Exp Econ (2010) 13: 399–411
DOI 10.1007/s10683-010-9248-2

An experimental analysis of team production in networks

Enrique Fatas · Miguel A. Meléndez-Jiménez · Hector Solaz

Received: 14 May 2008 / Accepted: 24 June 2010 / Published online: 13 July 2010

Abstract Experimental and empirical evidence highlights the role of networks on social outcomes. This paper tests 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 subject types in a standard linear team production game. Contribution levels differ significantly across networks and the star is the most efficient incomplete network. Moreover, our results suggest that subjects act as conditional cooperators with respect to the information received from the network.

Keywords Team production · Networks · Information

JEL Classification C92 · H41

Electronic supplementary material The online version of this article (doi:10.1007/s10683-010-9248-2) contains supplementary material, which is available to authorized users.

E. Fatas (✉) · H. Solaz
LINEEX, Universidad de Valencia, Valencia, Spain
e-mail: fatas@uv.es

Present address:
E. Fatas
ERI-CES Edificio Institutos, Campus Tarongers, 46022 Valencia, Spain

M.A. Meléndez-Jiménez
Departamento de Teoría e Historia Económica, Universidad de Málaga, Málaga, Spain

1 Introduction

The analysis of public goods games has been a mainstream topic in the field of experimental economics (see survey by Ledyard 1995). In the last decades, there is a huge experimental body analyzing how contributions for the provision of public goods react to changes in various features of the problem at hand.[1] However, the effects of the network structure of the group have not been examined.

The network structure of the group is of special relevance if we interpret the public goods game as a team production problem. In real-world organizations, it is rarely the case that all the members of a team interact directly with each other (i.e., the complete network), and a huge variety of structures is possible, represented by the set of networks that can be formed within the set of agents. Moreover, it is quite likely that each agent only observes the behavior of those with whom the agent 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 to know which kind of network structure provides the most efficient outcome. Modeling the team production problem as a linear public goods game, this paper studies whether subjects' behaviors change when we vary the observational structure. In that case, we aim to identify which network features foster high levels of contributions.

Our experiment considers 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 comprised of 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, subjects are not informed about the behavior of those who are not their neighbors.

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, each subject has two links and, in the complete network, each subject has three links (since we consider groups of four). The star and the line are asymmetric. In the star, all the subjects have a single link except for the central one, which has three. In the line, two subjects have two links each and the other two subjects have only one link each.[2] This design allows us to compare the behaviors of subjects with different numbers of links in the same (asymmetric) network, as well as of subjects with the same number of links in different networks.

We find that network structure is 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 largest average contribution, although its differences with the complete network are not statistically significant. The first round of the game already reveals differences in contributions across some networks, suggesting 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 individual contributions) makes a difference.

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

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

Moreover, we determine from the data whether players act as conditional cooperators, given the information that they receive from the network, that is, 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 a subject observes from neighbors in the previous round, as well as the first-round 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-round 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 this 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 presents our conclusions.

2 Related literature

The role of information in social dilemmas was first analyzed by Fox and Guyer (1978) in the lab. The authors 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, forthcoming) 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] The authors 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 traceable information. The observational structure (network) varies in each treatment: Each subject is informed about the contribution levels of a subset of the group members, determined by an exogenous network structure. It was not until very recently that certain experiments on networks were carried out in economics.[6] For example,

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

[4] Gachter 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).

Kirchkamp and Nagel (2007), Cassar (2007), and Riedl and Ule (2002) conducted experiments aimed at studying the role of networks in cooperation levels in prisoner's dilemma games, and Deck and Johnson (2004), Callander and Plott (2005), Falk and Kosfeld (2003), Berninghaus et al. (2006, 2007) examined network formation.[7]

Carpenter (2007) and Choi et al. (2005) may be the papers closest to ours. Carpenter (2007) was the first to introduce a network effect in a public goods experiment. In the author's design, subjects observe the contributions made by all group members and are able to monitor (punish) a subset of the group. He restricts the analysis to symmetric (monitoring) networks. Choi et al. (2005) implement three different directed network structures (star, circle, and complete network) to study observational learning in the lab. Our work studies 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, that is, if one player is linked to another player, the latter is also linked to the former. We classify 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. All our treatments follow a partners matching protocol, that is, the group composition is kept constant. Moreover, the subjects' positions within the network are randomly determined at the beginning of the experiment and kept fixed throughout all the rounds.

The experiment was computerized using z-Tree (Fischbacher 2007). In all the treatments, the groups repeatedly play the VCM game for 20 rounds. The network determines the observational structure, that is, after each round, the subjects are only able to observe the contribution levels of their neighbors.

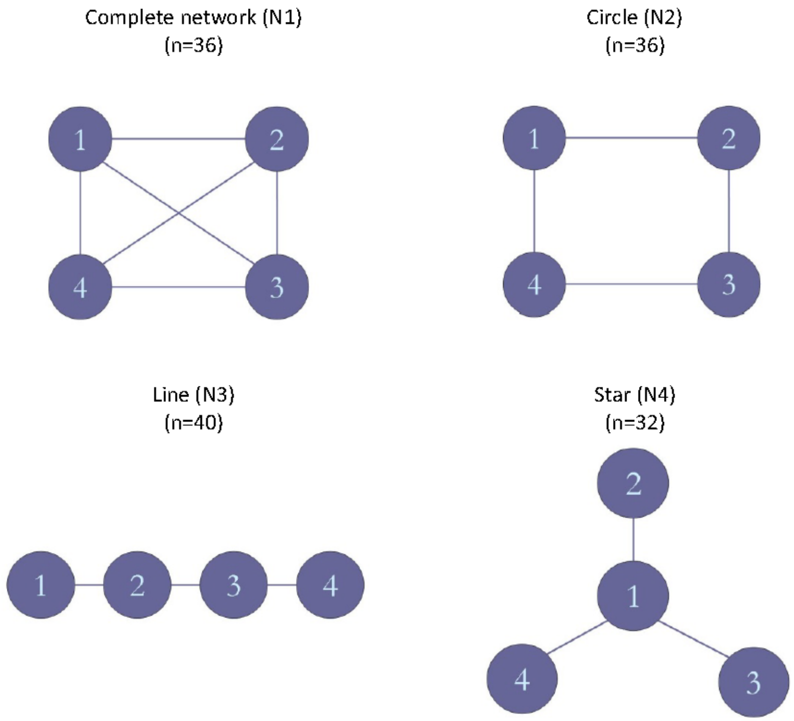
The game proceeds as follows.[9] At the beginning of each round, subjects are endowed with 50 experimental currency units (ECUs). Each subject $i \in G$ simultaneously makes a contribution c_i to the group account. Subjects make their choices by

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

[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.

[9] A translated version of the instructions is provided in the electronic supplementary material.

Table 1 Treatments



typing on a keyboard. 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 that subject's private account. Thus, at a particular round, subject i's earnings (in ECUs) are given by

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

After 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 the Laboratory for Research in Experimental Economics (LINEEX), at the University of Valencia. The participants consisted of 144 business and economics undergraduate students, all of them inexperienced in public goods games experiments or network experiments. We ran eight 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),

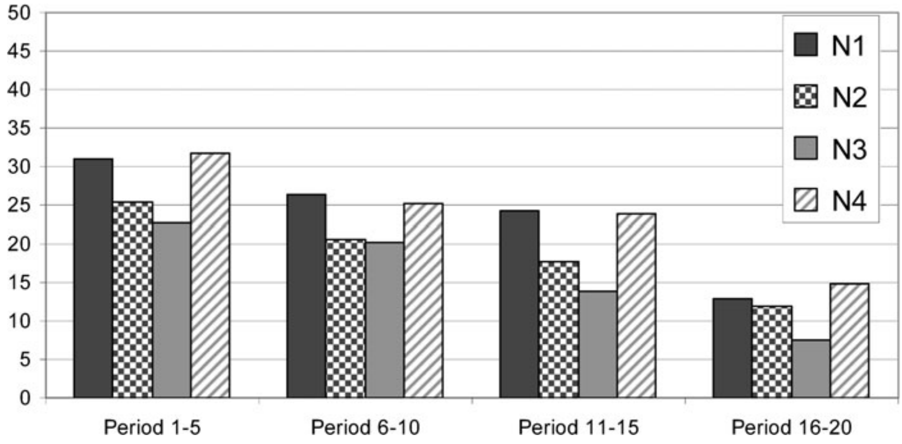


Fig. 1 Comparison of average network contributions

and 32 subjects participated in N4 (6 + 2 groups). The average payment was around 14€ and, on average, each session lasted around 50 minutes, including the initial instructions and the payment of subjects.

4 Experimental results

We divide the analysis into two parts. Section 4.1 examines the relation between networks and contribution levels. We determine that different organizational structures foster different contribution levels. In particular, the star is the best incomplete network. Then, we investigate the determinants of these differences. Section 4.2 investigates the behaviors of the different types of subjects. Within each asymmetric network (line and star), the behaviors of subjects of different types are not significantly different. In contrast, we find significant differences in the behaviors of some types of subjects across different networks.

4.1 Analysis of contributions across networks

Figure 1 shows the temporal path (in blocks of five rounds) of the average contribution to the public good for each treatment. Visual inspection reveals 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 remaining networks, and, in the last block of five rounds, the average contribution level in N4 is the highest.

Table 2 shows the average contribution levels, disaggregating by both network and type of subject. The upper part of Table 2 displays the first-round data, whereas the lower part averages 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

Table 2 Average contributions

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

Standard deviations in parentheses

the first round.[10] To check for statistical significance, we compute Mann–Whitney tests, which show that only the differences between N4 and N3 are significant at the 10% level.[11]

Given the nature of our data (a panel of subjects that interact in fixed groups), we rely on a more sophisticated (econometric) analysis to compare the individual contributions across networks throughout the 20 rounds. To this aim, Table 3 reports the results of two (panel data) models with random effects at the individual level.[12]

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

[11] In the first round, since there is no prior interaction, we can consider all the observations as independent. Thus, we perform the Mann–Whitney tests using all the individual contributions.

[12] In all the models discussed in Sect. 4, we use generalized least squares estimations and adjust the standard errors to account for the fact that observations are not independent within groups (using a relatively conservative clustering approach due to Liang and Zeger 1986). Moreover, in all the models we use random-effects estimations. Fixed-effects models would prevent us from estimating the coefficient of

Table 3 Panel data random effects regressions: contribution levels

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

Here ***, **, and * denote statistical significance at the $p < .01$, $p < .05$, and $p < .10$ levels, respectively. Standard deviations in parentheses

In model 1, we analyze how the repetitions of the game and the network structure affect the contribution levels. To this aim, we consider *round* (from 1 to 20) and four treatment dummies, N1, N2, N3, and N4, as independent variables. Each dummy takes on the value of one if the observation comes from a subject allocated in the

any time-invariant regressor, like network and type dummies, i.e. those ones that we are most interested in. Even if in some cases (models 2, 10 and 12) Hausman tests suggest the use of fixed-effects estimations, the results (coefficients and significances of the time-variant regressors) do not change with respect to the random-effects estimations that we report. Note that, in any case, the results of the Hausman tests should be interpreted with caution, since the tests require using regressions that do not correct the standard errors at the group level. We also note that, in all our models, the Breusch and Pagan Lagrange multiplier test for random effects yields a significant chi2-test statistic, which supports the use of the random-effects estimator. We use the software Stata.

corresponding network, and zero otherwise. As has been found in many other public goods game experiments, contributions decline significantly over time. To check for significant differences in contribution levels across networks, we perform pairwise comparisons of the dummies coefficients 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.[13] This result is not surprising, since N1 and N2 are equivalent in informational terms.[14]

In model 2, we analyze whether the differences observed in the previous model come from dissimilar dynamics in each network. To this end, 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 fewer differences across networks.[15] Hence, given the (different) initial contribution levels of each network, a dynamic where subjects act as conditional cooperators with respect to the information received from the network is likely to explain the behavior in the VCM.

4.2 Analysis of contributions by types

Table 2 also allows us to 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, and 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

[13] All the results of model 1 are robust to a nonparametric analysis that compares average group contributions across networks by means of Mann–Whitney tests. See the working paper version of this manuscript, Fatas et al. (2010), for details.

[14] Note that each subject is informed about the earnings from the public good. Thus, in N2, an easy calculation allows each subject to infer the contribution of the only member of the group not linked to her.

[15] 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.

Table 4 Contribution levels by type within each heterogeneous network

	(3) N3	(4) N3	(5) N4	(6) N4
Constant	27.226***	17.015***	34.678***	10.241***
	(3.469)	(2.720)	(1.324)	(3.813)
Round	−1.018***	−0.790***	−1.075***	−0.658***
	(.147)	(.126)	(.171)	(.157)
T2	−0.972	−1.731		
	(1.353)	(1.351)		
T3			1.977	3.034
			(2.042)	(2.431)
FirstCont		0.150**		0.319***
		(.062)		(.068)
LagAvgCont-i		0.268***		0.391***
		(.059)		(.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

Here ***, **, and * denote statistical significance at the $p < .01$, $p < .05$, and $p < .10$ levels, respectively. Standard deviations in parentheses

in N3, and T3 subjects contribute around 7% more in N4 than in N1.[16] To provide a formal analysis of the effects of the subjects' types on contributions throughout the 20 rounds, Tables 4 and 5 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).

In Table 4, we analyze the differences in contribution levels between types within each asymmetric network. In models 3 and 5, the independent variables are *round* and three dummies (T1, T2, and T3). Each dummy takes on the value of 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 (four) models, we conclude that there are no significant differences between types within any asymmetric network. Moreover, as in model 2, *FirstCont* and *LagAvgCont-i* are also positive and significant in models 4 and 6.

In Table 5, we study whether subjects of the same type act differently across networks. In models 7 to 12, using the dummies N1, N2, N3, and N4, we analyze whether there are differences in contribution levels across networks for each type of subject. In models 9 and 10, no significant differences in the contribution levels of T2 subjects between N2 and N3 are observed. Similarly, in models 11 and 12, there

[16]Note that the (magnitude of the) differences in the average contributions of the 20 rounds across types mimic the differences already observed in the first round.

Table 5 Contribution levels by type 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***	12.963***	27.972***	11.308***	36.225***	12.657***
	(1.584)	(2.824)	(4.733)	(2.921)	(4.297)	(3.240)
Round	−1.029***	−0.722***	−0.864***	−0.562***	−1.198***	−0.722***
	(.112)	(.128)	(.128)	(.126)	(.161)	(.146)
N3	−6.853**	−1.401	−3.34	−2.917		
	(2.842)	(1.793)	(4.757)	(2.377)		
N4					1.715	1.674
					(3.894)	(2.102)
FirstCont		0.320***		0.239***		0.132**
		(.052)		(.057)		(.059)
LagAvgCont-i		0.314***		0.392***		0.608***
		(.057)		(.089)		(.059)
# 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

Here ***, **, and * denote statistical significance at the $p < .01$, $p < .05$, and $p < .10$ levels, respectively. Standard deviations in parentheses

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.[17]

5 Conclusions

Several results in previous research show that information is an important feature to understand cooperation in public good games. The provision of information raises

[17] In Fatas et al. (2010), we complement our results with an additional section, in which we jointly analyze network and type effects by means of interaction terms. We find that all our results are robust to such a specification.

contribution levels in team production. This paper analyzes 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 structures of teams significantly affect contribution levels.

Our results have some interesting implications from an organizational point of view. Information matters (the contribution levels observed in N1 and in N4 are significantly larger than in N3), but the relation between the number of links and the team's performance 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) furthers the evolution of cooperation. Moreover, our results support the idea that subjects act as conditional cooperators, given the information they receive from the network.

Acknowledgements We thank Antonio J. Morales, María E. Rochina-Barrachina, Laura Crespo and Alicia Pérez-Alonso for their comments and suggestions. We are also especially thankful to two anonymous referees and the editor, whose detailed comments helped us improve the quality of the manuscript and shape the exposition. The usual disclaimers apply. Financial support from Ministerio de Innovación y Ciencia (BES-2007-17089 and ECO2008-04424), Conselleria d'Educació de la Generalitat Valenciana (GRIECES Prometeo Grant), and Junta de Andalucía (SEJ2007-2986 and SEJ1586) is gratefully acknowledged.

References

Andreoni, J., & Petrie, R. (2004). Public goods experiments without confidentiality: a glimpse into fundraising. *Journal of Public Economics*, *88*, 1605–1623.

Berninghaus, S. K., Ehrhart, K., & Ott, M. (2006). A network experiment in continuous time: the influence of link costs. *Experimental Economics*, *9*, 237–251.

Berninghaus, S. K., Ehrhart, K., Ott, M., & Vogt, B. (2007). Evolution of networks—an experimental analysis. *Journal of Evolutionary Economics*, *17*, 317–347.

Callander, S., & Plott, C. R. (2005). Principles of network development and evolution: an experimental study. *Journal of Public Economics*, *89*, 1469–1495.

Carpenter, J. P. (2007). Punishing free-riders: how group size affects mutual monitoring and the provision of public goods. *Games and Economic Behavior*, *60*, 31–55.

Cason, T., & Khan, F. (1999). A laboratory study of voluntary public goods provision with imperfect monitoring and communication. *Journal of Development Economics*, *58*, 533–552.

Cassar, A. (2007). Coordination and cooperation in local, random and small world networks: experimental evidence. *Games and Economic Behavior*, *58*, 209–230.

Choi, S., Gale, D., & Kariv, S. (2005). Behavioral aspects of learning in social networks: an experimental study. In J. Morgan (Ed.) *Behavioral and experimental economics*: *Vol. 13*. *Advances in applied microeconomics*.

Croson, R., & Marks, M. (1998). Identifiability of individual contributions in a threshold public goods experiment. *Journal of Mathematical Psychology*, *42*, 167–190.

Deck, C., & Johnson, C. (2004). Link bidding in a laboratory experiment. *Review of Economic Design*, *8*(4), 359–372.

Eckel, C., Fatas, E., & Wilson, R. (2009, forthcoming). An experimental analysis of status in organizations. *Journal of Public Economic Theory*.

Falk, A., & Kosfeld, M. (2003). *It's all about connections: evidence on network formation* (IZA discussion paper no. 777).

Fatas, E., Godoy, S., & Solaz, H. (2009). *Low powered monitoring systems in team production: an experimental analysis* (LINEEX working paper). University of Valencia.

Fatas, E., Meléndez-Jiménez, M. A., & Solaz, H. (2008). *Cooperation, punishment and networks* (Mimeo). LINEEX.

Fatas, E., Meléndez-Jiménez, M. A., & Solaz, H. (2010). *An experimental analysis of team production in networks* (Discussion Papers in Economic Behaviour 2010-03). ERICES (available at http://www.erices.es/upload/workingpaper/6_0310.pdf).

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

Fischbacher, U., Gächter, S., & Fehr, E. (2001). Are people conditionally cooperative? Evidence from a public goods experiment. *Economic Letters*, *71*(3), 397–404.

Fox, J., & Guyer, M. (1978). Public choice and cooperation in n-person prisoner's dilemma. *Journal of Conflict Resolution*, *22*(3), 469–481.

Gachter, S., Fehr, E., & Kment, C. (1996). Does social exchange increase voluntary cooperation? *Kyklos*, *49*(4), 541–554.

Goyal, S. (2005). Learning in networks. In G. Demange & M. Wooders (Eds.), *Group formation in economics: networks, clubs and coalitions*. Cambridge: Cambridge University Press.

Jackson, M. O. (2005). A survey of network formation models: stability and efficiency. In: G. Demange & M. Wooders (Eds.), *Group formation in economics: networks, clubs and coalitions*. Cambridge: Cambridge University Press.

Kirchkamp, O., & Nagel, R. (2007). Naive learning and cooperation in network experiments. *Games and Economic Behavior*, *58*, 269–292.

Kosfeld, M. (2004). Economic networks in the laboratory: a survey. *Review of Network Economics*, *3*, 20–41.

Ledyard, J. (1995). Public goods: a survey of experimental research. In A. Roth & J. Kagel (Eds.), *The Handbook of Experimental Economics*. Princeton: Princeton University Press.

Liang, K.-Y., & Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, *73*, 13–22.

Riedl, A., & Ule, A. (2002). *Exclusion and cooperation in social network experiments* (Mimeo). University of Amsterdam.

Zelmer, J. (2003). Linear public goods experiments: a meta-analysis. *Experimental Economics*, *6*(3), 299–310.