

جامعة نيويورك أبوظبي

 NYU | ABU DHABI



# **Social Networks and Organizational Helping Behavior: Experimental Evidence from the Helping Game**

**Ernesto Reuben and Hande Erkut**

**Working Paper # 0090**

**May 2023**

Division of Social Science Working Paper Series

New York University Abu Dhabi, Saadiyat Island P.O Box 129188, Abu Dhabi, UAE

<http://nyuad.nyu.edu/en/academics/academic-divisions/social-science.html>

# Social networks and organizational helping behavior: Experimental evidence from the helping game

Hande Erkut

WZB Berlin Social Science Center, email: [hande.erkut@wzb.eu](mailto:hande.erkut@wzb.eu)

Ernesto Reuben

New York University Abu Dhabi, Center for Behavioral Institutional Design,  
Luxembourg Institute of Socio-Economic Research, email: [ereuben@nyu.edu](mailto:ereuben@nyu.edu)

## Abstract

This paper studies the causal impact of social ties and network structure on helping behavior in organizations. We introduce and experimentally study a game called the ‘helping game,’ where individuals unilaterally decide whether to incur a cost to help other team members when helping is rivalrous good. We find that social ties have a strong positive effect on helping behavior. Individuals are more likely to help those with whom they are connected, but the likelihood of helping decreases as the social distance between individuals increases. Additionally, individuals who are randomly assigned to be more central in the network are more likely to help others.

This version: May 2023

*Acknowledgements:* We gratefully acknowledge financial support from Tamkeen under the NYU Abu Dhabi Research Institute Award CG005 and from the Russell Sage Foundation small grants program in behavioral economics.

# 1 Introduction

The success of organizations greatly depends on the helping behavior of its members. Organizational helping behavior has been investigated in many empirical studies<sup>1</sup> and has been shown to be responsible for enhanced organizational performance (e.g., Sundstrom et al., 1990; Cohen and Bailey, 1997; Podsakoff et al., 2000; Chiaburu and Harrison, 2008). Although helping plays a crucial role in understanding performance in organizations, economists have not given much attention to organizational helping behavior, unlike other types of prosocial behavior such as generosity and cooperation.

In this paper, we experimentally study organizational helping behavior. We introduce a new game called the “helping game,” where each person unilaterally decides whether to help as many group members as they want. In the game, helping is costly to the helper but is beneficial to the group member being helped such that it increases total payoffs. Hence, the most efficient outcome occurs when everyone helps each other. Importantly, even though helping more people is more efficient, the more people a person helps, the smaller the benefit received by each individual helped. In other words, helping is rivalrous. Our game is related to, but is distinct from, two games that examine prosocial behavior: dictator games and common pool resource games. Dictator games (Forsythe et al., 1994) measure generosity. Namely, how much money people give away unilaterally to others. Our helping game is different because the benefits of helping are rivalrous, and there is scope for group members to help each other. Common pool resource games (Ostrom et al., 1994) capture individuals’ willingness to cooperate to preserve a rivalrous common resource. Unlike our helping game, cooperation in the common pool resource game benefits everyone in the group. In other words, the benefits of cooperation are non-excludable, whereas in the helping game, individuals can help a subset of people in their group and exclude others.<sup>2</sup>

An important empirical finding from field studies is that helping behavior is strongly associated with social ties (e.g., Stoller and Pugliesi, 1991; Hill et al., 2021). However, since these studies use correlational data, it is hard to identify whether social ties promote helping or whether helping leads to the formation of social ties. We examine the causal impact of social ties and network structure on helping behavior by varying exogenously the social network of group members in the helping game. We implemented five different network structures and randomly assigned group members to positions in these networks to systematically study the

---

<sup>1</sup>Helping in organizations is examined in the context of organizational citizenship behavior (Organ, 1988), prosocial organizational behavior (Brief and Motowidlo, 1986), organizational spontaneity (George and Brief, 1992), contextual performance (Borman and Motowidlo, 1993), and extra-role behavior (Van Dyne et al., 1995).

<sup>2</sup>Our helping game is also distinct from public goods games, which has been studied extensively by experimental economists (for a review of the literature, see Ledyard, 1995; Chaudhuri, 2011). The public goods game differs from the helping game as it studies cooperation to provide goods that are both non-excludable and non-rivalrous.

effect of two important characteristics: distance between nodes and degree centrality.

As suggested by the contact hypothesis of Allport et al. (1954), social distance in networks—the length of the shortest path length between two individuals—has been shown to be an important determinant for prosocial behavior (e.g., Hoffman et al., 1996; Charness and Gneezy, 2008; Leider et al., 2009; Goeree et al., 2010; Branas-Garza et al., 2010; Fatas et al., 2010). Hence, the distance between two group members is potentially an important determinant of helping behavior in the helping game. Unlike previous studies that measure social distance in existing friendship networks (e.g., Leider et al., 2009; Goeree et al., 2010; D’Exelle and Riedl, 2013), we induce social ties between strangers and exogenously vary the distance between them in the social network. This method allows us to randomly assign distance and measure its causal effect on helping. We expect that participants will be more likely to help those with whom they are linked but that this likelihood will decrease as the distance between two group members increases.

A second network characteristic that has been shown to predict prosocial behavior is degree centrality. Namely, it is often found that individuals with a higher number of ties tend to be more cooperative and more likely to help others (e.g., Farmer and Rodkin, 1996; Settoon and Mossholder, 2002; Wasko and Faraj, 2005; D’Exelle and Riedl, 2013). However, a longstanding question in this literature is whether this empirical finding is due to more prosocial individuals forming more ties or because having ties makes individuals more prosocial (Burt, 1992; Simpson and Willer, 2015). By randomly assigning individuals to varying levels of degree centrality, we can test whether higher degree centrality alone increases an individual’s propensity to help others.

We randomly generate social ties between group members in the helping game by allowing participants to communicate with chat messages with some participants but not with others. Introducing communication in our experiment mirrors two defining features of social ties in organizations (Lott and Lott, 1965; Carron et al., 1985). First, there is compelling evidence that free-form communication foments closer emotional interactions and enhances group identities (e.g., Chen and Li, 2009; Bichieri et al., 2010; Andreoni and Rao, 2011; Kuwabara, 2011; Brandts et al., 2016; Wang and Houser, 2019). Second, communication has been shown to be a very effective way of aligning expectations to reduce strategic uncertainty and facilitate coordination (see Duffy and Feltovich, 2002; Brandts and Cooper, 2007; Brandts et al., 2019). Given these effects of communication, it is not surprising that it has been used to measure social networks in various settings (Schwartz and Wood, 1993; Diesner et al., 2005; Kossinets and Watts, 2006; Panzarasa et al., 2009). In addition, studying the impact of communication *per se* is of interest given that communication and productivity have been found to be positively correlated in organizations (Hellweg and Phillips, 1982).

Our results show that social ties have a strong positive effect on helping behavior, but their

impact depends on the network structure. First, while individuals who are connected in the social ties network are more likely to help each other, the likelihood of helping decreases as the distance between them increases. Second, we find that individuals who were randomly assigned to more central positions have higher helping rates. Interestingly, the impact of social ties on helping can be fully accounted for by the combined effects of distance between nodes and degree centrality. Finally, we find that social ties matter not only to establish helping behavior but also to sustain this behavior over time. Specifically, distance in the network and degree centrality are still significant determinants of helping for pairs of individuals with an established history of mutual help.

This paper is related to the literature that examines ‘helping’ using laboratory experiments. In this literature, helping is studied in the context of indirect reciprocity. Namely, acting prosocially towards a stranger because they have been prosocial to others (Nowak and Sigmund, 1998). This research demonstrates that helping as indirect reciprocity is common (e.g., Wedekind and Milinski, 2000; Seinen and Schram, 2006) and is substantially motivated by reputation-building considerations (Engelmann and Fischbacher, 2009). Our conceptualization of helping behavior is very different. In our game, individuals can help more than one person, and help occurs within a group of people who interact with each other repeatedly. Moreover, we focus on understanding how different social networks impact overall helping.

This paper also contributes to the larger experimental literature on prosocial behavior and communication using games such as the dictator, common-pool resource, and public good games. Within this literature, it is a well-established result that free-form communication, which fosters social ties, has a strong positive effect on prosocial behavior (Davis and Holt, 1993; Ostrom, 2000; Chaudhuri, 2011). This literature mostly focuses on the complete communication network, where everybody can communicate with each other. Nevertheless, there are some studies that focus on other communication structures. These include one-way communication (e.g., Koukoulis et al., 2012; Andreoni and Rao, 2011), communication within subgroups (e.g., Polzer et al., 2001; Angelovski and Reuben, 2023), and communication when some individuals are excluded (Abbink et al., 2021). These studies typically find that partial communication works less well in promoting prosocial behavior compared to cases where all individuals in the group can communicate with each other.<sup>3</sup> Our study contributes to this literature by showing that differences in prosocial behavior between different communication structures can be quantified as the effect of two network characteristics: distance and degree centrality.

Finally, this paper contributes to the literature on the effects of different communication network structures on coordination games.<sup>4</sup> The findings of this literature suggest that network

---

<sup>3</sup>In contest settings, intra-group communication has been found to increase effort, whereas inter-group communication decreases it (Sutter and Strassmair, 2009; Cason et al., 2012, 2017).

<sup>4</sup>There is also a literature that focuses on the effects of network structure on actions. See Kosfeld (2004) and

characteristics, such as clustering and centrality, matter for the outcome. For instance, Charness et al. (2021) show that a zero-clustering network promotes more efficient coordination than a positive-clustering network in stag hunt games. Brandts and Cooper (2018) show that, in a decentralization game, the total surplus is higher in a centralized network structure than in a decentralized network structure due to better coordination between divisions of a firm. Finally, Choi and Lee (2014) find that complete networks (as opposed to star, kite, and line networks) promote the highest rate of coordination and the most symmetric distribution of outcomes in a battle of the sexes game. They also show that one’s position in the network matters: hub players manage to coordinate more often on their favorable outcome than periphery players.

## 2 Experimental design

### 2.1 Helping game

In the helping game consists of  $i \in \{1, \dots, n\}$  players in an organization. Each player  $i$  simultaneously decides whether or not to help each other player  $j \neq i$ ,  $h_{i \rightarrow j} \in \{0, 1\}$ . Helping is costly to the helper but benefits the player being helped. More specifically, if we denote the number of players  $i$  helps as  $H_i = \sum_{j \neq i}^n h_{i \rightarrow j}$ , then  $i$ ’s total cost of helping is given by the cost function  $C_i(H_i)$  and the benefit to each player  $j$  that  $i$  helps is given by the benefit function  $b_{i \rightarrow j}(H_i)$ . Thus,  $i$ ’s payoff is given by

$$\pi_i = \sum_{j \neq i}^n h_{j \rightarrow i} \times b_{j \rightarrow i}(H_j) - C_i(H_i).$$

To describe the characteristics of the helping game, it helps to denote the total benefit generated by  $i$ ’s help as  $B_i(H_i) = \sum_{j \neq i}^n h_{i \rightarrow j} \times b_{i \rightarrow j}(H_i)$  and the efficiency of  $i$ ’s help as  $E_i(H_i) = B_i(H_i) - C_i(H_i)$ . We assume that helping increases efficiency, i.e.,  $E_i' > 0$ , but this increase is decreasing in the number of players  $i$  helps,  $E_i'' < 0$ . Moreover, we also assume that all players that  $i$  helps receive the same individual benefit from  $i$ ’s help and this benefit is decreasing in the number of players helped by  $i$ .

In the experiment, we implement organizations of  $n = 6$  subjects. Each subject in an organization is identified with a label: A, B, C, D, E, or F. The costs and benefits of helping (in points) are shown in Table 1. Hence, for example, if subject A helps only C and F, then both C and F get 63 points from A’s help, the total benefit generated by A is 126 points, A’s total cost of helping is 38 points, and the increase in efficiency is 89 points. Note that C and F do not need to help A to receive the benefits generated by A’s helping decision.

Subjects played the helping game for 15 periods. The composition of the organizations and the subjects’ labels did not change during the experiment.

---

Choi et al. (2016) for reviews of this literature.

**Table 1. Helping payoff matrix for subject  $i$** 

The number of people $i$ helps $H_i$	Total cost of $i$ 's help $C_i(H_i)$	Total benefit of $i$ 's help $B_i(H_i)$	Benefit received by each a person helped by $i$ $B_i(H_i)/H_i$
0	-	-	-
1	25	75	75
2	37	126	63
3	45	165	55
4	52	192	48
5	58	210	42

## 2.2 Procedures

The experiment was programmed in z-Tree (Fischbacher 2007) and was conducted at the Behavioral and Experimental Laboratory (BEELab) of Maastricht University in November 2016. Subjects were undergraduate students recruited with ORSEE (Greiner 2015). We used standard experimental economics procedures such as monetary incentives, anonymous interaction, neutral framing, and no deception.

Upon arrival, each subject was randomly assigned to a seat in the laboratory. After that, subjects read the instructions and answered a few understanding questions (the instructions are available in Appendix D). Once everyone was ready, subjects played the fifteen periods of the helping game.

To facilitate subjects' understanding of the consequences of their helping decisions, we used an interactive screen. The screen shows a visual representation of who the subject is helping and the benefit each person receives as a result of their help. Subjects could also observe who they helped and who helped them in previous periods. The screen is presented in Figure A1 and is explained in detail in Appendix A.

To avoid losses, each subject started each period with an endowment of 100 points. At the end of the experiment, the points from all 15 periods were summed up, converted to money, and paid to the subjects in private. Points were converted to Euros at a rate of 100 points = €0.56. Average earnings were around €20.00, and the experiment lasted around 45 minutes. In total, we have 258 subjects playing in 43 organizations.

## 2.3 Communication

To generate social ties between group members, we allow participants to communicate with each other according to a communication network. We implement five different communication networks to capture different types of social structures typically found in organizations.

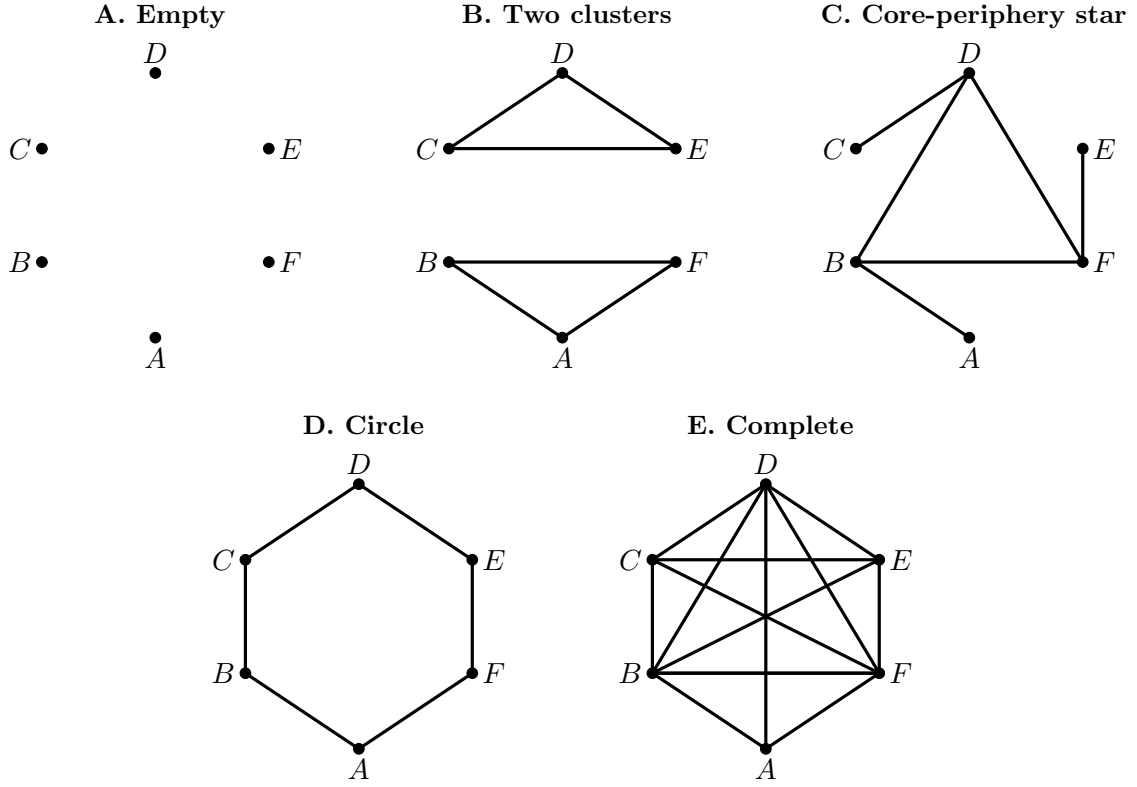


Figure 1. Communication networks used in the experiment

Organizations were randomly assigned to one of these networks, which remained unchanged throughout the entire experiment. In all networks with communication, subjects get the chance to chat for three minutes at the beginning of every third period, starting from the first period.<sup>5</sup> Subjects can chat freely but are instructed not to reveal identifying information or use bad language.

The five different communication networks are visualized in Figure 1. They are:

- a The **empty** network in which there is no communication between subjects.
- b The **two clusters** network in which the organization is divided into two separate groups. Subjects communicate within their group, and there is no communication between groups. In this network, we implement one chat box for each group.
- c The **core-periphery star** network in which there is a core of three subjects who are connected to each other and a periphery of three subjects, each connected to one of the subjects in the core. We implemented this by giving subjects in the core two chat boxes, one to communicate with their periphery subject and the other to communicate

<sup>5</sup>As Bochet et al. (2006) and Muñoz Herrera and Reuben (2023), we introduce the communication stage every three periods instead of every period so that the experiment does not last too long. The effect of communication has been shown to be strong enough to promote prosociality even if it does not occur every period (e.g., see Bochet et al., 2006; Koukoumelis et al., 2012; Muñoz Herrera and Reuben, 2023).



simultaneously with all core subjects.

d The **circle** network in which each subject communicates independently with their two direct neighbors. For example, in Figure 1D, subject A can communicate with B and F in separate chat boxes.

e The **complete** network in which all six subjects can communicate with each other in a single chat box.

We use these networks because they are often used as stylized models of different social structures, and some of them emerge as the equilibrium outcome in various theoretical models of social network formation (for an overview, see Goyal, 2023). They are also used in studies of communication within organizations (Choi and Lee, 2014).

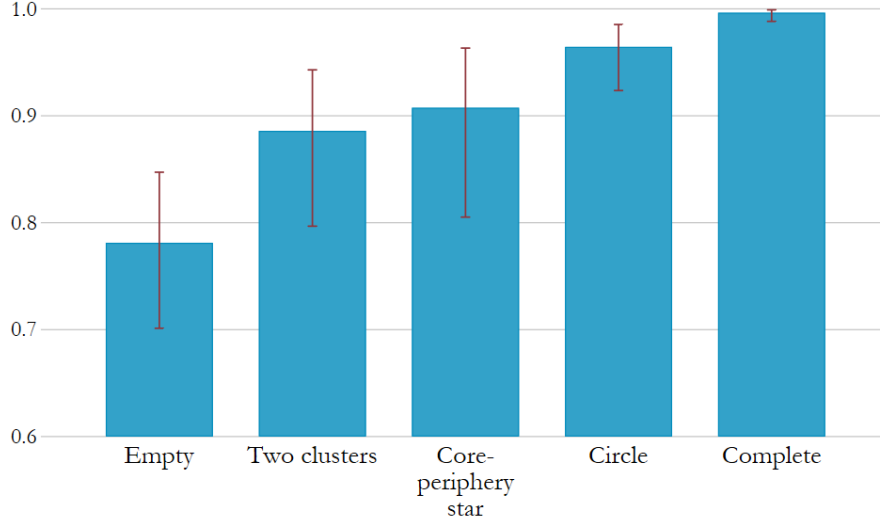
### 3 Empirical strategy

We measure the effect of social ties on helping through different channels. We model subject  $i$ 's decision to help subject  $j$  as a function of network characteristics and their position in the network. Specifically, subject  $i$ 's likelihood to help group member  $j$  is given by:

$$h_{ij} = \alpha + \beta\delta^{d_{ij}-1} + \gamma n_i + \zeta K. \quad (1)$$

The equation has the following parameters.

- $\alpha$  is a constant that captures the likelihood of helping without social ties.
- $\beta$  is the weight subjects give to social distance as a motivation for helping. In line with the contact hypothesis (Allport et al., 1954) and the empirical literature on the impact of social networks on prosocial behavior (Hoffman et al., 1996; Charness and Gneezy, 2008; Leider et al., 2009; Goeree et al., 2010; Branas-Garza et al., 2010; Fatas et al., 2010), we model the effect of social distance as a function of the shortest path length between subjects in the social network. The variable  $d_{ij}$  equals the shortest path length between  $i$  and  $j$ . For example, if  $i$  and  $j$  can communicate with each other directly, then  $d_{ij} = 1$ , while if they cannot communicate directly but have a common neighbor with whom they both communicate, then  $d_{ij} = 2$ . If there is no communication path between  $i$  and  $j$ , then  $d_{ij} = \infty$ . Following the literature on social networks, we allow the effect of social distance to depend on a parameter  $\delta \in (0, 1]$ , which captures the rate at which the impact of social ties decays as the distance between subjects increases (Jackson and Wolinsky, 1996; Bala and Goyal, 2000). If  $\delta < 1$ , there is some decay, and if  $\delta = 1$ , there is no decay.
- $\gamma$  captures the effect of a subject's randomly-assigned position in the network. Specifically, it measures the impact of their degree centrality  $n_i$  (i.e., the number of subjects  $i$  can directly communicate with) on their helping behavior.



**Figure 2. Probability of helping another subject by network structure**

- $K$  is the dummy variable that takes a value of 1 if there are any social ties within the organization and 0 otherwise. Hence, the coefficient  $\zeta$  captures the effect of social ties on helping that cannot be explained by social distance or degree centrality.

If we assume that all these parameters have positive values, we can predict that the total amount of help in the different networks will have the following ordering: **complete** > **circle** = **core-periphery star** > **two clusters** > **empty** (see Appendix C for details).<sup>6</sup> In the next section, we will use the exogenous variation in the presence of social ties, social distance, and degree centrality induced by randomly assigning subjects to the different networks and to positions within those networks to estimate the value of each parameter.

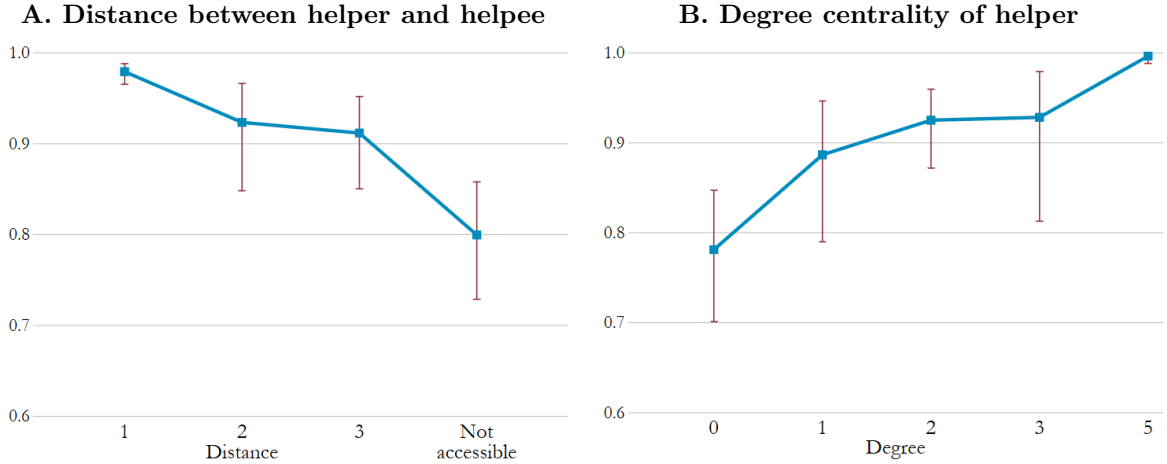
## 4 Results

A first look at the data suggests that helping is common in our experiment. Figure 2 depicts the mean helping rate in each network (bars) and their corresponding 95% confidence intervals (error bars). To test whether differences in helping between network structures are statistically significant, we run a probit model with the subjects helping decision as the dependent variable and network dummies as independent variables. We use subject random effects and cluster standard errors at the organization level. We evaluate differences between coefficients with pairwise Wald tests.<sup>7</sup>

Without the possibility to communicate, subjects manage to help each other substantially.

<sup>6</sup>The predicted total amount of help equals  $6 \times (\alpha + \beta\delta + 5\gamma + \zeta)$  in **complete**,  $6 \times (\alpha + \frac{1}{5}\beta(2\delta^1 + 2\delta^2 + \delta^3) + 2\gamma + \zeta)$  in **circle** and **core-periphery star**,  $6 \times (\alpha + \frac{2}{5}\beta\delta^1 + 2\gamma + \zeta)$  in **two clusters**, and  $6 \times \alpha$  in **empty**.

<sup>7</sup>Our results carry through with other specifications, such as a linear probability model, or with pairwise non-parametric tests with organization means as observations.



**Figure 3. Likelihood of helping another subject by social distance and degree centrality**

In the **empty** network, the helping rate is 78.1%. This high helping rate is consistent with the literature showing that the possibility of exclusion in networks is a strong motivator for cooperative behavior (e.g., Cinyabuguma et al., 2005).

In line with the literature on the effects of communication on prosocial behavior, when subjects are able to communicate with everyone in their organization, helping becomes ubiquitous. The helping rate in the **complete** network is 99.6%.

Interestingly, consistent with the idea that communication foments social ties, the helping rate in the three networks with partial communication is significantly higher than in the **empty** network ( $p < 0.024$ ) but significantly lower than in the **complete** network ( $p < 0.003$ ).<sup>8</sup>

#### 4.1 Help and social network characteristics

In this subsection, we analyze whether the differences in help observed between the various network structures can be explained by the social distance between subjects and their degree centrality.

Figure 3A shows the mean likelihood that a subject helps someone depending on the social distance between them. The likelihood of helping is lowest when two subjects are not accessible to each other and gradually increases as the social distance between them decreases. Figure 3B shows the mean likelihood of helping depending on the number of other subjects a subject has social ties with. The likelihood of helping others increases with degree centrality.

Next, we evaluate the impact of social distance and degree centrality simultaneously by estimating the parameters of equation 1 using non-linear least squares regressions. In all regressions, we cluster standard errors on organizations. The estimated parameters, in percentage

<sup>8</sup>Pairwise tests indicate that the helping rate in the **circle** network is significantly higher than in **two clusters** ( $p = 0.013$ ) but not higher than in the **core-periphery star** ( $p = 0.145$ ). There is no difference between the **two clusters** and the **core-periphery star** ( $p = 0.489$ ).

points, are shown in Table 2.<sup>9</sup>

In regression I, we include only the constant  $\alpha$ , which captures the likelihood of helping without social ties, and  $\zeta$ , which in this regression captures the mean effect of social ties on helping across all network structures. On average, helping in networks with social ties is 15.7 percentage points higher.

In regression II, we add the parameters measuring the effect of social distance between the helper and the helpee,  $\beta$  and  $\delta$ . The estimated parameters suggest that being able to directly communicate with a helpee significantly increases the likelihood of helping by 14.7 percentage points (compared to the **empty** network). The fact that  $\delta$  is significantly positive further shows that indirect communication also increases help. Moreover, the fact that the estimated  $\delta$  is less than one suggests that the effect of communication decays with social distance. For example, the point estimate for  $\delta$  implies that having a social distance of  $d_{ij} = 2$  increases the likelihood of helping by 10.0 percentage points. However, we should note that the estimated  $\delta$  is not significantly different from one (Wald test,  $p = 0.133$ ), and hence we cannot conclusively say whether there is decay.<sup>10</sup> Interestingly, once we account for the impact of social distance, the estimate for  $\zeta$  shrinks to less than a third and is no longer statistically significant, suggesting that social distance explains a substantial fraction of the impact of social ties on helping.

In regression III, we include the parameter for degree centrality,  $\gamma$ . We find that even after accounting for the effect of social distance, there is a small but positive effect of degree centrality. Namely, being randomly assigned to a more central position in the network significantly increased the subjects' helping behavior. Accounting for degree centrality further decreases the estimate of  $\zeta$ , which is now very close to zero. In other words, the impact of social ties on helping can be fully explained by the combined impact of social distance and degree centrality.<sup>11</sup>

In the next regressions, we explore the dynamics of helping behavior by looking at reciprocal helping. In regressions IV, V, and VI, we estimate the same specifications, but we restrict the sample to helpers who were helped by the helpee in the previous period. In regressions VII, VIII, and IX, we further restrict the sample to pairs of subjects who helped each other in the previous period.

As one would expect, previous help is positively associated with a higher likelihood of

---

<sup>9</sup>The estimated parameters are very similar with maximum likelihood estimation and if we include subject random effects.

<sup>10</sup>If we allow for a more flexible specification where we introduce each social distance as a dummy variable, we find that increasing social distance from  $d_{ij} = 1$  to  $d_{ij} = 2$  results in a marginally significant decrease in the likelihood of helping ( $p = 0.079$ ), but a further increase from  $d_{ij} = 2$  to  $d_{ij} = 3$  does not have an additional effect ( $p = 0.589$ ).

<sup>11</sup>As a robustness check, in Appendix B, we rerun the specification of regression III multiple times, excluding one of the network structures each time. We find that the estimated parameters are robust to the exclusion of specific network structures.

**Table 2. Determinants of the probability of helping another subject**

*Note:* Non-linear least squares regressions of subject  $i$ 's probability of helping subject  $j$  (see equation 1). Robust standard errors clustered on organizations are in parentheses. \*\* and \* indicate statistical significance at 0.01 and 0.05.

	All periods			Received help in previous period			Mutual help in previous period		
	I	II	III	IV	V	VI	VII	VIII	IX
	Baseline help ( $\alpha$ )	78.12** (3.74)	78.12** (3.74)	78.12** (3.74)	88.21** (1.89)	88.21** (1.89)	88.21** (1.89)	91.34** (1.46)	91.34** (1.46)
Social ties ( $\zeta$ )	15.65** (4.07)	5.00 (7.10)	2.76 (7.16)	8.40** (1.98)	4.11 (2.46)	2.54 (2.50)	6.18** (1.51)	3.41* (1.66)	1.98 (1.69)
Social distance ( $\beta$ )		14.71* (6.03)	13.22* (6.05)		5.99** (1.62)	4.94** (1.62)		3.92** (0.56)	2.92** (0.86)
Decay ( $\delta$ )		0.68** (0.21)	0.76** (0.18)		0.60** (0.19)	0.73** (0.17)		0.56** (0.18)	0.74** (0.16)
Degree centrality ( $\gamma$ )			1.10** (0.24)			0.77** (0.16)			0.71** (0.13)
Observations	19,350	19,350	19,350	16,719	16,719	16,719	16,044	16,044	16,044
Clusters	43	43	43	43	43	43	43	43	43
$R^2$	0.047	0.073	0.075	0.022	0.031	0.032	0.016	0.021	0.023

helping. In the absence of social ties, on average, 88.2% of subjects who were helped in the previous period reciprocate by helping in the following period. At 91.3%, this fraction is even higher for pairs of subjects who previously helped each other.

Remarkably, we find that social ties have qualitatively similar effects. First, both lower social distance and higher degree centrality significantly increase the likelihood of helping. Second, accounting for the impact of these two variables explains the overall impact of communication on helping. Understandably, the estimated impact is smaller in magnitude since helping levels are already very high. In other words, we find that social ties play a role in sustaining helping behavior even after a reciprocal helping relationship has been established.

## 5 Conclusion

In this study, we explore experimentally the relation between social ties and organizational helping behavior, a pivotal determinant of organizational success. We devise a novel game called the “helping game” in which helping is rivalrous and costly for the helper but beneficial for the recipient, with the optimal outcome occurring when everyone helps each other. We vary the social network structure in which individuals are embedded by allowing them to communicate with some individuals in the organization but not with others. This allows us to generate social

ties exogenously and determine the causal impact of two key network characteristics on helping behavior: the social distance between individuals and their degree centrality.

Our findings demonstrate that exogenously-formed social ties have a significantly positive impact on helping behavior. However, their impact is contingent upon the network structure. Our first finding is that both direct and indirect social ties increase helping behavior, with the propensity to help diminishing as the social distance between individuals increases. This finding implies that direct contact between individuals in an organization is important to foment helping behavior. From the perspective of the literature on the effects of free-form communication on prosocial behavior, this finding is also telling. The fact that indirect communication is less effective than direct communication in promoting helping suggests that even though communication is unrestricted, intermediaries do not transmit all the relevant information or are unable to convey it in the same way.

Our second main finding is that individuals who were randomly assigned to more central positions in the network exhibit higher helping rates, even after controlling for the effects of social distance. This finding contributes to the ongoing discussion on network position and prosocial behavior (e.g., Farmer and Rodkin, 1996; Settoon and Mossholder, 2002; Wasko and Faraj, 2005; D'Exelle and Riedl, 2013). Our results demonstrate that an individual's position within the network causally influences their helping behavior. We find this to be an intriguing result since we are unaware of a well-established psychological mechanism that could explain why an exogenous increase in an individual's number of social ties leads to an increase of their prosocial behavior within the framework of the helping game, where individuals can target helping decisions and all actions are public information. Due to our experimental design, which doesn't allow for the endogenous formation of social ties, we are unable to compare the influence of degree centrality on helping behavior with the reverse influence of helping behavior on degree centrality. We think that investigating this comparison would be a promising avenue for future research.

Importantly, we show that the effect of social ties on helping behavior can be captured by a simple model that combines an effect for social distance and one for degree centrality. Hence, even though we focus on specific network structures, the model's estimated parameters can be used to predict helping patterns in other networks.

In our experiment, we did not include a cost for social ties. Hence, the network structure that maximizes payoffs is the full network. However, if social ties are costly, then the model can help us determine the network structure that maximizes help at the lowest cost.<sup>12</sup> Finally, we find that social ties are not only instrumental in establishing helping behavior but are also important in maintaining this behavior over time. More specifically, within pairs of individuals

---

<sup>12</sup>For linear costs, the optimal network structure is the star network for intermediate linking costs (see, Bala and Goyal, 2000). However, other structures might be optimal if costs are non-linear.

with an established history of mutual help, distance within the network and degree centrality continue to be significant determinants of helping behavior.

## References

- Abbink, K., Dong, L., and Huang, L. (2021). Talking behind your back: Asymmetric communication in a three-person dilemma. *Management Science*, 68(7):5187–5200.
- Allport, G. W., Clark, K., and Pettigrew, T. (1954). *The nature of prejudice*. Addison-Wesley, Reading, MA.
- Andreoni, J. and Rao, J. M. (2011). The power of asking: How communication affects selfishness, empathy, and altruism. *Journal of Public Economics*, 95(7-8):513–520.
- Angelovski, A. and Reuben, E. (2023). Intragroup enforcement of cooperation and the provision of intergroup public goods. Mimeo, NYU Abu Dhabi.
- Bala, V. and Goyal, S. (2000). A noncooperative model of network formation. *Econometrica*, 68(5):1181–1229.
- Bichieri, C., Lev-on, A., and Chavez, A. (2010). The medium or the message? Communication relevance and richness in trust games. *Synthese*, 176:125–147.
- Bochet, O., Page, T., and Putterman, L. (2006). Communication and punishment in voluntary contribution experiments. *Journal of Economic Behavior & Organization*, 60(1):11–26.
- Borman, W. C. and Motowidlo, S. M. (1993). Expanding the criterion domain to include elements of contextual performance. In Schmitt, N. and Borman, W. C., editors, *Personnel Selection in Organizations*, pages 71–98. Wiley.
- Branas-Garza, P., Cobo-Reyes, R., Espinosa, M. P., Jiménez, N., Kovářík, J., and Ponti, G. (2010). Altruism and social integration. *Games and Economic Behavior*, 69(2):249–257.
- Brandts, J., Charness, G., and Ellman, M. (2016). Let’s talk: How communication affects contract design. *Journal of the European Economic Association*, 14:943–974.
- Brandts, J. and Cooper, D. J. (2007). It’s what you say, not what you pay: An experimental study of manager–employee relationships in overcoming coordination failure. *Journal of the European Economic Association*, 5(6):1223–1268.
- Brandts, J. and Cooper, D. J. (2018). Truth be told an experimental study of communication and centralization. Working paper 1046, Barcelona School of Economics.
- Brandts, J., Cooper, D. J., and Rott, C. (2019). Communication in laboratory experiments. In Schram, A. and Ule, A., editors, *Handbook of Research Methods and Applications in Experimental Economics*, page 401–418. Edward Elgar Publishing, Glos, UK.

- Brief, A. P. and Motowidlo, S. J. (1986). Prosocial organizational behaviors. *Academy of Management Review*, 11(4):710–725.
- Burt, R. S. (1992). *Structural holes: The social structure of competition*. Harvard University Press, Cambridge, MA.
- Carron, A. V., Widmeyer, W. N., and Brawley, L. R. (1985). The development of an instrument to assess cohesion in sport teams: The group environment questionnaire. *Journal of Sport and Exercise Psychology*, 7(3):244–266.
- Cason, T. N., Sheremeta, R. M., and Zhang, J. (2012). Communication and efficiency in competitive coordination games. *Games and Economic Behavior*, 76(1):26–43.
- Cason, T. N., Sheremeta, R. M., and Zhang, J. (2017). Asymmetric and endogenous within-group communication in competitive coordination games. *Experimental Economics*, 20(4):946–972.
- Charness, G., Feri, F., Meléndez-Jiménez, M. A., and Sutter, M. (2021). An experimental study on the effects of communication, credibility, and clustering in network games. *The Review of Economics and Statistics*, pages 1–45.
- Charness, G. and Gneezy, U. (2008). What’s in a name? Anonymity and social distance in dictator and ultimatum games. *Journal of Economic Behavior & Organization*, 68(1):29–35.
- Chaudhuri, A. (2011). Sustaining cooperation in laboratory public goods experiments: a selective survey of the literature. *Experimental Economics*, 14(1):47–83.
- Chen, Y. and Li, X. (2009). Group identity and social preferences. *The American Economic Review*, 99:431–457.
- Chiaburu, D. S. and Harrison, D. A. (2008). Do peers make the place? conceptual synthesis and meta-analysis of coworker effects on perceptions, attitudes, ocbs, and performance. *Journal of Applied Psychology*, 93:1082–1103.
- Choi, S., Gallo, E., and Kariv, S. (2016). Networks in the laboratory. In Bramoullé, Y., Galeotti, A., and Rogers, B. W., editors, *The Oxford Handbook of the Economics of Networks*, pages 440–476. Oxford University Press.
- Choi, S. and Lee, J. (2014). Communication, coordination, and networks. *Journal of the European Economic Association*, 12(1):223–247.
- Cinyabuguma, M., Page, T., and Putterman, L. (2005). Cooperation under the threat of expulsion in a public goods experiment. *Journal of Public Economics*, 89(8):1421–1435.
- Cohen, S. G. and Bailey, D. E. (1997). What makes teams work: Group effectiveness research from the shop floor to the executive suite. *Journal of Management*, 23(3):239–290.
- Davis, D. D. and Holt, C. A. (1993). *Experimental Economics*. Princeton University Press, Princeton, NJ.



- Diesner, J., Frantz, T. L., and Carley, K. M. (2005). Communication networks from the Enron email corpus “It’s always about the people. Enron is no different”. *Computational & Mathematical Organization Theory*, 11(3):201–228.
- Duffy, J. and Feltovich, N. (2002). Do actions speak louder than words? an experimental comparison of observation and cheap talk. *Games and Economic Behavior*, 39(1):1–27.
- D’Exelle, B. and Riedl, A. (2013). Social embeddedness and resource sharing. *Unpubl. Manuscr.*
- Engelmann, D. and Fischbacher, U. (2009). Indirect reciprocity and strategic reputation building in an experimental helping game. *Games and Economic Behavior*, 67(2):399–407.
- Farmer, T. W. and Rodkin, P. C. (1996). Antisocial and prosocial correlates of classroom social positions: The social network centrality perspective. *Social Development*, 5(2):174–188.
- Fatas, E., Meléndez-Jiménez, M. A., and Solaz, H. (2010). An experimental analysis of team production in networks. *Experimental Economics*, 13:399–411.
- Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, 10(2):171–178.
- Forsythe, R., Horowitz, J. L., Savin, N. E., and Sefton, M. (1994). Fairness in simple bargaining experiments. *Games and Economic behavior*, 6(3):347–369.
- George, J. M. and Brief, A. P. (1992). Feeling good-doing good: a conceptual analysis of the mood at work-organizational spontaneity relationship. *Psychological Bulletin*, 112(2):310.
- Goeree, J. K., McConnell, M. A., Mitchell, T., Tromp, T., and Yariv, L. (2010). The 1/d law of giving. *American Economic Journal: Microeconomics*, 2(1):183–203.
- Goyal, S. (2023). *Networks: An Economics Approach*. MIT Press, Cambridge, MA.
- Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with orsee. *Journal of the Economic Science Association*, 1(1):114–125.
- Hellweg, S. A. and Phillips, S. L. (1982). Communication and productivity in organizations. *Public Productivity Review*, 6(4):276–288.
- Hill, K., Hirsch, D., and Davis, A. (2021). The role of social support networks in helping low income families through uncertain times. *Social Policy and Society*, 20(1):17–32.
- Hoffman, E., McCabe, K., and Smith, V. L. (1996). Social distance and other-regarding behavior in dictator games. *American Economic Review*, 86(3):653–660.
- Jackson, M. O. and Wolinsky, A. (1996). A strategic model of social and economic networks. *Journal of Economic Theory*, 71(1):44–74.
- Kosfeld, M. (2004). Economic networks in the laboratory: A survey. *Review of Network Economics*, 3(1).

- Kossinets, G. and Watts, D. J. (2006). Empirical analysis of an evolving social network. *Science*, 311(5757):88–90.
- Koukoulis, A., Levati, M. V., and Weisser, J. (2012). Leading by words: A voluntary contribution experiment with one-way communication. *Journal of Economic Behavior & Organization*, 81(2):379–390.
- Kuwabara, K. (2011). Cohesion, cooperation, and the value of doing things together: How economic exchange creates relational bonds. *American Sociological Review*, 76:560–580.
- Ledyard, J. O. (1995). Public goods: A survey of experimental research. In Kagel, J. H. and Roth, A. E., editors, *The Handbook of Experimental Economics*, pages 111–194. Princeton University Press, Princeton, NJ.
- Leider, S., Möbius, M. M., Rosenblat, T., and Do, Q.-A. (2009). Directed altruism and enforced reciprocity in social networks. *The Quarterly Journal of Economics*, 124(4):1815–1851.
- Lott, A. J. and Lott, B. E. (1965). Group cohesiveness as interpersonal attraction: A review of relationships with antecedent and consequent variables. *Psychological Bulletin*, 64(4):259.
- Muñoz Herrera, M. and Reuben, E. (2023). The role of personal and impersonal business relationships on market efficiency. *Journal of Law, Economics, and Organization*.
- Nowak, M. A. and Sigmund, K. (1998). Evolution of indirect reciprocity by image scoring. *Nature*, 393(6685):573–577.
- Organ, D. W. (1988). *Organizational citizenship behavior: The good soldier syndrome*. Lexington Books/DC Heath and Com.
- Ostrom, E. (2000). Collective action and the evolution of social norms. *Journal of Economic Perspectives*, 14(3):137–158.
- Ostrom, E., Gardner, R., and Walker, J. (1994). *Rules, Games, and Common-Pool Resources*. University of Michigan Press, Ann Arbor, MI.
- Panzarasa, P., Opsahl, T., and Carley, K. M. (2009). Patterns and dynamics of users’ behavior and interaction: Network analysis of an online community. *Journal of the American Society for Information Science and Technology*, 60(5):911–932.
- Podsakoff, P. M., MacKenzie, S. B., Paine, J. B., and Bachrach, D. G. (2000). Organizational citizenship behaviors: A critical review of the theoretical and empirical literature and suggestions for future research. *Journal of Management*, 26(3):513–563.
- Polzer, J. T., Milton, L. P., and Gruenfeld, D. H. (2001). Asymmetric subgroup communication in nested social dilemmas. Working paper 02-007, Harvard Business School.
- Schwartz, M. F. and Wood, D. C. (1993). Discovering shared interests using graph analysis. *Communications of the ACM*, 36(8):78–89.

- Seinen, I. and Schram, A. (2006). Social status and group norms: Indirect reciprocity in a repeated helping experiment. *European Economic Review*, 50(3):581–602.
- Settoon, R. P. and Mossholder, K. W. (2002). Relationship quality and relationship context as antecedents of person-and task-focused interpersonal citizenship behavior. *Journal of Applied Psychology*, 87(2):255.
- Simpson, B. and Willer, R. (2015). Beyond altruism: Sociological foundations of cooperation and prosocial behavior. *Annual Review of Sociology*, 41(1):43–63.
- Stoller, E. P. and Pugliesi, K. L. (1991). Size and effectiveness of informal helping networks: A panel study of older people in the community. *Journal of Health and Social Behavior*, pages 180–191.
- Sundstrom, E., De Meuse, K. P., and Futrell, D. (1990). Work teams: Applications and effectiveness. *American Psychologist*, 45:120–133.
- Sutter, M. and Strassmair, C. (2009). Communication, cooperation and collusion in team tournaments? an experimental study. *Games and Economic Behavior*, 66(1):506–525.
- Van Dyne, L., Cummings, L. L., and Parks, J. M. (1995). Extra-role behaviors-in pursuit of construct and definitional clarity (a bridge over muddied waters). *Research in Organizational Behavior*, 17:215–285.
- Wang, S. and Houser, D. (2019). Demanding or deferring? an experimental analysis of the economic value of communication with attitude. *Games and Economic Behavior*, 115:381–395.
- Wasko, M. M. and Faraj, S. (2005). Why should i share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*, 29(1):35–57.
- Wedekind, C. and Milinski, M. (2000). Cooperation through image scoring in humans. *Science*, 288(5467):850–852.

# Appendices

## A Decision screen

Figure A1 shows the screen seen by subjects when making their helping decision. Subjects were randomly assigned to labels A, B, C, D, E, or F and kept the label throughout the experiment. The screen is seen from the point of view of subject A in period one. On the upper-left part of the screen, A decides whom to help. The figure located on the upper-right part of the screen is a visual representation of who is helped by A and the benefit each person receives as a result of A's helping decision. Once A decides to help someone and chooses 'yes' on the upper left part of the screen, a blue line between A and this group member is formed on the upper-right part of the screen. In the example shown in the figure, A helps C and F. Also, A observes the benefits generated by her helping decision by looking at the number next to each label. Once A finalizes her helping decision, she presses the OK button and moves to the next period. The lower part of the screen shows the points others received from A's helping behavior in previous periods (left) and the points A received from the helping decisions of other group members in previous periods (right).

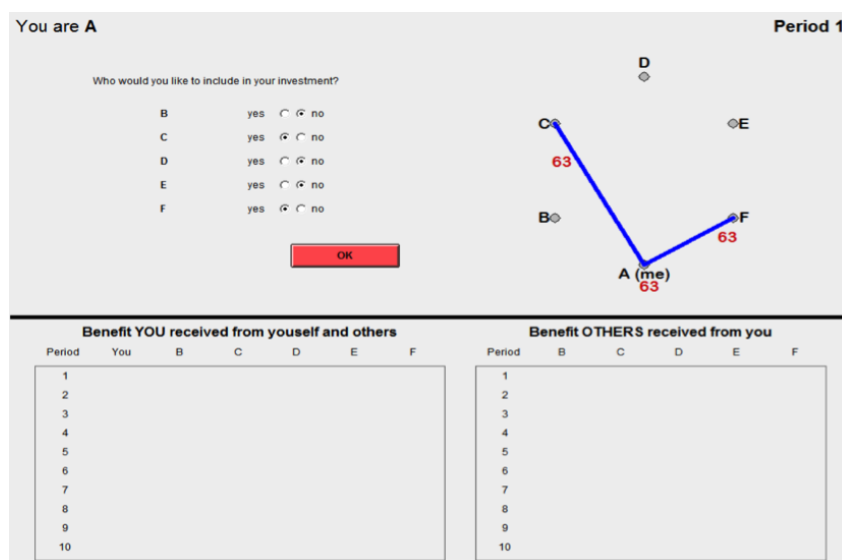


Figure A1. Screenshot of helping decision screen

## B Robustness of parameter estimates to specific network structures

Table A1 shows the parameter estimates of equation 1 (regression III in Table 2) when we exclude one network structure at a time. Note that when we exclude either the empty or the two clusters networks, we cannot estimate the parameter  $\zeta$  since pairs that share a social tie perfectly coincide with pairs in networks where social ties are present.

By and large, the point estimates of the various parameters are stable to the exclusion of specific network structures. The standard deviations increase. Mostly noticeably, the standard

deviation of the decay parameter  $\delta$  in the regression where we exclude the **circle** network increases to the point where the parameter is no longer significantly different from zero. We do not find this surprising since the **circle** network is the network that generates the greatest variation in social distances in our experiment.

**Table A1. Probability of helping excluding one network structure at a time**

*Note:* Non-linear least squares regressions of subject  $i$ 's probability of helping subject  $j$  (see equation 1). Robust standard errors clustered on organizations are in parentheses. \*\* and \* indicate statistical significance at 0.01 and 0.05.

	Network structure excluded from sample				
	Empty	Two clusters	C.-P. star	Circle	Complete
Baseline help ( $\alpha$ )	80.89** (6.13)	78.14** (3.75)	78.12** (3.75)	78.12** (3.75)	78.12** (3.75)
Social ties ( $\zeta$ )			3.45 (7.19)	2.77 (7.09)	3.05 (7.29)
Social distance ( $\beta$ )	13.22* (6.07)	15.34** (4.28)	14.39* (6.03)	12.68* (6.04)	13.21* (6.07)
Decay ( $\delta$ )	0.76** (0.18)	0.82** (0.11)	0.89** (0.11)	0.50 (0.46)	0.76** (0.19)
Degree centrality ( $\gamma$ )	1.10** (0.24)	1.22** (0.38)	0.73** (0.17)	1.15** (0.23)	0.96** (0.80)
Observations	15,300	15,300	15,750	15,300	15,750
Clusters	34	34	35	34	35
$R^2$	0.051	0.083	0.093	0.074	0.054

## C Predictions of equation 1

Table A2 shows the predicted level of help for each pair of positions in each network structure according to the model presented in equation 1. Positions are labeled as A, B, C, D, E, or F and can be seen in Figure 1. The likelihood that a player in position  $i$  helps a player in position  $j$  if given by  $h_{i \rightarrow j}$ . For example, take player A's likelihood of helping player C.

- In the **complete** network, A's likelihood of helping C is  $h_{A \rightarrow C} = \alpha + \beta\delta^1 + 5\gamma + \zeta$  in the as A has a degree centrality of 5 and A's distance to C equals 1.
- In the **core-periphery star** network, A's likelihood of helping C decreases to  $h_{A \rightarrow C} = \alpha + \beta\delta^3 + \gamma + \zeta$  as A's degree centrality equals 1 and A's distance to C equals 3.
- In the **circle** network, A's likelihood of helping C is also lower than in the **complete** network. It equals  $h_{A \rightarrow C} = \alpha + \beta\delta^2 + 2\gamma + \zeta$  since A has a degree centrality of 2 and A's

distance to C is 2.

- In the **two clusters** network, A's likelihood of helping C is even smaller at  $h_{A \rightarrow C} = \alpha + 2\gamma + \zeta$  as A maintains a degree centrality of 2, but A and C are not connected.
- Lastly, the lowest predicted likelihood of A helping C is  $h_{A \rightarrow C} = \alpha$  in the **empty** network, where there are no social ties in the network.

**Table A2. Predicted level of help for each pair of positions in each network structure**

	Complete	Circle	Two clusters	C.-P. star	Empty
$h_{A \rightarrow B}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + \gamma + \zeta$	$\alpha$
$h_{A \rightarrow C}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^3 + \gamma + \zeta$	$\alpha$
$h_{A \rightarrow D}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^3 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + \gamma + \zeta$	$\alpha$
$h_{A \rightarrow E}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^3 + \gamma + \zeta$	$\alpha$
$h_{A \rightarrow F}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + \gamma + \zeta$	$\alpha$
$h_{B \rightarrow A}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 3\gamma + \zeta$	$\alpha$
$h_{B \rightarrow C}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + 3\gamma + \zeta$	$\alpha$
$h_{B \rightarrow D}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 3\gamma + \zeta$	$\alpha$
$h_{B \rightarrow E}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^3 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + 3\gamma + \zeta$	$\alpha$
$h_{B \rightarrow F}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 3\gamma + \zeta$	$\alpha$
$h_{C \rightarrow A}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^3 + \gamma + \zeta$	$\alpha$
$h_{C \rightarrow B}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + \gamma + \zeta$	$\alpha$
$h_{C \rightarrow D}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + \gamma + \zeta$	$\alpha$
$h_{C \rightarrow E}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^3 + \gamma + \zeta$	$\alpha$
$h_{C \rightarrow F}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^3 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + \gamma + \zeta$	$\alpha$
$h_{D \rightarrow A}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^3 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + 3\gamma + \zeta$	$\alpha$
$h_{D \rightarrow B}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 3\gamma + \zeta$	$\alpha$
$h_{D \rightarrow C}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 3\gamma + \zeta$	$\alpha$
$h_{D \rightarrow E}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + 3\gamma + \zeta$	$\alpha$
$h_{D \rightarrow F}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 3\gamma + \zeta$	$\alpha$
$h_{E \rightarrow A}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^3 + \gamma + \zeta$	$\alpha$
$h_{E \rightarrow B}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^3 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + \gamma + \zeta$	$\alpha$
$h_{E \rightarrow C}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^3 + \gamma + \zeta$	$\alpha$
$h_{E \rightarrow D}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + \gamma + \zeta$	$\alpha$
$h_{E \rightarrow F}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + \gamma + \zeta$	$\alpha$
$h_{F \rightarrow A}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + 3\gamma + \zeta$	$\alpha$
$h_{F \rightarrow B}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 3\gamma + \zeta$	$\alpha$
$h_{F \rightarrow C}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^3 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^2 + 3\gamma + \zeta$	$\alpha$
$h_{F \rightarrow D}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^2 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 3\gamma + \zeta$	$\alpha$
$h_{F \rightarrow E}$	$\alpha + \beta\delta^1 + 5\gamma + \zeta$	$\alpha + \beta\delta^1 + 2\gamma + \zeta$	$\alpha + 2\gamma + \zeta$	$\alpha + \beta\delta^1 + 3\gamma + \zeta$	$\alpha$

## **D Sample instructions**

Below are the instructions for the experiment. The parts of the instructions that differ between network structures are highlighted in the text.

### **Welcome**

Welcome to our decision-making experiment. You will receive some money based on your choices and the choice of others during the experiment. It is important that you do not talk to any of the other participants unless you are told to do so. If you have a question at any time, raise your hand and a monitor will come to your desk to answer it.

### **Description of each period**

In this experiment, you will interact with 5 other people. The people you interact with will not change during the experiment. Everyone's identity (including yours) will remain anonymous throughout the experiment. Each person is identified with a letter: A, B, C, D, E and F. You will be informed the letter you have been assigned to once the experiment starts. Nobody's letter will change during the experiment. So for instance, letter B will be the same person throughout the experiment.

The experiment will consist of 15 periods. At the end of the experiment, the points you get from all 15 periods will be summed up, converted to money and paid to you in private. 1 point worth 0.56 cents

In each period, everyone is endowed with 100 points each. In each period, each person will choose how to invest his/her endowment and who benefits from his/her investment. Note that you have to invest all your endowment.

### **Consequences of your investment decision**

The points generated by your investment will depend on the number of people you include in your investment. As the number of people you include increases, the total amount of points generated by your investment increases, but the benefit received by each included person decreases. Note that your investment always includes yourself. Hence, the minimum number of included people is one. You can see the total amounts generated and the benefits per included person in the table below:

The number of people you include in your investment	Total amount of points generated by your investment	Benefit received by each person you include
1	100	100
2	150	75
3	189	63
4	220	55
5	240	48
6	252	42

### Investment screen

In each period, you have to decide whom to include in your investment. To do this, you use a decision screen like the one below:

**You are A** **Period 1**

Who would you like to include in your investment?

B    yes  no

C    yes  no

D    yes  no

E    yes  no

F    yes  no

D

C

E

B

F

A (me)  
100

Benefit YOU received from yourself and others							Benefit OTHERS received from you						
Period	You	B	C	D	E	F	Period	B	C	D	E	F	
1							1						
2							2						
3							3						
4							4						
5							5						
6							6						
7							7						
8							8						
9							9						
10							10						

As you can see, the screen consists of 4 parts. On the upper-left part, you decide whom to include in your investment. The figure located on the upper-right part of the screen is a visual representation of whom is included in your investment and the benefit each person receives. A line between you and another person signifies that that person is included in your investment. You can see the benefits your investment generates by looking at the number next to each letter.

If you click NO for all the people, it means that you only include yourself in your investment. This case, which is depicted above, implies your receive 100 points from your investment and everyone else receives 0 points.

By clicking YES, you can include people in your investment. For example, once you click



YES for B, you will see that a blue line is formed between yourself (referred as ‘me’) and B. You will also see that the benefit B receives increases to 75 points while the benefit you receive decreases to 75 points. This is the example shown below:

**You are A** **Period 1**

Who would you like to include in your investment?

B    yes  no

C    yes  no

D    yes  no

E    yes  no

F    yes  no

**OK**

D  
C  
E  
B  
A (me)  
F

75      75

---

**Benefit YOU received from yourself and others**

Period	You	B	C	D	E	F
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						

**Benefit OTHERS received from you**

Period	B	C	D	E	F
1					
2					
3					
4					
5					
6					
7					
8					
9					
10					

Once you finalize your decision, you can click the red OK button to proceed to the next period. Before clicking OK button, make sure that the blue lines are formed for the people you want to include in your investment.

Once you click the OK button, the information on whom you included in your investment, who included you in their investment, and the amount of points you earned in this period will shortly appear. You can also see this information for the previous 10 periods on the lower part of the screen.

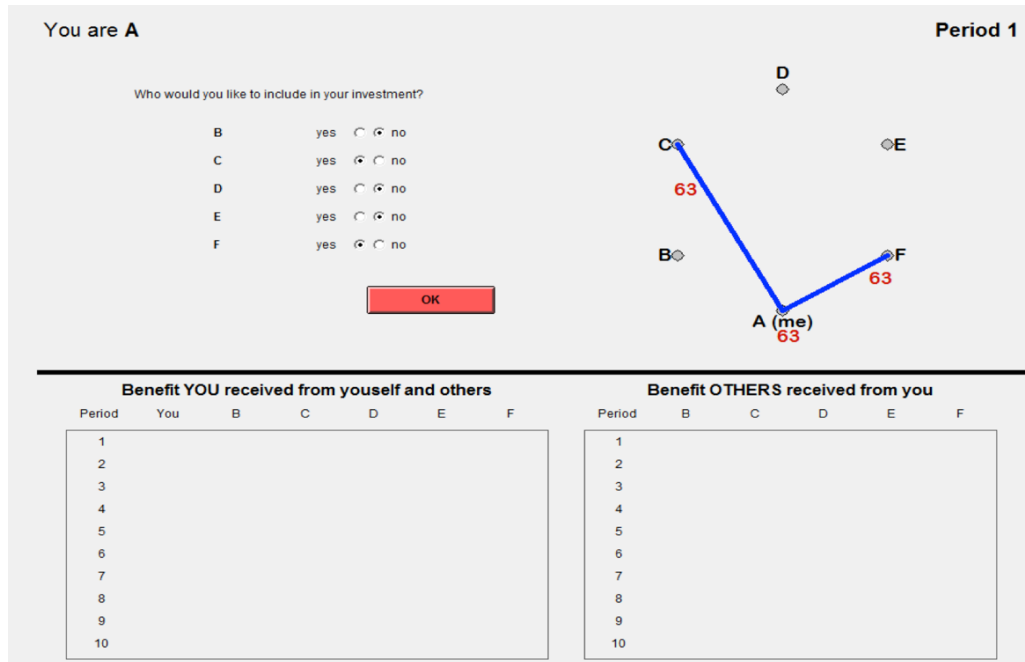
The lower part of the screen shows the benefits generated by investments in past periods. Specifically, the box on the lower-left side shows the benefits your investment generated in the previous periods and the box on the lower-right side shows the benefits you received from the investments of others in the previous periods.

### Example

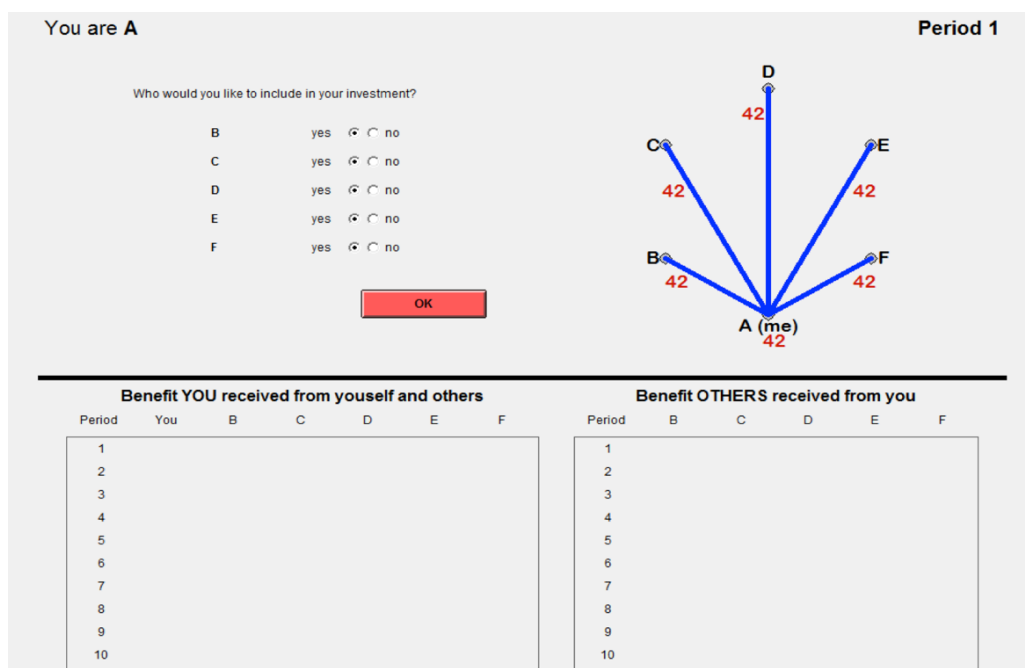
Let us give an example of the consequences of a possible investment decision of yours. Assume you decide to include only yourself in your investment. Since you include 1 person (yourself), 100 points are generated by your investment, and the person you include (which is yourself) receives a benefit of 100 points from your investment decision.

Alternatively, assume that you decide to include C, F, and yourself in your investment as

in the figure below. Since you include 3 persons (C, F, and yourself), 189 points are generated by your investment. Thus, each person you include (C, F, and yourself) receives a benefit of 63 points from your investment decision.



Or, assume that you decided to include all individuals that you interact with in your investment and invest your 100 points as in the figure below. Since you include 6 persons (B, C, D, E, F and yourself), 252 points will be generated by your investment. Thus, each person you include (B, C, D, E, F and yourself) will receive a benefit of 42 points from your investment decision.



## Earnings

Like yourself, the people you interact with will also make investment decisions and their decisions will have consequences for you. In other words, just like others benefit from your investment if you include them, you also benefit from the investment decisions of others if they include you. Your total earnings will depend on the benefit you receive from your investment and the benefits you receive from others' investments.

Let us give an example of the consequences of a possible investment decision of others. Assume that:

- You include B, E and yourself in your investment, and
- B includes E and you in his/her investment, and
- E includes B and you in his/her investment.

In this case, your investment generates 189 points from which you get a benefit of 63. B's investment generates 189 points from which you get a benefit of 63 and E's investment generates 189 points from which you get a benefit of 63. Thus you get  $63+63+63= 189$  points in total.

Alternatively, assume that:

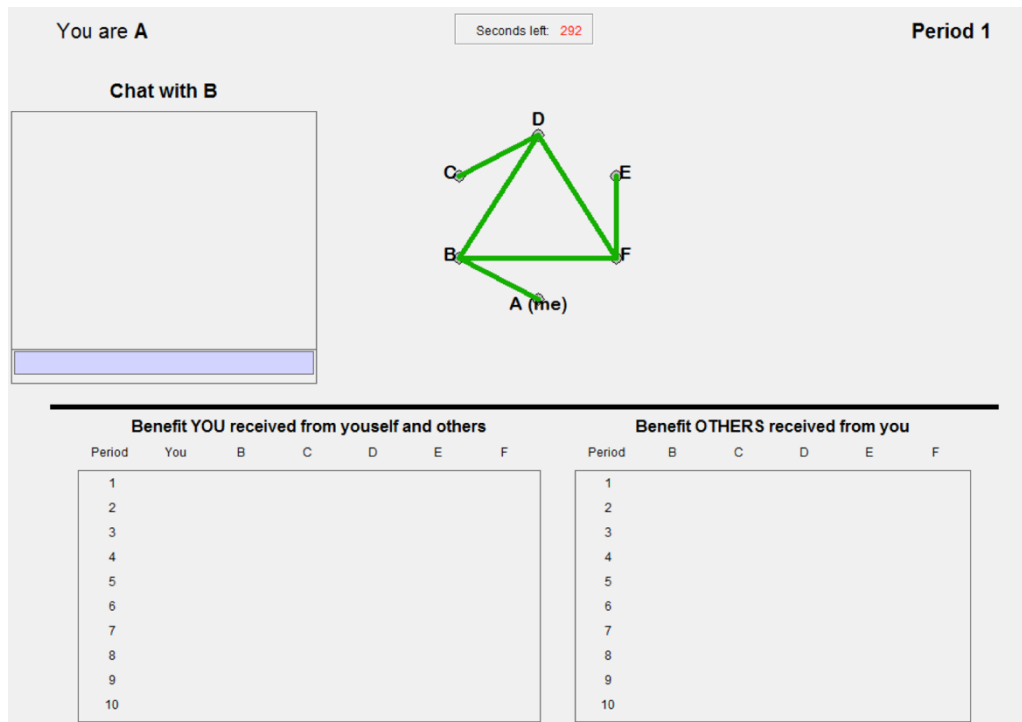
- You include B, E and yourself in your investment, and
- B includes E and you in his/her investment, and
- E only includes B in his/her investment.

In this case, your investment generates 189 points from which you get a benefit of 63. B's investment generates 189 points from which you get a benefit of 63 and E's investment generates 150 points from which you get a benefit of 0 since you were not included. Thus you get  $63+63+0= 126$  points in total.

*[Note: The instructions below, describing how participants can communicate with each other, were not included in treatments without communication (i.e., the **empty** network.)]*

## Communication

In some periods, you will chat with some of the people you interact with before you make your investment decision. In these periods, you will face with two computer screens sequentially. First you will face with a communication screen and after you finish chatting, you will face with a contribution screen to give your investment decision. The communication screen will look like the following:



[Note: The screenshot above corresponds to the **core-periphery star** network. The instructions for the other networks included the screenshot visualizing the respective network]

On the upper-left part of the screen, you will observe the chat box. You will be able to chat with the people that you are allowed to chat in this box.

On the upper-right part of the screen, you will observe the figure that shows the communication structure. A green line between two people means that these two people can chat with each other. You can see the communication structure that you will face during the experiment on the figure above. [**core-periphery star**: You observe a line between D and B, B and F, and, F and D meaning that D, B and F can chat between each other. Moreover, as you observe in the figure, B and A can chat between each other, E and F can chat between each other and, C and D can chat between each other.] [**circle**: You observe a line between A and B, between B and C, between C and D, between D and E, between E and F, and, between F and A meaning the following: A and B can chat between each other; B and C can chat between each other; C and D can chat between each other; D and E can chat between each other; E and F can chat between each other and, F and A can chat between each other.] [**two clusters**: You observe a line between C and D, B and C, and, B and D meaning that B, C and D can chat between each other. Likewise, as you observe in the figure, A, E and F can also chat between each other.] [**complete**: You observe a line between all people, meaning everybody can chat with each other.]

The lower part of the screen shows contributions in past periods. Specifically, the box on the lower-left side shows your contributions in the previous periods and the box on the lower-right

side shows others contributions to you in the previous periods. In these two boxes you can see the past contributions for previous 10 periods.

Once you are done with chatting, please press OK button located on the lower-right part of the screen to proceed to the contribution screen where you will give your investment decision.