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An experimental analysis of team production in Networks

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AN EXPERIMENTAL ANALYSIS OF TEAM PRODUCTION IN NETWORKS*

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ABSTRACT

Experimental and empirical evidence highlights the role of networks on social outcomes. In this paper we test the properties of exogenously fixed networks in team production. Subjects make the same decisions in a team-work environment under four different organizational networks: The line, the circle, the star, and the complete network. In all the networks, links make information available to neighbors. This design allows us to analyze decisions across networks and a variety of subjects' types in a standard linear team production game. Contribution levels differ significantly across networks and the star is the most efficient incomplete one. Moreover, our results suggest that subjects act as conditional cooperators with respect to the information received from the network.

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1. Introduction

The analysis of public goods 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 contributions for the provision of public goods react to changes in several features of the problem at hand.[1] There is, however, an interesting aspect that has not been explored in the lab: The effects of the internal (network) structure of the group.

The network structure of the group is of special relevance if we interpret the public goods game as a team production problem. In real life organizations, it is rarely the case that all the members of a team interact directly with each other (i.e., the complete network). On the contrary, there is a huge variety of possible structures, represented by the set of networks that can be formed within the set of agents. Moreover, it is quite likely that each agent may only observe the behavior of those ones with whom she interacts directly. This idea leads us to explore whether different observational structures within a team result in 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 objective of this paper can now be advanced. Succinctly expressed, it is to study whether, in a team production problem (modeled as a linear public goods game), subjects' behavior changes when we vary the observational structure. If so, we aim to identify which network features foster high levels of contributions.

In our experiment, we consider teams of four subjects that repeatedly play a standard public goods game based on the Voluntary Contribution Mechanism (VCM). The observational structure is determined by an exogenous and fixed network within the team members. After each round, each subject is informed about the contributions of her neighbors in the network (i.e., the subjects linked to her). However, a subject is not informed about the behavior of those ones that are not (directly) linked to her.

We consider four treatments, which correspond to four stylized networks: The complete network, the circle, the star and the line. The circle and the complete network are symmetric. In the circle, all the subjects have two links and, in the complete network, all the subjects have three links (since we consider groups of size four). The star and the line are asymmetric. In the

[1] Zelmer (2003) provides a meta-analysis of public goods experiments.

star, all the subjects have one link but the central one, who has three links. In the line, two subjects have two links and two subjects have only one link.[2] This design allows us to compare the behavior of subjects with different number of links allocated in the same (asymmetric) network and, additionally, we can compare subjects with the same number of links allocated in different networks: Subjects with three links (complete network vs. star), subjects with two links (circle vs. line) and subjects with one link (star vs. line).

Our results support that the network structure becomes the major determinant of behavior, rather than the absolute amount of information available at the group level. The star, with only three links, fosters the maximum average contribution, even when the differences with the complete network are not statistically significant. In the first round there are already differences in contributions across some networks. This fact suggests that, in some cases, subjects who perceive different observational environments (networks) start contributing differently. In particular, our results suggest that the presence of a central subject in the group (able to observe all the individual contributions) makes a difference.

Moreover, we test from the data whether players act as conditional cooperators given the information that they receive from the network, i.e., whether they react positively to the levels of contribution observed in the previous round.[3] To this aim, in the regressions we control for the average contribution that the subject observed from her neighbors in the previous round and, also, for the first period contribution. We show that these variables are positive and significant and that they encompass the network effects (when we control for these variables the network effects are significantly reduced). This result suggests that the first period contributions (which, as already mentioned, differ across some networks) and the information that subjects receive in the previous round (determined by the network) explain the behavior in the VCM.

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 concludes.

[2] Note that the networks that we study in the lab are well defined for any group size.

[3] Several experiments on public good games (e.g. Fischbacher et al. 2001) strongly suggest that a significant proportion of subjects are conditional cooperators.

2. Related literature

The role of information in social dilemmas played in the lab was first analyzed by Fox and Guyer (1978). They consider n-person prisoner's dilemma games and show that the provision of information about the choices of others increases cooperation rates (relative to a scenario in which subjects are just informed about the number of cooperators). More recently, in a public goods experiment, Cason and Khan (1999) show that the provision of continuous information fosters higher levels of contribution than the provision of information at regular intervals. Eckel et al. (2009) support the idea that the perceived quality of information matters and Andreoni and Petrie (2004) show that the visual identification of other members of the group (and their past choices) has a positive effect on contributions.[4] Finally, Croson and Marks (1998) and Fatas et al. (2009) study the effects of fully traceable information.[5] They first show that to inform subjects about the (randomly ordered) vector of contributions does not improve efficiency with respect to a baseline scenario (where subjects only receive aggregate information). However, when information is traceable, the levels of contribution significantly increase.

In all the treatments of our experiment, after each round, the subjects receive information that can be traced back. In each treatment we vary the observational structure (network): Each subject is informed about the contribution levels of a subset of the group members, which is determined by an exogenous network structure. It was not until very recently that some experiments on networks emerged in economics.[6] Kirchkamp and Nagel (2007), Cassar (2007) and Riedl and Ule (2002) conduct experiments to study the role of networks in cooperation levels in prisoners' dilemma games. Some other recent economic experiments study network formation, for instance, Deck and Johnson (2004), Callander and Plott (2005), Falk and Kosfeld (2003), Berninghaus et al. (2006) and Berninghaus et al. (2007).[7]

Carpenter (2007) and Choi, Gale and Kariv (2005) may be the closest papers to ours. Carpenter (2007) is the first to introduce a network effect in a public goods experiment. In his design, subjects observe the contributions made by all the group members, and they are able to monitor (punish) a subset of the group. He restricts the analysis to symmetric (monitoring)

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[4] Gächter et al. (1996) also analyze the impact of information and anonymity and their results suggest that providing information ex-post has a very limited effect.

[5] Croson and Marks (1998) study a complex environment, with multiple equilibria in which the public good is provided. Fatas et al. (2009) consider a standard public goods game and a coordination game.

[6] This contrasts with a large theoretical background. See Jackson (2005) and Goyal (2005).

[7] Other network experiments study, among other topics, coordination games and buyer-seller networks. See Kosfeld (2004) for a survey on this emergent literature.

networks. Choi, Gale and Kariv (2005) implement three different directed-network structures (star, circle and complete network) to study observational learning in the lab. In our paper, we study in the lab a public goods game in which a network determines which members of the group each subject observes.[8] Moreover, we consider both symmetric (complete network and circle) and asymmetric (star and line) structures. In our view, our experiment is the first systematic study of (observational) networks in a team production environment.

3. Experimental Design and Procedures

We consider groups of four players, *G* = {1, 2, 3, 4}. Our experiment consists of four treatments. Each treatment corresponds to a network defined on *G* 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 players represents a link. We assume that networks are undirected, i.e., if a player is linked to another one, the later one is also linked to the former one. We classify the players according to their number of links: Players of type 1 (T1), type 2 (T2) and type 3 (T3) have 1, 2 and 3 links, respectively. Hence, N1 consists of four T3 players, N2 consists of four T2 players, N3 consists of two T2 players and two T1 players, and N4 consists of one T3 player and three T1 players. In all our treatments we follow a partners matching, that is, the group composition is kept constant. Moreover, the subjects' positions within the network (i.e., their player numbers) are randomly determined at the beginning of the experiment and fixed throughout all the rounds.

[Table 1 around here]

The experiment was computerized using ZTREE (Fischbacher, 2007). In all the treatments, the groups repeatedly play the Voluntary Contribution Mechanism game (VCM) for 20 rounds. The network determines the observational structure: After each round, each subject is only able to observe the contribution levels of the group members that are linked to her.

The game proceeds as follows. At the beginning of each round, subjects are endowed with 50 Experimental Currency Units (ECUs). Each (subject) $i \in G$ simultaneously chooses her contribution to the group account, c_i. Subjects make their choices by typing on a keyboard.

[8] In a companion paper, Fatas et al. (2008), we analyze sanctioning behavior under different network structures. In this case, the network defines both the observational and the monitoring structure.

Each ECU that is contributed to the group account yields a payoff of 0.5 ECUs to each member of the group. Each ECU that is not contributed by a subject is credited to her private account. Thus, at a particular round, subject i's earnings (in ECUs) are given by:

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

At the end of each round, the computer screen of each subject displays her initial endowment, the contribution of the group members linked to her and her earnings from both accounts. In all treatments, the choice $c_i = 0$ maximizes subject i's earnings at any round. Since the game is finitely repeated, there is a unique subgame perfect equilibrium, in which all members of the group contribute zero in all rounds.

The experiment was conducted at LINEEX (Laboratory for Research in Experimental Economics), at the University of Valencia. The participants were 144 business and economics undergraduate students, all of them inexperienced in public good games experiments or network experiments. We ran 8 sessions (two for each treatment) and no subject participated in more than one session. Specifically, 36 subjects participated in treatment N1 (6+3 groups, in two sessions), 36 subjects participated in N2 (6+3 groups), 40 subjects participated in N3 (6+4 groups), and 32 subjects participated in N4 (6+2 groups). The average payment was around 14€ and, on average, a session lasted around 50 minutes, including the initial instructions and the payment of subjects.

4. Experimental Results

We divide the analysis in three parts. In Section 4.1 we study the relationship between networks and contribution levels. We shall see that different organizational structures foster different contribution levels. In particular, the star is the best non-complete network. Then, we investigate the determinants of these differences. In Section 4.2 we study the behavior of the different types of subjects. Within each asymmetric network (line and star), the behavior of subjects of different types is not significantly different. In contrast, we find significant differences in the behavior of some types of subjects across different networks. Finally, In Section 4.3, we consider a specification where we jointly analyze network and type effects by means of interaction terms. We find that all the results of Sections 4.1 and 4.2 are robust to such a specification.

4.1 Analysis of Contribution across Networks.

[Figure 1 around here]

Figure 1 shows the temporal path (in blocks of five rounds) of the average contribution to the public good for each treatment. By visual inspection, we observe that the average contribution levels are higher in N1 and N4 than in the other two networks. Additionally, in all the treatments, there is a significant decline in contributions. In this respect, the temporal path is flatter in N4 than in the other three networks and, in the last block of five periods, the average contribution level in N4 is the highest.

[Table 2 around here]

In Table 2, we show the average contribution levels, disaggregating both by networks and by types of subjects. In the upper part of the table we consider only the data from the first round, and in the lower part we consider all the 20 rounds.

We are first interested in studying whether the perception of the game depends on the network in which the subject is allocated. A visual inspection of Table 2 suggests differences in contribution levels across networks in the first round.[9] To check the significance of these differences, we rely on Mann-Whitney tests, which show that only the differences between N4 and N3 are significant at the 10% level.

Over the 20 rounds, Mann-Whitney tests show that the average contributions in N1 and N4 are significantly larger than the average contribution in N3 at the 5% and 1% levels, respectively. In contrast, we neither find any statistical difference between N1 and N4 nor between N2 and any of the other networks.[10]

Given the nature of our data (a panel of subjects that interact in fixed groups), we shall now discuss the results of a more sophisticated (econometric) analysis that compares the individual

[9] Interestingly, in treatment N4, in the first period no individual contribution is below 5 and, moreover, T3 subjects do not contribute less than 10.

[10] When we perform the Mann-Whitney tests corresponding to the first round, we consider the individual contributions of all subjects (since they are independent). In contrast, when we perform the tests corresponding to all the 20 rounds, we need to take into account the fact that each group provides an independent observation. Therefore, we consider the average group contribution aggregated for the 20 rounds.

contributions across networks throughout the 20 rounds. To this aim, in Table 3 we report the results of two (panel data) models with random effects at the individual level.[11]

[Table 3 around here]

In model 1, we analyze how the repetitions of the game and the network structure affect the contribution levels. To this aim, we consider as independent variables *round* (from 1 to 20) and four treatment dummies: N1, N2, N3 and N4. Each dummy takes value one if the observation comes from a subject allocated in the corresponding network and zero otherwise. As it has been found in many other public good game experiments, there is a significant decline in contributions over time. To check if there are significant differences in contribution levels between (pairs of) networks, we compare the coefficients of the dummies by means of t-tests (which provide estimates, standard errors, and p-values of linear combinations of the independent variables). We observe that both N1 and N4 outperform N3. This result is partially expected, because the total number of links in N1 is twice that in N3 (in N1 all subjects observe each other's behavior). However, N4 and N3 have the same number of links. The main difference between them is the presence in N4 of a subject that observes, and is observed by, everyone else. The presence of this "coordinator" suggests that N4 is the most hierarchical structure, even when the public good game is fully horizontal. We also observe that there are no significant differences between N1 and N2. This result is not surprising since N1 and N2 are equivalent in informational terms.[12] Note that all the results of model 1 are robust to the non-parametric analysis (Mann-Whitney tests) presented above.

In model 2, we analyze whether the differences observed in the previous model come from dissimilar dynamics in each network. To this aim, we introduce as explanatory variables the first contribution of the subject (FirstCont) and the average contribution in the previous round of those members of the group that are observed by the subject (LagAvgCont-i). We observe that the coefficients of both variables are positive and significant. Moreover, once we control for these variables, there are less differences across networks.[13] Hence, given the (different) initial contribution levels of each network, a dynamics where subjects act as conditional

[11] All the models discussed in Section 4 use Generalized Least Squares estimations (Tables 3, 4 and 5). For all the estimations we use the software STATA. Additionally, in all our models we adjust the standard errors to account for the fact that observations are not necessarily independent within groups. To this aim, we use a relatively conservative clustering approach, due to Liang and Zeger (1986).
[12] Note that each subject is informed about the earnings from the public good. Thus, in N2, a little calculation allows each subject to infer the contribution of the only member of the group that is not linked to her.
[13] Note that, although the difference between N1 and N3 is still significant, the coefficient is smaller than in model 1. The differences between N3 and N4 are significant only at the 10% level.

cooperators with respect to the information they receive from the network seems to explain the behavior in the VCM. In Tables 7 and 8 in the Appendix we estimate models 1 and 2 using different econometric techniques. We obtain that, with these alternative specifications, our results qualitatively follow.

4.2 Analysis of Contributions by Types.

If we focus again on Table 2, we can now study whether there are differences across types in the first round. To this aim, we compare by means of Mann-Whitney tests the individual contributions of: (i) different types of subjects allocated in the same (asymmetric) network (in N3 we compare T1 and T2 subjects; in N4 we compare T1 and T3 subjects) and (ii) the same type of subjects allocated in different networks (T1 subjects are compared in N3 and N4; T2 subjects in N2 and N3; T3 subjects in N1 and N4). The tests show that none of the differences are statistically significant.

Regarding the 20 rounds, in Table 2 we observe by visual inspection that within each asymmetric network (in which there are two types of subjects) there are no major differences between types. In contrast, across networks, T1 subjects contribute 40% more in N4 than in N3, T2 subjects contribute around 20% more in N2 than in N3, and T3 subjects contribute around 7% more in N4 than in N1.[14] In order to provide a formal analysis of the effects of the subjects' types on contributions throughout the 20 rounds, in Tables 4 and 5 we report the results of panel data models with random effects at the individual level (adjusting the standard errors to account for the fact that observations are not necessarily independent within groups).

[Table 4 around here]

In Table 4, (separately) within each asymmetric network, we analyze the differences on contribution levels between types. In models 3 and 5, the independent variables are *round* and three dummies (T1, T2 and T3). Each dummy takes value one if the observation comes from a subject of the corresponding type and zero otherwise. In models 4 and 6 we also include as independent variables *FirstCont* and *LagAvgCont-i*. From all the (four) models we conclude that there are no significant differences between types within any asymmetric network.

[14] Note that the (magnitude of the) differences in average contributions of the 20 rounds across types are very similar to the differences in differences in contributions of the first round.

Moreover, as in model 2, *FirstCont* and *LagAvgCont-i* are also positive and significant in models 4 and 6.

[Table 5 around here]

In Table 5, we study whether subjects of the same type act differently when they are allocated in different networks. In models 7 to 12, (separately) for each type of subject, we analyze if there are differences on contribution levels across networks, using the dummies N1, N2, N3 and N4. In models 9 and 10, we do not find significant differences in the contribution levels of T2 subjects between N2 and N3. Similarly, in models 11 and 12, there are no significant differences in the contribution levels of T3 subjects between N1 and N4. In contrast, model 7 suggests that T1 subjects do change their contributions depending on the observational structure: T1 players contribute significantly more in N4 than in N3. However, once we control for the first contribution level and the contribution that subjects observe in the previous round (model 8) these differences vanish. This result reinforces the idea that the main determinants of behavior in the VCM are: (i) How subjects perceive the network when they play the game for the first time and (ii) the conditional cooperation pattern, given the information provided by the network.

5. Conclusion

Several results in previous research show that information is an important feature to understand cooperation in public good games. The provision of information raises contribution levels in team production. In this paper, we analyze four treatments, which correspond to four well known stylized networks, in which a team production game is played. In each treatment the network determines the information that each subject receives. We provide evidence consistent with the idea that the organizational structure of teams significantly affects the 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 links and the performance of the team is not monotonic. Networks with the same total number of links (N3 and N4) yield very different outcomes from an organizational perspective. The results suggest that the existence of a commonly observed subject (as in N4) meliorates the evolution of cooperation. Moreover, our results support the idea that subjects act as conditional cooperators given the information they receive from the network in the previous round.

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APPENDIX

Experimental Instructions[15]

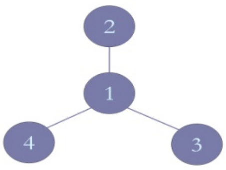
The aim of this Experiment is to study how individuals make decisions in certain contexts. The instructions are simple. If you follow them carefully you will earn a non-negligible amount of money in cash at the end of the experiment. Individual payments will remain private, as nobody will know the other participants' payments. Any communication among you is strictly forbidden and will result in an immediate exclusion from the Experiment.

1.- The experiment consists on 20 rounds. In each round you are member of the same group of 4 participants. Group composition is randomly determined at the beginning of the experiment and does not vary along it. You will not know the identities of the other group members.

2.- At the beginning of the experiment, you will be assigned a player number, which can be 1, 2, 3 or 4. This number will not change along all the experiment. Therefore, in your group there will be a player 1, a player 2, a player 3 and a player 4. You will be one of them.

3.- At each round, each participant receives an endowment of 50 ECUS. Your unique decision consists on choosing how many of them you assign to the Group Account. The remaining ECUS will remain in you Private Account.

4.- After these decisions are made, each participant will receive information about the assignments to the Group Account made by some other group members. This information is summarized in the following figure:



Player 1 will observe the assignments of players 2, 3 and 4
Player 2 will observe the assignment of player 1
Player 3 will observe the assignment of player 1
Player 4 will observe the assignment of player 1

5.- Your round profits comes both from the group and private accounts. To calculate the benefit of the Group Account we first sum the assignments that all group members have made to the Group Account (i.e., we sum the assignments of players 1, 2, 3 and 4 to the Group Account). This sum of assignments to the Group Account is multiplied by 2, and divided in 4 equal shares (one share for each member of the group).

6.- The Private Account benefit equals your assignment to the Private Account and does not depend on the decisions made by the other players.

7.- To summarize, your benefit in a given round is determined as follows:

Individual Benefit	=	Benefit from the Group Account *(0.5 x Sum of assignments of my group to the Group Account)*	+	Benefit from the Private Account *(50 ECUS – my assignment to the Group Account)*

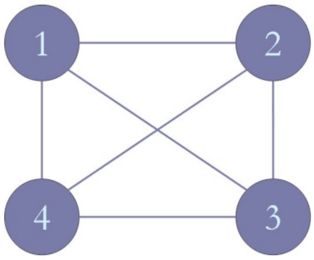
8.- At the end of every round, you will get information about current and past profits. The information consists of the benefit you obtain from the Group Account, the benefit you obtain from the Private Account, your total individual benefit and your accumulated benefit up to that moment.

9.- At the beginning of the experiment, just by showing up, you will start with an accumulated benefit of 500 ECU (Experimental Currency Units). The benefits that you obtain during the experiments will be added to that amount. At the end of the experiment your cumulative profits (plus the showing-up fee) will be privately paid in cash at the exchange rate of 100 ECU = €1.

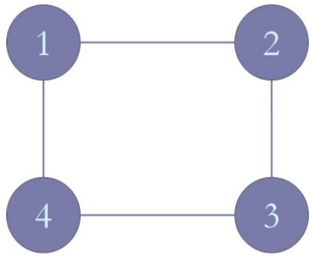
[15] We provide the experimental instruction of the star treatment. The instructions of the other treatments (complete network, circle and line) are analogous and just differ in point 4. Instructions are translated from Spanish. Original instructions are available from authors upon request.

Table 1. Treatments

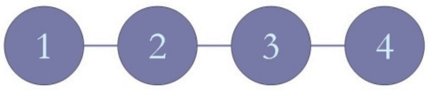
Complete network (N1)
(n=36)



Circle (N2)
(n=36)



Line (N3)
(n=40)



Star (N4)
(n=32)

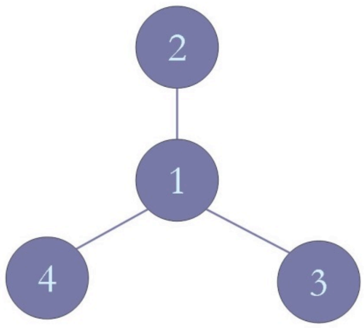


Figure 1. Average Contribution (Between Networks Comparison)

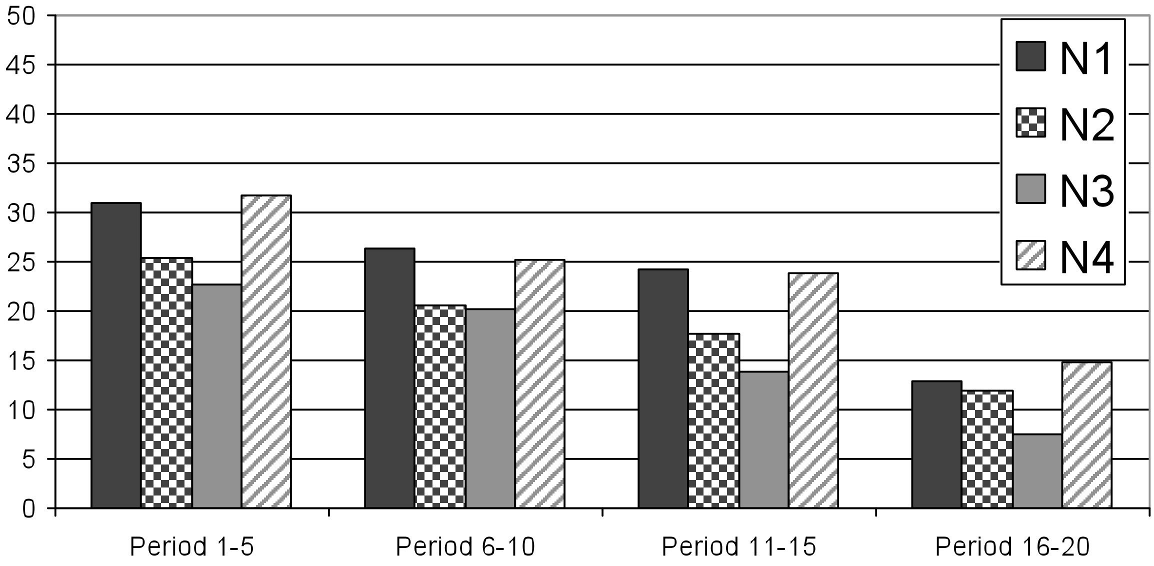


Table 2. Average Contributions

Contribution		All Types	T1	T2	T3
First Period	All Networks	26.743 (15.609)	27.114 (15.243)	24.982 (17.395)	28.614 (13.534)
	N1	28.306 (14.150)			28.306 (14.150)
	N2	24.417 (17.793)		24.417 (17.793)	
	N3	24.675 (16.112)	23.35 (15.432)	26 (17.060)	
	N4	30.188 (13.674)	30.25 (14.665)		30 (11.019)
All Periods	All Networks	20.401 (17.693)	20.270 (17.413)	17.707 (17.841)	23.959 (17.174)
	N1	23.647 (16.953)			23.647 (16.953)
	N2	18.9 (18.184)		18.9 (18.184)	
	N3	16.046 (16.974)	16.532 (16.937)	15.56 (17.018)	
	N4	23.879 (17.447)	23.385 (17.207)		25.362 (18.123)

Standard Deviation between brackets.

Table 3. Panel data random effects regressions. Contribution Levels.

	(1)	(2)
Constant	34.321 (3.454)***	14.561 (2.691)***
Round	-1.016 (.084)***	-0.692 (.076)***
N2	-4.747 (5.275)	-1.857 (2.550)
N3	-7.601 (3.606)**	-3.735 (1.900)**
N4	0.232 (3.552)	-0.835 (2.062)
FirstCont		0.237 (.039)***
LagAvgCont-i		0.397 (.046)***
N2 – N3	2.854 (4.690)	1.878 (2.045)
N3 – N4	-7.833 (2.605)***	-2.900 (1.621)*
N2 – N4	-4.980 (4.649)	-1.023 (2.372)
# Obs	2880	2736
R-sq:		
Between	0.0996	0.6528
Overall	0.1454	0.3810
Prob>chi2	0.0000	0.0000

***, **, and * denote statistical significance at the p < .01, p < .05, and p < .10 levels respectively.

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

	(3) N3	(4) N3	(5) N4	(6) N4
Constant	27.226 (3.469)***	17.015 (2.720)***	34.678 (1.324)***	10.241 (3.813)***
Round	-1.018 (.147)***	-0.790 (.126)***	-1.075 (.171)***	-0.658 (.157)***
T2	-0.972 (1.353)	-1.731 (1.351)		
T3			1.977 (2.042)	3.034 (2.431)
FirstCont		0.150 (.062)**		0.319 (.068)***
LagAvgCont-i		0.268 (.059)***		0.391 (.086)***
# Obs	800	760	640	608
R-sq:				
Between	0.0037	0.3739	0.0112	0.4400
Overall	0.1207	0.2210	0.1290	0.3110
Prob>chi2	0.0000	0.0000	0.0000	0.0000

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

Table 5. Contribution levels by types across networks

	T1 N3 vs. N4 (7)	T1 N3 vs. N4 (8)	T2 N2 vs. N3 (9)	T2 N2 vs. N3 (10)	T3 N1 vs. N4 (11)	T3 N1 vs. N4 (12)
Constant	34.193 (1.584)***	12.963 (2.824)***	27.972 (4.733)***	11.308 (2.921)***	36.225 (4.297)***	12.657 (3.240)***
Round	-1.029 (.112)***	-0.722 (.128)***	-0.864 (.128)***	-0.562 (.126)***	-1.198 (.161)***	-0.722 (.146)***
N3	-6.853 (2.842)**	-1.401 (1.793)	-3.34 (4.757)	-2.917 (2.377)		
N4					1.715 (3.894)	1.674 (2.102)
FirstCont		0.320 (.052)***		0.239 (.057)***		0.132 (.059)**
LagAvgCont-i		0.314 (.057)***		0.392 (.089)***		0.608 (.059)***
Nº Obs	880	836	1120	1064	880	836
R-sq:						
Between	0.1495	0.6245	0.0181	0.6846	0.0051	0.7396
Overall	0.1548	0.3371	0.0861	0.3841	0.1634	0.4473
Prob>chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

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

Table 6. Contribution levels by types and networks

Individual Contrib.	(13)	(14)
Constant	34.321 (3.455)***	14.475 (2.676)***
Round	-1.016 (.084)***	-0.691 (.077)***
N2	-4.747 (5.277)	-1.846 (2.541)
N3T1	-7.115 (3.716)*	-2.697 (1.853)
N3T2	-8.087 (3.613)**	-4.742 (2.257)**
N4T1	-0.262 (3.589)	-1.596 (2.194)
N4T3	1.715 (3.831)	1.432 (2.540)
FirstCont		0.238 (.038)***
LagAvgCont-i		0.398 (.047)***
N3	-7.601 (3.607)**	-3.719 (1.890)**
N4	0.232 (3.553)	-0.839 (2.057)
N2 – N3	2.854 (4.692)	1.874 (2.036)
N3 – N4	-7.833 (2.606)***	-2.881 (1.606)*
N2 – N4	-4.980 (4.650)	-1.006 (2.360)
N3T1 – N3T2	0.972 (1.301)	2.046 (1.663)
N4T1 – N4T3	-1.977 (1.937)	-3.028 (2.303)
N2T2 – N3T2	3.34 (4.696)	2.897 (2.381)
N3T1 – N4T1	-6.853 (2.801)**	-1.100 (1.749)
# Obs	2880	2736
R-sq:		
Between	0.1017	0.6594
Overall	0.1462	0.3833
Prob>chi2	0.0000	0.0000

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

Table 7. Alternative estimations of Model 1

	(1) GLS RE Subject cluster(Group)	GLS RE Subject	OLS	OLS cluster(Subject)	OLS cluster(Group)	Tobit RE Subject
Constant	34.321 (3.454)***	34.321 (1.756)***	34.321 (.825)***	34.321 (1.909)***	34.321 (3.454)***	40.311 (2.727)***
Round	-1.016 (.084)***	-1.016 (.043)***	-1.016 (.053)***	-1.016 (.066)***	-1.016 (.084)***	-1.494 (.066)***
N2	-4.747 (5.275)	-4.747 (2.400)**	-4.747 (.863)***	-4.747 (2.775)*	-4.747 (5.275)	-6.704 (3.737)*
N3	-7.601 (3.606)**	-7.601 (2.339)***	-7.601 (.841)***	-7.601 (2.068)***	-7.601 (3.606)**	-11.787 (3.637)***
N4	0.232 (3.552)	0.232 (2.474)	0.232 (.889)	0.232 (2.178)	0.232 (3.552)	-1.434 (3.838)
N2 vs. N3	2.854 (4.690)	2.854 (2.339)	2.854 (.841)***	2.854 (2.571)	2.854 (4.690)	5.083 (3.645)
N3 vs. N4	-7.833 (2.605)***	-7.833 (2.415)***	-7.833 (.868)***	-7.833 (1.911)***	-7.833 (2.605)***	-10.353 (3.749)***
N2 vs. N4	-4.980 (4.649)	-4.980 (2.474)**	-4.980 (.889)***	-4.980 (2.660)*	-4.980 (4.649)	-5.269 (3.847)
# Obs	2880	2880	2880	2880	2880	2880
	R-sq: **Between:** 0.0996 **Overall:** 0.1454	**R-sq:** **Between:** 0.0996 **Overall:** 0.1454	**R-sq:** 0.1454	**R-sq:** 0.1454	**R-sq:** 0.1454	
	Prob>chi2: 0.000	**Prob>chi2:** 0.000	**Prob>F:** 0.000	**Prob>F:** 0.000	**Prob>F:** 0.000	**Prob>chi2:** 0.000

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

RE = random effects; *cluster*(*var*) is implemented with the STATA option *vce*(*cluster var*)

Table 8. Alternative estimations of Model 2

	(2) GLS RE Subject cluster(Group)	GLS RE Subject	OLS	OLS cluster (Subject)	OLS cluster(Group)	Tobit RE Subject
Constant	14.561 (2.691)***	14.561 (1.543)***	11.331 (1.055)***	11.331 (1.817)***	11.331 (2.629)***	12.630 (2.767)***
Round	-0.692 (.076)***	-0.692 (.049)***	-0.586 (.052)***	-0.586 (.068)***	-0.586 (.077)***	-1.046 (.075)***
N2	-1.857 (2.550)	-1.857 (1.390)	-1.387 (.759)*	-1.387 (1.404)	-1.387 (2.051)	-2.636 (2.605)
N3	-3.735 (1.900)**	-3.735 (1.361)***	-2.925 (.749)***	-2.925 (1.483)**	-2.925 (1.550)*	-6.368 (2.540)**
N4	-0.835 (2.062)	-0.835 (1.426)	-0.940 (.776)	-0.940 (1.529)	-0.940 (1.744)	-3.181 (2.657)
FirstCont	0.237 (.039)***	0.237 (.032)***	0.214 (.018)***	0.214 (.036)***	0.214 (.035)***	0.345 (.060)***
LagAvgCont-i	0.397 (.046)***	0.397 (.021)***	0.507 (.019)***	0.507 (.041)***	0.507 (.060)***	0.548 (.034)***
N2 vs. N3	1.878 (2.045)	1.878 (1.348)	1.538 (.735)**	1.538 (1.368)	1.538 (1.606)	3.732 (2.531)
N3 vs. N4	-2.900 (1.621)*	-2.900 (1.412)**	-1.985 (.779)**	-1.985 (1.628)	-1.985 (1.474)	-3.188 (2.631)
N2 vs. N4	-1.023 (2.372)	-1.023 (1.440)	-0.447 (.788)	-0.447 (1.542)	-0.447 (2.006)	0.544 (2.693)
# Obs	2736	2736	2736	2736	2736	2736
R-sq: **Between** **Overall**	**R-sq:** **Between:** 0.6528 **Overall:**0.3810	**R-sq:** **Between:** 0.6528 **Overall:**0.3810	**R-sq:** 0.3863	**R-sq:** 0.3863	**R-sq:** 0.3863	
Prob>chi2	**Prob>chi2:** 0.000	**Prob>chi2:** 0.000	**Prob>F:** 0.0000	**Prob>F:** 0.0000	**Prob>F:** 0.0000	**Prob>chi2:** 0.000

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

RE = random effects; *cluster*(*var*) is implemented with the STATA option *vce*(*cluster var*)