattern of actions (see for instance, Fudenberg and Tirole (1991)). In our model, we use the term "à la Cournot" to express that players act as conditional cooperators *w.r.t.* the previous period pattern of contributions.

[19] If there are several neighbors of i at the same distance from j, we consider their average contribution.

[20] Note that if $j \in N_i(g)$, then $N_{i,j} = \{j\}$ and, since $d(i,j) = 1$, $\hat{c}_{i,j}(t) = c_j(t)$.

$$\text{For each } i \in N,\ c_i(t) = \frac{\sum_{j \in N \setminus \{i\}} \hat{c}_{i,j}(t-1)}{n-1}. \qquad (2)$$

5.2. Simulations and comparison to the experimental data

In order to compare the experimental results to the insights offered by our model, we simulate the model considering the initial conditions derived from each of our experimental groups in the lab.[21] We therefore obtain first one simulation per group and, then, average them. In particular, we calculate the average contribution that each subject who participated in the experiment made in the first block of 5 rounds,[22] which serves as initial conditions for the simulation of each group. The initial contributions therefore reflect: i) how agents perceive the network structure (the network and their position in the network) and ii) how this structure affects to their initial behavior.

In Table 6, we report the average contribution in each network given from the experimental data and compare it to the results of the simulations of our model for δ = 0.98 (within brackets). This comparison is presented disaggregating by types of players. Since we want to identify how the incompleteness of networks affects to the behavior in the VCM, in Table 1, the average contribution in our baseline network (N1) is normalized to 1 and we present the average contributions in each incomplete network (N2, N3 and N4) relative to the average contribution in N1.

[Table 6 around here]

Table 6 shows that the outcomes of the simulations with a δ close to 1 (δ = 0,98) are very similar to the experimental results. In our view, our model captures the effect of incompleteness in a very accurate way, both across networks and types. A small loss of information (associated to a δ = 0,98) is enough to capture the dynamics of our results. In Figure 2, we analyze the same comparison (simulation vs. experimental data) across the 20 rounds of play. Again, at each round the average contribution in N1 is normalized to 1. As Figure 2 shows, our stylized model is able to capture quite well the regularities observed in the experimental data.

[21] The system (1)-(2) can be analytically solved if we impose homogeneous initial conditions. This analysis, which is omitted, provides some results that (qualitatively) agree with our experimental results.
[22] Qualitatively similar results are obtained when the initial conditions are determined by decisions in round 1.

[Figure 2 around here]

6. Discussion

Several results in previous research show that information is an important mechanism to understand cooperation in public good games. It raises contribution levels in team production. In this paper we provide evidence consistent with the idea that the organizational structure of teams significantly changes contribution levels. In four different treatments, which represent four well known networks, a team production game is analyzed. Our analysis shows that the network structure significantly affects contribution levels.

Our results have some interesting implications from the organizational point of view. Information matters (the contribution levels observed in N1 and in N4 are significantly larger than in N3), but the relationship between the number of network links and the team's performance is not monotonic. Networks with the very same number of links (N3 and N4) yield very different outcomes from an organizational perspective. Our model suggests that the existence of a commonly observed subject (as in N4, the star network) meliorates the evolution of cooperation because it reduces the losses associated to the network incompleteness. In the star network, all subjects have a common reference point. Relative to others networks, conditional cooperation is better sustained.

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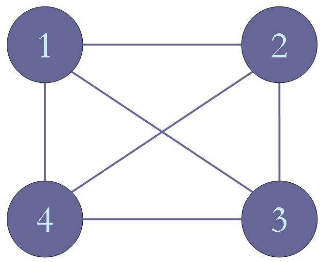
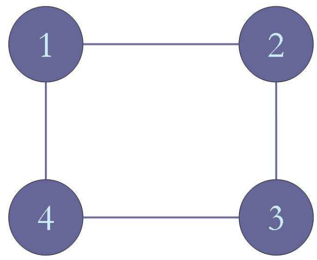
APPENDIX

Table 1: NETWORKS

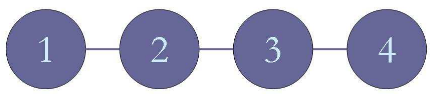
Complete (N1)
(n=36)



Circle (N2)
(n=36)



Line (N3)
(n=40)



Star (N4)
(n=32)

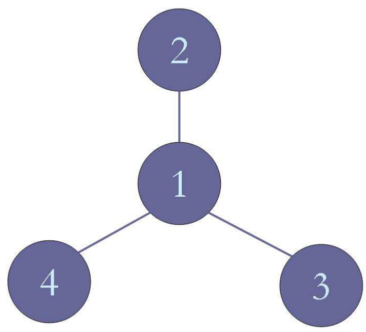


Figure 1: Avg. Contribution
(Between Networks comparison VCM Game)

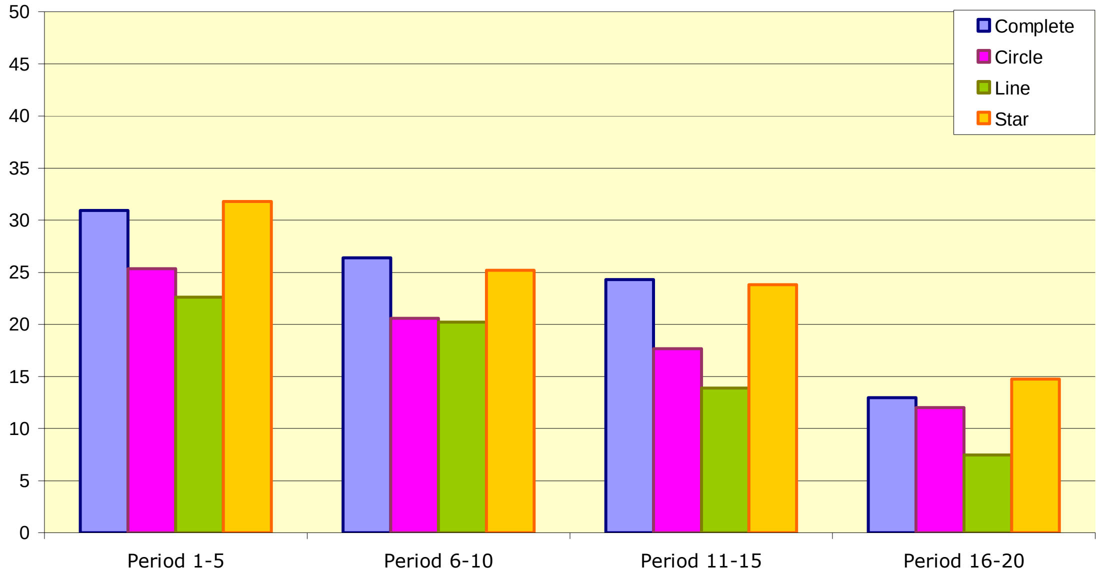


Table 2. Panel data random effects regressions. Contribution Levels VCM

	(1)	(2)
Constant	34.321 (3.454)***	34.910 (3.582)***
Period (t)	-1.016 (.084)***	-1.073 (.095)***
N2	-4.747 (5.275)	
N3	-7.601 (3.606)**	-7.601 (3.623)**
N4	0.232 (3.552)	0.232 (3.569)
N2 vs. N3	2.85375 (4.690)	
N3 vs. N4	-7.833 (2.605)***	-7.833 (2.617)***
N2 vs. N4	-4.9796 (4.649)	
# Obs	2880	2160
R-sq:		
Between	0.0996	0.1566
Overall	0.1454	0.1703
Prob>chi2	0.0000	0.0000

Standard errors are corrected for clustering at the group level. ***, **, and * denote statistical significance at the p < .01, p < .05, and p < .10 levels respectively.

Table 3. Avg Contributions

Contribution		All Types	T1	T2	T3
VCM	All Networks	20.401	20.270	17.707	23.959
	N1	23.647			23.647
	N2	18.9		18.9	
	N3	16.046	16.532	15.56	
	N4	23.879	23.385		25.362

Table 4. Contribution levels by types across networks
(within each heterogeneous network)

	(3) N3	**(4) N4**
Constant	27.226 (3.469)***	34.678 (1.324)***
Period	-1.018 (.147)***	-1.075 (.171)***
T2	-0.972 (1.353)	
T3		1.977 (2.042)
# Obs	800	640
R-sq:		
Between	0.0037	0.0112
Overall	0.1207	0.1290
Prob>chi2	0.0000	0.0000

*p<0.10 ** p<0.05 *** p<0.01
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Table 5. Contribution levels by types across networks

	T1 N3 vs. N4 (5)	T2 N2 vs. N3 (6)	T3 N1 vs. N4 (7)
Constant	20.748 (3.378)***	24.200 (4.833)***	33.284 (4.386)***
Period	-0.401 (.207)**	-0.505 (.158)***	-0.918 (.182)***
N3		8.437 (6.775)	
N4	18.505 (3.871)***		14.746 (4.725)***
Nº Obs	880	1120	880
R-sq: **Between** **Overall**	 0.4527 0.2607	 0.0697 0.0673	 0.2529 0.1996
Prob>chi2	0.0000	0.0000	0.0000

*p<0.10 ** p<0.05 *** p<0.01

Table 6. Average contribution relative to N1

Experimental data vs. Simulations (δ=0.98)

Avg. CONTRIBUTIONS		All Types	Type 1	Type 2	Type 3
VCM	N1	1 (1)			1(1)
	N2	0.82 (0.77)		0.82 (0.77)	
	N3	0.67 (0.66)	0.67 (0.66)	0.66 (0.66)	
	N4	1.02 (1)	1.01 (1)		1.03 (1)

Values of the simulations within brackets

Figure 2. Experimental data vs. Simulations (δ=0.98) across rounds.