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

HANDE ERKUT
WZB Berlin Social Science Center, e-mail: hande.erkut@wzb.eu

ERNESTO REUBEN
New York University Abu Dhabi, Center for Behavioral Institutional Design, Luxembourg Institute of Socio-Economic Research, e-mail: 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: April 2025

ACKNOWLEDGEMENTS

We gratefully acknowledge financial support from Tamkeen under the NYU Abu Dhabi Research Institute Award CG005 and the Russell Sage Foundation small grants program in behavioral economics. This is the authors' version of work accepted for publication in the *Journal of Public Economics*. Changes resulting from the publishing process may not be reflected here. A final version is published at DOI: 10.1016/j.jpubeco.2025.105388.

جامعة نيويورك أبوظبي
NYU | ABU DHABI

مركز التصميم السلوكي المؤسساتي
CENTER for BEHAVIORAL INSTITUTIONAL DESIGN

1. Introduction

The success of organizations greatly depends on the helping behavior of their members. Organizational helping behavior has been investigated in many empirical studies[1] 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. Since the benefits of receiving help surpass the costs of helping, 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 other games used to examine prosocial behavior: dictator games, common pool resource games, and public good games. Dictator games (Forsythe et al., 1994) measure generosity. Namely, how much money people give unilaterally to another person.[2] 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 and public good games capture individuals' willingness to cooperate (see Ostrom et al., 1994; Ledyard, 1995). In these games, the benefits of cooperation are non-excludable and, therefore, are accrued by everyone in the group. By contrast, in the helping game, individuals can help a subset of people and exclude others. In addition, public goods games differ from the helping game in that cooperation is non-rivalrous.

An important empirical finding is that helping behavior is strongly associated with social ties (e.g., Stoller and Pugliesi, 1991; Hill et al., 2021). In sociology, social ties are understood as relationships characterized by factors such as the amount of time individuals spend together, the emotional intensity of their interactions, and the degree to which they trust each other (Granovetter, 1973). In economics, this definition of social ties has been formalized as utility interdependence

[1] 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).

[2] Most dictator games involve only two people. However, there are a few examples of multilateral dictator games (Bolton et al., 1998; Brañas-Garza, 2006).

arising from interpersonal interactions (Van Dijk and Van Winden, 1997). However, because field studies rely on correlational data, it is challenging to identify whether social ties foster helping behavior or whether helping behavior leads to forming social ties. While the idea that helpful individuals naturally form more social ties is intuitive, this paper focuses on the less obvious reverse effect: the extent to which social ties directly encourage helping behavior.

To study the impact of social ties on helping behavior, we randomly generate social ties among participants in a helping game by allowing them to communicate via chat messages with some members of their organization. Communication in our experiment mirrors key features of social ties in organizations (Lott and Lott, 1965; Carron et al., 1985). First, free-form communication has been shown to foster closer emotional connections, strengthen group identities, and enable social sanctions (e.g., Chen and Li, 2009; Bichieri et al., 2010; Andreoni and Rao, 2011; Kuwabara, 2011). Second, communication enhances trust by aligning expectations and reducing strategic uncertainty (see Duffy and Feltovich, 2002; Brandts and Cooper, 2007; Brandts et al., 2019). Given these effects, it is unsurprising that measures of communication have been used to map social networks in various contexts (Schwartz and Wood, 1993; Diesner et al., 2005; Kossinets and Watts, 2006; Panzarasa et al., 2009). Additionally, studying the impact of communication *per se* is relevant given that communication and productivity are positively correlated in organizations (Hellweg and Phillips, 1982).

Although anonymous communication in the laboratory may represent a weaker social tie than naturally occurring ties in the field, it offers distinct advantages. First, it allows us to vary the presence of social ties exogenously. Second, it enables us to introduce social ties while keeping other variables constant. In field settings, social ties can be correlated with other determinants of helping behavior. For example, individuals within an organization often interact more with people in their physical proximity. However, being close to each other can also mean there are more opportunities to help, and the net benefits of helping might be greater due to task similarity. In our experiment, all participants in an organization have the same opportunities to help each other and face the same costs and benefits regardless of whether they share a social tie. Hence, we can focus on whether social ties themselves encourage helping behavior.

We examine the impact of network structure on helping behavior by randomly assigning organizations to one of five different social networks and randomly assigning participants to positions within these networks. We study two extreme networks, in which there are either no social ties or everyone shares a social tie, and three networks in which participants share a social tie with only some participants in their organization. To explain differences in helping behavior between networks, we examine the effect of two important network characteristics: the distance between nodes and degree centrality.

Social distance in networks—the length of the shortest path length between two individuals—is an important predictor 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 participants 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, 2018), we induce social ties between strangers and exogenously vary the distance between them, allowing us to measure its causal effect on helping.

Intuitively, one might expect that the likelihood of helping decreases as the social distance between individuals increases. However, the rate at which helping diminishes with distance depends on the mechanisms through which social ties generated by communication foster helping. While it is well-established that free-form communication significantly enhances prosocial behavior (e.g., Davis and Holt, 1993; Ostrom, 2000), the underlying reasons for this effect remain unclear. One possibility is that communication transmits information that builds trust, such as signaling intentions to help or reciprocate. Another is that communication strengthens emotional bonds, leading to greater preference interdependence, as suggested by the contact hypothesis (Allport et al., 1954).[3] The two mechanisms have distinct implications for the role of social distance. If communication works through information transmission, social distance should have little impact on helping, as information can propagate efficiently through the network. For instance, it is trivial for intermediaries to communicate a participant's intentions to others, such as a promise to help only those who reciprocate. By contrast, if communication primarily fosters emotional connections, helping is likely to decline with social distance since proximity is a key determinant of emotional reactions (Loewenstein, 1996) and has been shown to impact individuals' willingness to enforce and comply with prosocial behavior (Reuben and van Winden, 2008; Bicchieri et al., 2022).

A second network characteristic that consistently predicts prosocial behavior is degree centrality. Empirical studies find that individuals with more ties tend to behave more cooperatively (e.g., Farmer and Rodkin, 1996; Settoon and Mossholder, 2002; Wasko and Faraj, 2005; D'Exelle and Riedl, 2018). However, an open question in the literature is whether this pattern arises because more prosocial individuals form more social ties or because having more ties encourages prosocial behavior (Burt, 1992; Simpson and Willer, 2015). In the context of the helping game, the effect of degree

[3]It is worth noting that empirical support for the contact hypothesis is mixed: some studies find that exposure to out-group members reduces in-group-out-group bias (Rao, 2019), while others find no significant effect (Barron et al., 2023). By introducing exogenous variation in social ties, this study provides causal evidence on the role of contact in shaping helping behavior.

centrality on helping behavior is not necessarily straightforward. While direct communication can strengthen emotional bonds that encourage helping, in a setting where assisting more individuals reduces the benefit received by each, communication may also be used to discourage participants from helping others. By randomly varying individuals' degree centrality, we can isolate its causal impact on helping behavior.

Our results show that social ties have a strong positive effect on helping behavior, but their impact depends on the network structure. First, the likelihood of helping decreases as the social distance between participants increases. Second, we find that individuals 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 and degree centrality. Finally, we find that social ties matter not only in establishing helping behavior but also in sustaining this behavior over time. Specifically, distance in the network and degree centrality are still significant determinants of helping among 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—helping strangers because they have a track record of helping 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; Heursen, 2023). 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 interacting with each other repeatedly. Moreover, we focus on understanding how different social networks impact overall helping.

This paper also contributes to the broader experimental literature on prosocial behavior and communication. A robust finding in this literature is that allowing free communication within a complete communication network has a strong positive effect on prosocial behavior (Ostrom et al., 1994; Ledyard, 1995; Chaudhuri, 2011). Some studies have explored the effects of partial communication structures, such as one-way communication (Koukoumelis et al., 2012; Andreoni and Rao, 2011), communication within subgroups (Polzer et al., 2001; Angelovski and Reuben, 2023), and communication that excludes certain individuals (Abbink et al., 2021). These studies find that partial communication is less effective at fostering prosocial behavior compared to complete communication networks.[4] Our study extends this literature by demonstrating that differences in prosocial behavior across communication structures can be explained by two network characteristics:

[4]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).

distance and degree centrality. Furthermore, our finding that helping decreases with social distance suggests that emotional bonds created through communication are a key mechanism driving the positive impact of communication on prosocial behavior.[5]

Finally, this paper contributes to the literature on the effects of different communication network structures on coordination games.[6] The findings of this literature suggest that network characteristics, such as clustering and centrality, matter for the outcome (e.g., Rezaei et al., 2024). 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

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

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

To describe the characteristics of the helping game, we denote the total benefit generated by i's help as $B_i(H_i) = \sum_{j \neq i}^{n} h_{i \to j} \times b_{i \to j}(H_i)$ 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 decreases with the number of players

[5] The analysis of the communication data reinforces the importance of emotional bonds as positive sentiment in the text predicts higher helping rates.

[6] There is also literature that focuses on the effects of network structure on actions. See Kosfeld (2004) and Choi et al. (2016) for reviews of this literature.

Table 1. Helping payoff matrix for subject i

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 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

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. For example, if A helps only C and F, then they both get 63 points, which means that the total benefit generated by A is 126 points. Since A's total cost of helping is 37 points, the increase in efficiency equals 89 points. Note that C and F do not need to help A to receive the benefits of A's help.

Subjects played the helping game for 15 periods. The composition of the organizations and the subjects' labels did not change during the experiment. We opted for fixed groups instead of randomly rematching subjects in each period because organizations typically involve people interacting repeatedly.

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 a seat in the laboratory. Thereafter, subjects read the instructions and answered a few understanding questions (the instructions are available in Appendix A). Once everyone was ready, subjects played the 15 periods of the helping game. To facilitate subjects' understanding, we used an interactive screen to visualize who the subject is helping and the corresponding benefits. Subjects could also observe who they helped and who helped them in previous periods. The screen is further explained in Figure A1 in Appendix B.

To avoid losses, each subject started each period with an endowment of 100 points. At the end

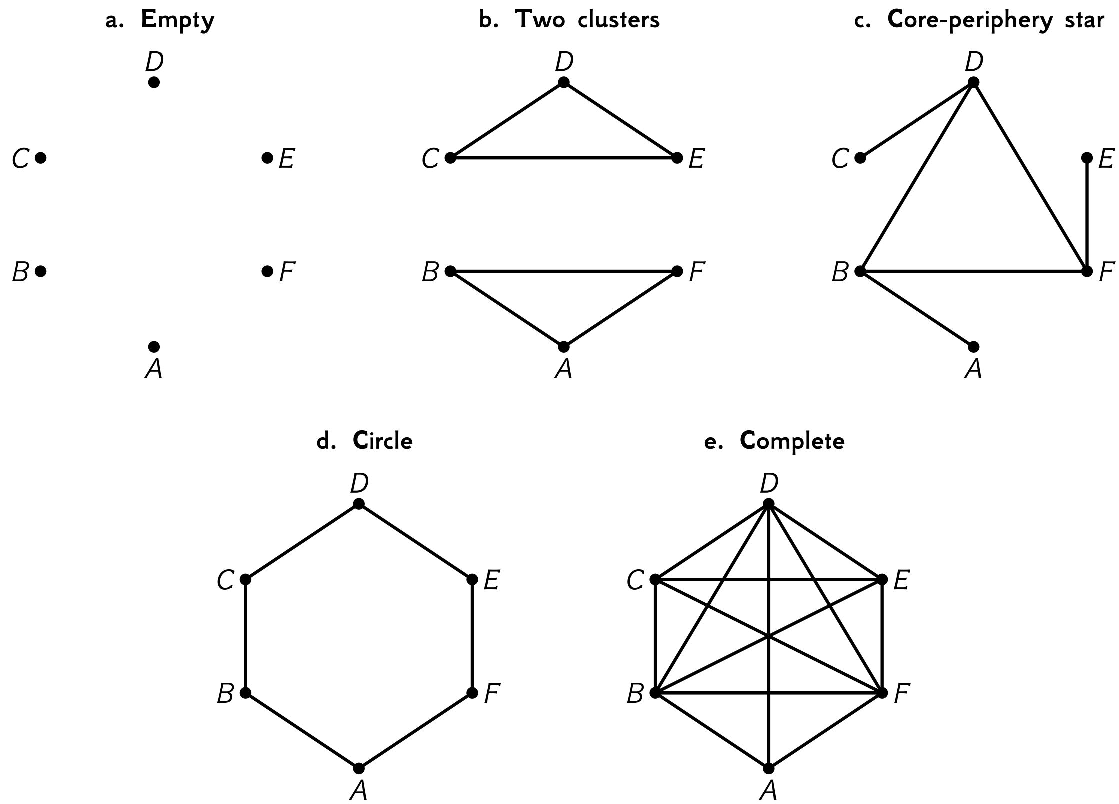


Figure 1. Communication networks used in the experiment

of the experiment, the points from all 15 periods were summed up, converted into money at a rate of 100 points = €0.56, and paid in private. Average earnings were around €20, and the experiment lasted 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 in a communication network. We implement five different communication networks to capture different types of social structures typically found in organizations. Organizations were randomly assigned to one of these networks, which remained unchanged throughout the entire experiment. In all networks with communication, subjects can chat for three minutes at the beginning of every third period, starting from the first period.[7] Subjects can chat freely, but cannot reveal identifying information or use foul language.

Figure 1 visualizes the five different communication networks. They are:

a. The **empty** network in which there is no communication between subjects.

[7] As Bochet et al. (2006) and Muñoz Herrera and Reuben (2023), we introduce the communication stage every three periods so that the experiment does not last too long. Communication has been shown 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).

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 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 of theoretical models of network formation (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:

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

The equation has the following parameters.

- α is a constant that captures the likelihood of helping without social ties.
- β 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.

- γ captures the effect of a subject's randomly-assigned position in the network. Specifically, it measures the impact of their degree centrality (i.e., the number of subjects i can directly communicate with divided by the total number of other subjects in the network) on their helping behavior.
- K is the dummy variable that takes a value of 1 if there are social ties within the organization and 0 otherwise. Hence, the coefficient ζ 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 Table A1 of Appendix C for details).[8] 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 positions within those networks to estimate the value of each parameter.

4. Results

Helping is common in our experiment. Figure 2**a** depicts the mean helping rate in each network and their corresponding 95% confidence intervals. To test whether differences between network structures are statistically significant, we run a probit model with subjects' helping decisions 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.[9]

In the **empty** network, the helping rate is 78.1%. The high helping rate is consistent with repeated public goods game experiments showing that the possibility of exclusion promotes cooperative behavior. For example, Cinyabuguma et al. (2005) report that subjects contribute more than 80% of their endowment (see also Maier-Rigaud et al., 2010; Dannenberg et al., 2020).

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

[9]Our results carry through with other specifications, such as a linear probability model, or with pairwise non-parametric tests with organization means as observations.

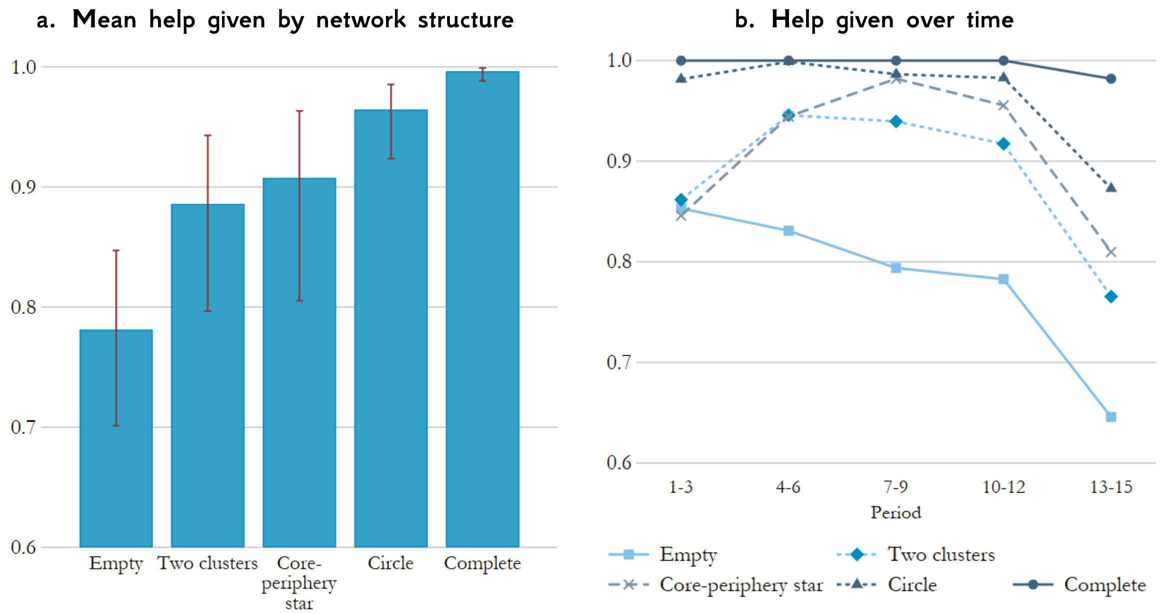


Figure 2. Probability of helping another subject

When subjects can communicate with everyone in their organization, helping becomes ubiquitous. Compared to the **empty** network, the helping rate in the **complete** network increases by 21.5 percentage points to 99.6%. This effect is consistent with previous findings on the impact of communication on prosocial behavior. For instance, in repeated public good games, Bochet et al. (2006) find that chatroom communication increases cooperation rates from 47.5% to 81.4% of subjects' endowments. The somewhat smaller impact of communication in our game is probably due to an already high helping rate in the **empty** network.

Interestingly, consistent with the idea that social ties generated through communication promote help by creating direct emotional bonds between participants, 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 ($p < 0.003$).[10]

To illustrate how help changes over periods, Figure 2**b** shows the mean helping rate in each network in blocks of three periods (communication occurred every three periods). Help decreases in the **empty** network. In the other networks, help is consistently high or increasing until there is an endgame effect in the final periods. Help drops significantly in the **empty** but not the **complete** network.[11] Interestingly, the endgame effect is still present in partial communication networks and is not statistically different from the endgame effect in **empty** network.

[10]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** ($p = 0.145$). The difference between the **two clusters** and the **core-periphery star** is also not statistically significant ($p = 0.489$).

[11]Communication between all group members also eliminates the endgame effect in repeated public goods games (Bochet et al., 2006).

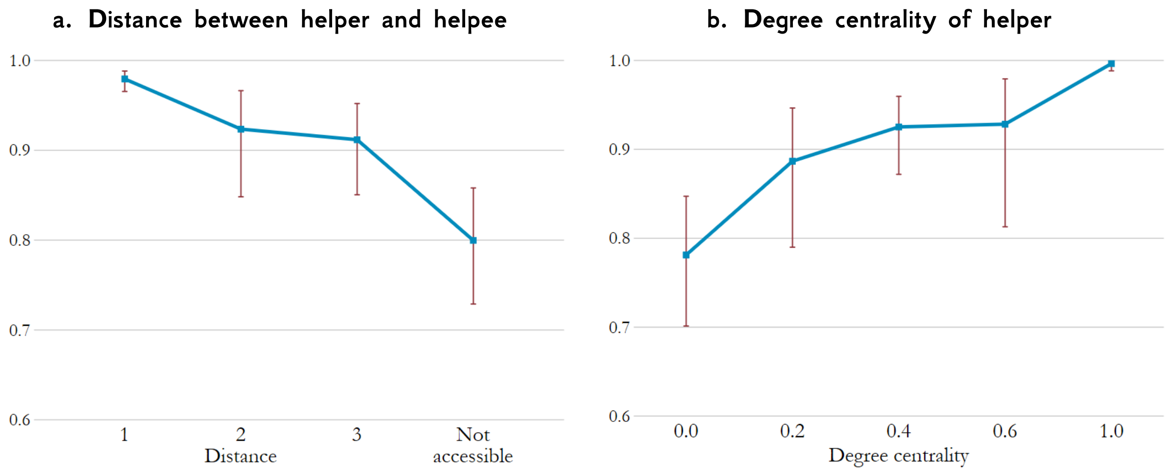


Figure 3. Likelihood of helping another subject by social distance and degree centrality

4.1. Help and social network characteristics

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

Figure 3**a** shows the mean likelihood that a subject helps another subject depending on their social distance. 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 3**b** shows the mean likelihood of helping depending on the number of other subjects a subject has social ties with. The likelihood of helping increases with degree centrality. Figure A2 in Appendix D shows that these patterns are stable over periods.

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 points, are shown in Table 2.[12]

In regression I, we include only the constant α, which captures the likelihood of helping without social ties, and ζ, 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 helper and helpee, β and δ. The estimated parameters suggest that being able to communicate with a helpee directly significantly increases the likelihood of helping by 14.7 percentage points (compared to the **empty** network). The fact that δ is significantly positive shows that indirect communication

[12]The estimated parameters are very similar with maximum likelihood estimation and if we include subject random effects.

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 (α)	78.12**	78.12**	78.12**	88.21**	88.21**	88.21**	91.34**	91.34**	91.34**
	(3.74)	(3.74)	(3.74)	(1.89)	(1.89)	(1.89)	(1.46)	(1.46)	(1.46)
Social ties (ζ)	15.65**	5.00	2.76	8.40**	4.11	2.54	6.18**	3.41*	1.98
	(4.07)	(7.10)	(7.16)	(1.98)	(2.46)	(2.50)	(1.51)	(1.66)	(1.69)
Social distance (β)		14.71*	13.22*		5.99**	4.94**		3.92**	2.92**
		(6.03)	(6.05)		(1.62)	(1.62)		(0.56)	(0.86)
Decay (δ)		0.68**	0.76**		0.60**	0.73**		0.56**	0.74**
		(0.21)	(0.18)		(0.19)	(0.17)		(0.18)	(0.16)
Degree centrality (γ)			5.49**			3.85**			3.56**
			(1.19)			(0.82)			(0.67)
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

also increases help, but the fact that it is less than one suggests that the effect of communication decays with social distance. For example, the estimate of δ 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 δ is not significantly different from one (Wald test, $p = 0.133$); hence, we cannot conclusively say whether there is decay.[13] Interestingly, once we account for the impact of social distance, the estimate for ζ 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, γ. 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 subjects' help. Accounting for degree centrality further decreases the estimate of ζ, 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.[14]

In the next regressions, we explore the dynamics of helping behavior by looking at reciprocal

[13] 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 ($p = 0.589$).

[14] As a robustness check, in Table A2 of Appendix D, we evaluate whether the estimated parameters are stable over periods by rerunning specification III for the first and second halves of the experiment. In addition, in Table A3 of Appendix E, we rerun specification III, excluding one network structure at a time. We find that the estimated parameters are relatively stable over periods and are robust to the exclusion of specific network structures.

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 restrict the sample to pairs of subjects who helped each other in the previous period.

As expected, previous help is positively associated with a higher likelihood of helping. In the absence of social ties, on average, 88.2% of subjects who were helped in the previous period reciprocate with help 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 since helping levels are already very high. In other words, we find that social ties play a role in sustaining helping behavior even after establishing a reciprocal helping relationship.

4.2. Textual analysis

To gain insight into the nature of the communication, we conducted a textual analysis of the chat messages using generative AI (ChatGPT). This analysis coded several dimensions of the conversations, including the emotional valence of the messages, the degree to which participants sought consensus and coordinated their actions, the extent to which participants advocated for others to help them, and the extent to which they encouraged helping fewer other participants. We conducted the analysis with three different GPTs (GPT-4, GPT-4o, and GPT-4o-mini) to evaluate whether the results are sensitive to the generative AI's training data and model. The details of this analysis are available in the Online Appendix.

The analysis of emotional valence reveals that conversations were predominantly positive, supporting the idea that communication fosters positive emotional ties. Emotional valence was highest in the **complete** network and lowest in **two clusters**, although the differences are not substantial, suggesting that, conditional on having the ability to communicate, positive emotional effects are relatively consistent across networks. In all networks, participants made substantial efforts to reach consensus and coordinate their actions. However, they also used communication to advocate for personal help and, in some cases, to argue for reducing help to others. Interestingly, advocating to help fewer participants varies noticeably across networks; it is more prevalent in **two clusters** compared to the other three networks. When testing whether these variables predict helping behavior, we find that higher emotional valence and greater efforts to reach consensus and coordinate actions are associated with increased subsequent helping rates. By contrast, advocating to reduce help for others predicts lower subsequent helping rates, highlighting that participants understand and respond to the rivalrous nature of helping.

5. Conclusion

In this study, we experimentally explore the relationship 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. The optimal outcome occurs when everyone helps each other. [15] 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 while ensuring that participants have the same opportunities to help each other and face the same benefits and costs of helping. Our design allows us to 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 decreasing as the social distance between individuals increases. This finding implies that direct contact between individuals in an organization is important to foment helping behavior. It is also consistent with the conclusions of DeGroot and Brownlee (2006), who argue that more organic departmental structures that promote interaction between workers lead to more helping behavior compared to rigid, hierarchical structures. This finding is also informative for the literature on the effects of free-form communication on prosocial behavior. The fact that indirect communication is less effective than direct communication in promoting helping suggests that an important role of communication is to foment emotional ties, for which direct contact is essential.

Our second main finding is that individuals 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, 2018). Our results demonstrate that an individual's position within the network causally

[15] Although many instances of helping in organizations are rivalrous, there are situations where rivalry might be reduced. For example, when help is organized so that it is experienced simultaneously by multiple recipients, such as an experienced coworker organizing an informal training session, rivalry might be reduced. These situations are closer to a public good game, while our game is best suited to capture help that occurs in pairwise interactions.

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 in 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 does not allow for the endogenous formation of social ties, we cannot compare the influence of degree centrality on helping behavior with the reverse influence of helping behavior on degree centrality. 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. Our model predicts that communication is not just information transmission but that one's position in a network matters for helping behavior, and our data confirms this prediction by producing a similar ordering of communication networks with respect to help. 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 complete network. However, if social ties are costly, then the model can help us determine the network structure that maximizes help at the lowest cost.[16] 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 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.

[16]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.

Bala, V. and Goyal, S. (2000). A noncooperative model of network formation. *Econometrica*, 68(5):1181–1229.

Barron, K., Harmgart, H., Huck, S., Schneider, S. O., and Sutter, M. (2023). Discrimination, narratives, and family history: An experiment with jordanian host and syrian refugee children. *Review of Economics and Statistics*, 105(4):1008–1016.

Bicchieri, C., Dimant, E., Gächter, S., and Nosenzo, D. (2022). Social proximity and the erosion of norm compliance. *Games and Economic Behavior*, 132:59–72.

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.

Bolton, G. E., Katok, E., and Zwick, R. (1998). Dictator game giving: Rules of fairness versus acts of kindness. *International Journal of Game Theory*, 27:269–299.

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.

Brañas-Garza, P. (2006). Poverty in dictator games: Awakening solidarity. *Journal of Economic Behavior & Organization*, 60(3):306–320.

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. 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.

Dannenberg, A., Haita-Falah, C., and Zitzelsberger, S. (2020). Voting on the threat of exclusion in a public goods experiment. *Experimental Economics*, 23:84–109.

Davis, D. D. and Holt, C. A. (1993). *Experimental Economics*. Princeton University Press, Princeton, NJ.

DeGroot, T. and Brownlee, A. L. (2006). Effect of department structure on the organizational citizenship behavior–department effectiveness relationship. *Journal of Business research*, 59(10-11):1116–1123.

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. (2018). Gender inequality and resource sharing: Evidence from rural Nicaragua. *Journal of Development Perspectives*, 2:62–87.

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.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, 78(6):1360–1380.

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.

Heursen, L. (2023). Does relative performance information lower group morale? *Journal of Economic Behavior & Organization*, 209:547–559.

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.

Koukoumelis, 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.

Loewenstein, G. (1996). Out of control: Visceral influences on behavior. *Organizational Behavior and Human Decision Processes*, 65(3):272–292.

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.

Maier-Rigaud, F. P., Martinsson, P., and Staffiero, G. (2010). Ostracism and the provision of a public good: experimental evidence. *Journal of Economic Behavior & Organization*, 73(3):387–395.

Muñoz Herrera, M. and Reuben, E. (2023). The role of personal and impersonal business relationships on market efficiency. *Journal of Law, Economics, and Organization*, 40(3):753–785.

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.

Rao, G. (2019). Familiarity does not breed contempt: Generosity, discrimination, and diversity in delhi schools. *American Economic Review*, 109(3):774–809.

Reuben, E. and van Winden, F. (2008). Social ties and coordination on negative reciprocity: The role of affect. *Journal of Public Economics*, 92(1-2):34–53.

Rezaei, S., Rosenkranz, S., Weitzel, U., and Westbrock, B. (2024). Social preferences on networks. *Journal of Public Economics*, 234:105113.

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 Dijk, F. and Van Winden, F. (1997). Dynamics of social ties and local public good provision. *Journal of Public Economics*, 64(3):323–341.

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.

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. 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.

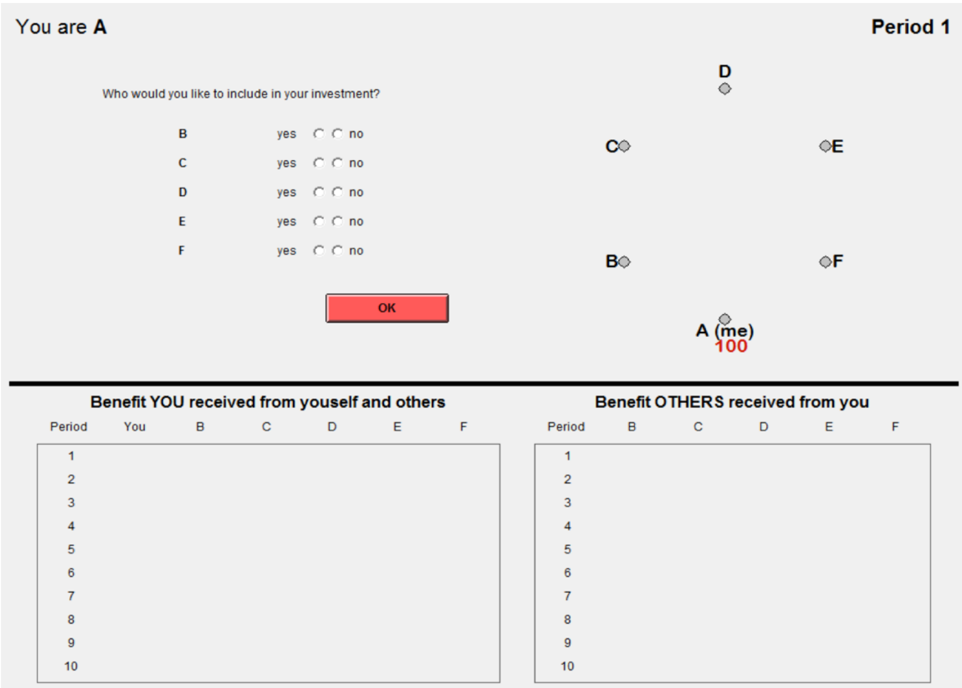
Consequences of your investment decision

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

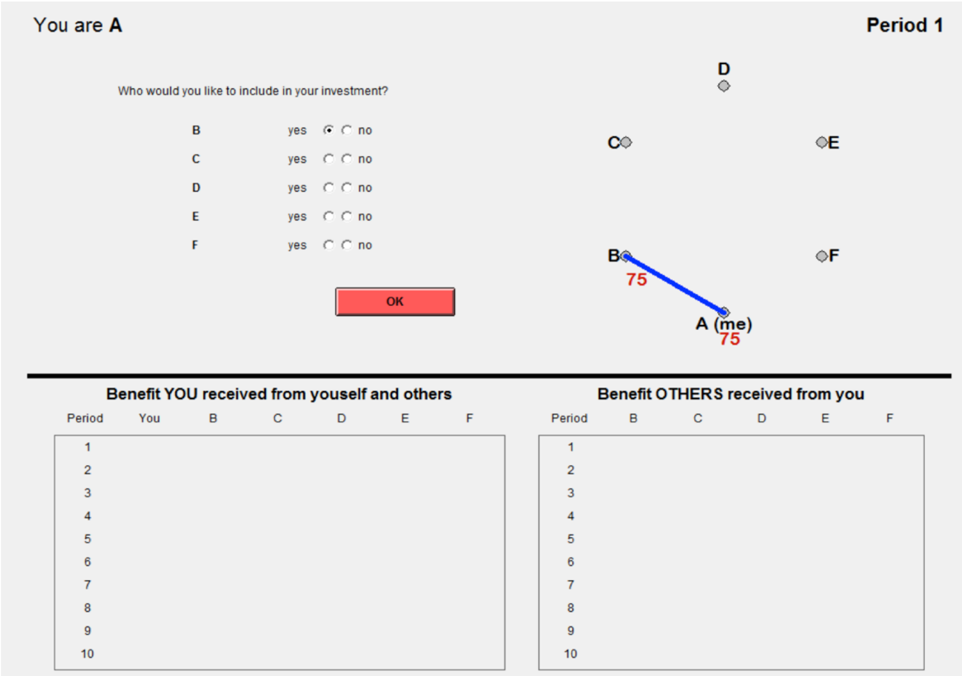
In each period, you have to decide whom to include in your investment. To do this, you use a decision screen like the one below:



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:



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.

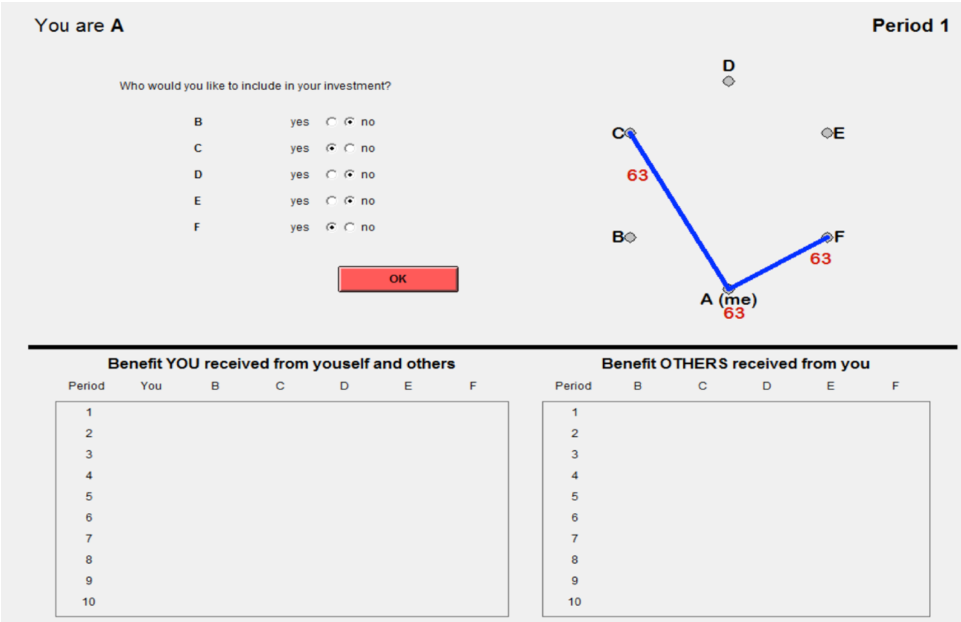
Once you click the OK button, the information on whom you included in your investment, who included you in their investment, and the amount of points you earned in this period will shortly appear. You can also see this information for the previous 10 periods on the lower part of the screen.

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.

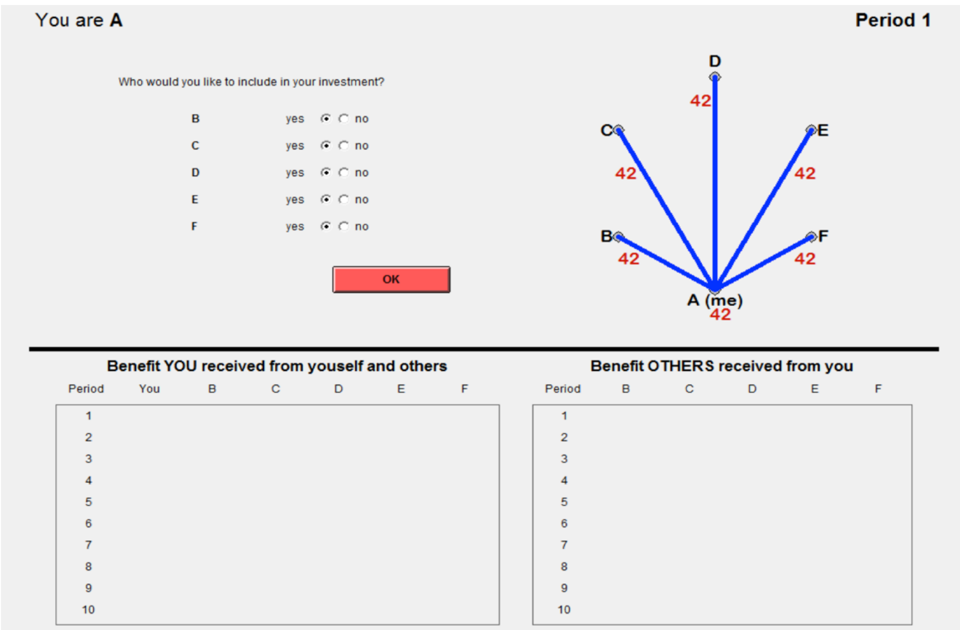
Example

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:

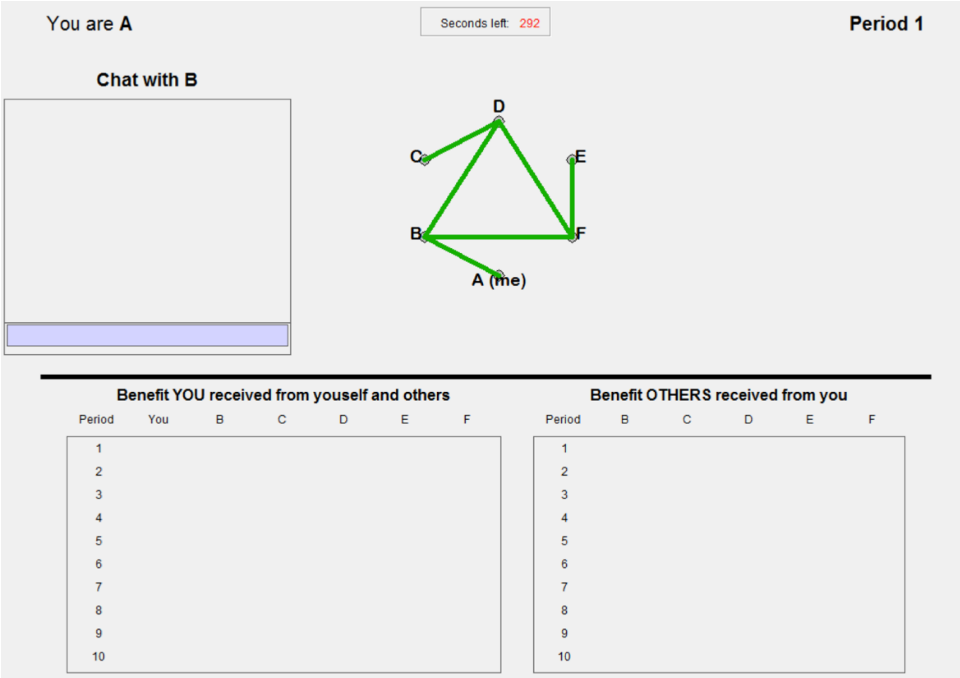
- You include B, E and yourself in your investment, and
- B includes E and you in his/her investment, and
- E only includes B in his/her investment.

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.

B. Decision screen

Figure A1 shows the screen where subjects make their helping decisions. Subjects are randomly assigned to labels A, B, C, D, E, or F, which they keep throughout the experiment. The screen is seen from subject A's point of view in period one. On the upper left, A decides whom to help. On the upper right, there is a visualization of who is helped by A (in the figure, A is helping C and F). When A chooses 'yes' on the upper left, a blue line between A and the respective subject appears on the upper right. A also observes the benefits generated by their help as a number next to each label. The lower part of the screen shows the points others received from A's help in previous periods (left) and the points A received from the help of other subjects in previous periods (right).

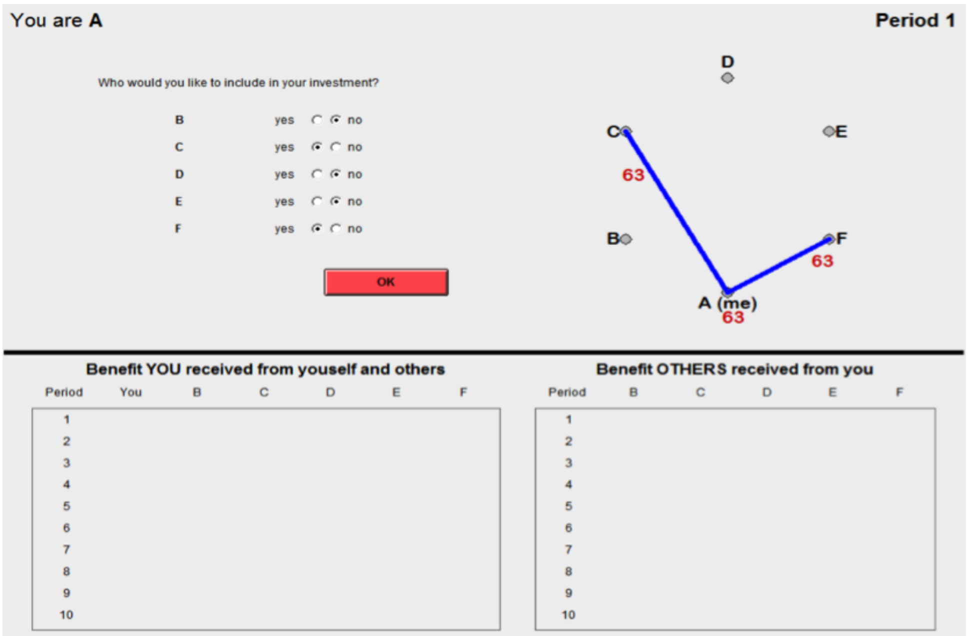


Figure A1. Screenshot of helping decision screen

C. Predictions of equation 1

Table A1 shows the predicted level of help for each pair of positions in each network structure according to 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 $h_{i \to j}$. For example, take player A's likelihood of helping player C, $h_{A\to C}$:

- In the **complete** network, $h_{A\to C} = \alpha+\beta+\gamma+\zeta$ as A has a degree centrality of 5 and A's distance to C equals 1.
- In the **core-periphery star** network, $h_{A\to C} = \alpha+\beta\delta^2+\gamma/5+\zeta$ as A's degree centrality equals 1 and A's distance to C equals 3.
- In the **circle** network, $h_{A\to C} = \alpha+\beta\delta^1+2\gamma/5+\zeta$ since A has a degree centrality of 2 and A's distance to C is 2.
- In the **two clusters** network, $h_{A\to C} = \alpha+2\gamma/5+\zeta$ as A maintains a degree centrality of 2, but A and C are not connected.
- Lastly, in the **empty** network, $h_{A\to C} = \alpha$ as there are no social ties.

Table A1. Predicted level of help for each pair of positions in each network structure

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

D. Effect of social distance and degree centrality over periods

Figure A2**a** shows the mean likelihood that a subject helps someone depending on the social distance between them, calculated every five periods (i.e., for periods 1-5, 6-10, and 11-15). Figure A2**b** shows the mean likelihood of helping depending on subjects' degree centrality, also calculated every five periods. The pattern where the likelihood of help gradually decreases with social distance is seen consistently in all five-period blocks. The pattern where the likelihood of help increases with subjects' degree centrality is also relatively consistent. The only exception occurs in periods 1-5, where help by subjects with a degree centrality of 0.4 is higher than those with a degree centrality of 0.6.

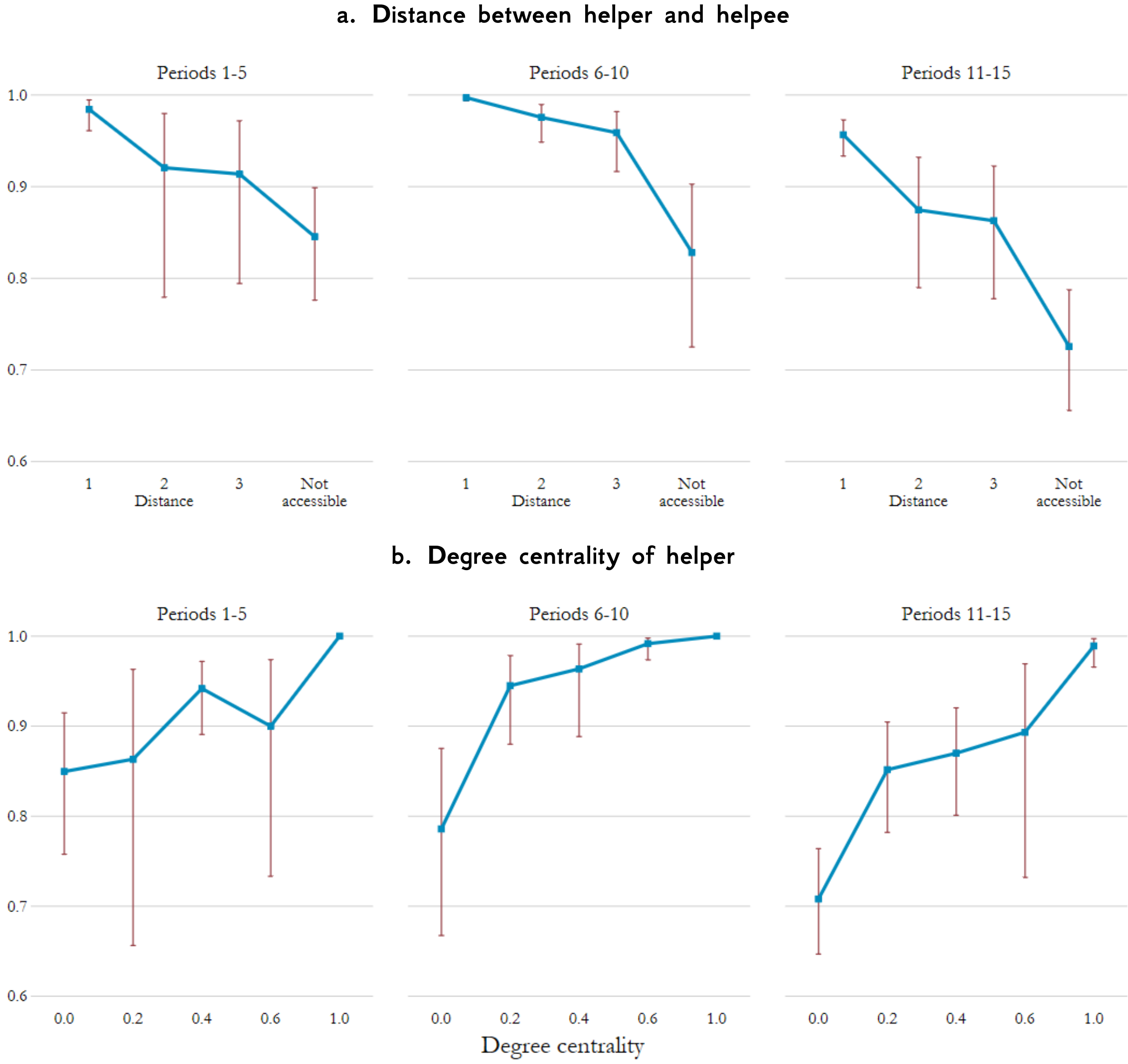


Figure A2. Likelihood of helping another subject by social distance and degree centrality calculated every five periods

Table A2 shows the parameter estimates of equation 1 when they are estimated separately for the first half (periods 1 to 7) and the second half (periods 8 to 15) of the experiment. The point estimate for baseline help α is smaller in the second half of the experiment, capturing the decline in cooperation seen in the empty network. The parameter for the presence of social ties ζ is larger in the second half of the experiment but remains statistically insignificant, indicating that differences in help between networks are explained by social distance and degree centrality. In both parts of the experiment, social distance has a positive and significant impact on helping that decreases as the distance between participants increases. The parameter estimates for β and δ are very similar. Finally, we observe a positive and significant coefficient for degree centrality γ, indicating that subjects help more the more social ties they have. This effect is slightly stronger in the second half of the experiment.

Table A2. Probability of helping for periods 1 to 8 and periods 9 to 15

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.

	Periods 1 to 8	Periods 9 to 15
Baseline help (α)	83.33**	73.56**
	(4.46)	(3.57)
Social ties (ζ)	0.92	4.38
	(6.71)	(8.38)
Social distance (β)	11.77*	14.49*
	(4.90)	(7.47)
Decay (δ)	0.73**	0.78**
	(0.25)	(0.17)
Degree centrality (γ)	3.99*	6.79**
	(1.86)	(1.19)
Observations	9,030	10,320
Clusters	43	43
R^2	0.060	0.089

E. Robustness of parameter estimates to specific network structures

Table A3 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 ζ 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 δ 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 A3. 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	C.-P. clusters	Circle star	Complete
Baseline help (α)	80.89**	78.14**	78.12**	78.12**	78.12**
	(6.13)	(3.75)	(3.75)	(3.75)	(3.75)
Social ties (ζ)			3.45	2.77	3.05
			(7.19)	(7.09)	(7.29)
Social distance (β)	13.22*	15.34**	14.39*	12.68*	13.21*
	(6.07)	(4.28)	(6.03)	(6.04)	(6.07)
Decay (δ)	0.76**	0.82**	0.89**	0.50	0.76**
	(0.18)	(0.11)	(0.11)	(0.46)	(0.19)
Degree centrality (γ)	5.49**	6.12**	3.67**	5.74**	4.78
	(1.20)	(1.92)	(0.87)	(1.16)	(4.02)
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

F. Textual analysis

We conducted a textual analysis of the content of the chat messages using ChatGPT. Specifically, we asked ChatGPT to read each conversation and code it using the following descriptions:

- **Emotional valence**: What is the sentiment in a given conversation? Answer with a continuous numerical variable that ranges from -1.0 (negative) to 1.0 (positive) and corresponds to the overall emotional leaning of the text.
- **Reaching consensus**: How much effort do they put into reaching a consensus in a given conversation? Answer with a continuous numerical variable that ranges from 0 to 1.0 (positive). 0 means they put in no effort, and 1 means they put in a fair amount of effort.
- **Coordination**: How much effort do they put into coordinating their actions in a given conversation? Answer with a continuous numerical variable that ranges from 0 to 1.0 (positive). 0 means they put in no effort, and 1 means they put in a fair amount of effort.
- **Advocating to receive help**: How much effort do they put into convincing group members to invest in them in a given conversation? Answer with a continuous numerical variable that ranges from 0 to 1.0 (positive). 0 means they put in no effort, and 1 means they put in a

fair amount of effort.

- **Advocating to reduce help to others**: How much effort do they put into convincing group members not to invest in others in a given conversation? Answer with a continuous numerical variable that ranges from 0 to 1.0 (positive). 0 means they put in no effort, and 1 means they put in a fair amount of effort.

Table A4 contains descriptive statistics of the textual analysis variables by network structure. Emotional valence could range from −1 to 1, but it is significantly greater than zero in all network structures ($p < 0.001$), suggesting that communication fosters positive emotional ties. Emotional valence is highest in the **complete**, followed by **circle**, **core-periphery star**, and is lowest in **two clusters**. If we test whether these differences are statistically significant by regressing emotional valence on dummy variables for the different networks, we obtain a p-value of 0.058. All remaining variables ranged from 0 to 1. Judging by the mean values, participants made substantial efforts to reach consensus (means between 0.47 and 0.49) and coordinate their actions (means between 0.58 and 0.61) in all network structures. The values measuring advocacy for personal help and reducing help to others are somewhat lower, with means between 0.15 and 0.28. Advocating to help fewer participants is the only variable that varies significantly across networks ($p = 0.046$).

Table A4. Descriptive statistics of the textual analysis variables

Note: Means and standard deviations (in parentheses) of the variables coded by ChatGPT's GPT-4 model based on the content of the chat messages. Emotional valence ranged from −1 to 1. All other variables ranged from 0 to 1. The p-value corresponds to the F-test evaluating whether there are differences between network structures based on linear regressions clustering standard errors on organizations.

	Network structure				
	Two clusters	C.-P. star	Circle	Complete	p-value
Emotional valence	0.24 (0.16)	0.33 (0.18)	0.36 (0.18)	0.37 (0.23)	0.058
Reaching consensus	0.47 (0.17)	0.49 (0.22)	0.49 (0.18)	0.47 (0.25)	0.937
Coordination	0.58 (0.12)	0.61 (0.13)	0.61 (0.12)	0.61 (0.17)	0.766
Advocating to receive help	0.28 (0.16)	0.27 (0.16)	0.23 (0.13)	0.24 (0.17)	0.161
Advocating to reduce help to others	0.19 (0.07)	0.16 (0.07)	0.15 (0.04)	0.15 (0.06)	0.046

Table A5 tests the relationship between the variables derived from the content of the chat messages and helping behavior. More specifically, we run a regression for each variable of the textual analysis. In all regressions, the dependent variable equals the mean helping rate over three-period blocks per organization (subjects chatted every three periods). The independent variable consists of the mean value of the textual analysis variable in the preceding three periods. To facilitate comparing coefficients, we standardized all independent variables to have a mean of zero and a standard deviation of one. All regressions include network fixed effects and robust standard errors clustered on organizations. Emotional valence, efforts to reach consensus, and efforts to coordinate actions are all significant predictors of subsequent helping rates ($p < 0.012$). Advocating to receive help has a positive coefficient, but it is not statistically significant ($p = 0.173$). By contrast, advocating to reduce help for others has a negative coefficient indicating a reduction in helping rates, but it is only marginally significant ($p = 0.092$).

Table A5. Helping rate depending on lagged variables form the textual analysis

Note: Linear regressions with the mean helping rate over three-period blocks per organization as the dependent variable. The independent variable in each regression is the lagged value of one of the textual analysis variables. All regressions include network fixed effects and robust standard errors clustered on organizations. **, *, $^{+}$ indicate statistical significance at 0.01, 0.05, and 0.10.

	Textual analysis variable				
	Emotional valence	Reach consensus	Coor-dination	Receive help	Reduce others' help
Coefficient	3.28^{**}	1.98^{*}	2.44^{**}	1.19	-2.94^{+}
Standard error	(1.19)	(0.74)	(0.74)	(0.86)	(1.69)
Observations	136	136	136	136	136
Clusters	34	34	34	34	34

Robustness of the textual analysis

To ensure that the results of the textual analysis do not depend on the specific ChatGPT model used to quantify the chat content, we redid the analysis with two other models. First, instead of using GPT-4, we used GPT-4o. According to OpenAI, GPT-4o outperforms GPT-4 on various tasks, such as doing mathematical operations, reading comprehension, and integrating audio and image inputs. Importantly, OpenAI also claims that GPT-4o is better at understanding idioms, metaphors, and cultural references present in everyday communication (see https://platform.openai.com/docs). Second, we redid the analysis once again using GPT-4o-mini, a more cost-effective version of GPT-4o optimized to be faster but with slightly worse performance.

The variables used in the textual analysis are highly correlated across models. Table A6 shows the correlation coefficients between the three different GPT models. Correlation coefficients are highest for emotional valence, ranging from 0.86 to 0.93, and are only slightly lower for advocating to receive help from others where they range from 0.75 to 0.77. For reaching consensus and attempting to coordinate, we find similarly high correlation coefficients between GTP-4 and GTP-4o but somewhat lower coefficients between these models and GTP-4o-mini. Finally, for advocating to reduce help toward others, we find a very high correlation between GTP-4o and GTP-4o-mini and a somewhat lower correlation between these models and GTP-4. Nonetheless, all correlation coefficients are significantly different from zero ($p < 0.001$).

Table A6. Correlation coefficients between different GPT models for the textual analysis variables

Note: Pearson correlation coefficients between GPT models for each textual analysis variable. Emotional valence ranged from −1 to 1. All other variables ranged from 0 to 1.

	GTP-4 vs. GTP-4o	GTP-4 vs. GTP-4o-mini	GTP-4o vs. GTP-4o-mini
Emotional valence	0.87	0.86	0.93
Reaching consensus	0.81	0.58	0.57
Coordination	0.70	0.39	0.42
Advocating to receive help	0.75	0.75	0.77
Advocating to reduce help to others	0.42	0.47	0.70

Table A7 contains the descriptive statistics of the textual analysis variables by network structure when using the GTP-4o (Panel A) and GTP-4omini (Panel B) models. The results are remarkably similar to those obtained with the GPT-4 model (seen in Table A4). Namely, emotional valence is significantly greater than zero in all network structures ($p < 0.001$). Moreover, it is highest in the **complete**, followed by **circle**, **core-periphery star**, and **two clusters**. Similarly, we find relatively high values for building consensus and coordinating actions in all network structures, and somewhat lower values for advocating for personal help and reducing help to others.

Finally, Table A8 tests the relationship between helping behavior and the textual analysis variables derived from the GTP-4o and GTP-4o-mini models. As with GTP-4, we run regressions of the mean helping rate over three-period blocks per organization on the mean value of the textual analysis variable per organization in the preceding three-period block. As before, in all regressions we standardize the independent variables to have a mean of zero and a standard deviation of one, we include network fixed effects, and use robust standard errors clustered on organizations. Panel A corresponds to the GPT-4o model and Panel B to the GPT-4o-mini model.

Once again, we find that the results obtained with GPT-4 (see Table A4), are relatively robust.As seen in Table A8, emotional valence and efforts to reach consensus are significant predictors of subsequent helping rates with both GPT-4o and GPT-4o-mini. The coefficients for efforts to coordinate actions are positive, but they are statistically significant only with the GPT-4o model. The coefficients for advocating to receive help are positive for both GPT-4o and GPT-4o-mini and of very similar magnitude as the coefficient for GPT-4. With GPT-4o and GPT-4o-mini, these coefficients become marginally significant. Lastly, as with GPT-4, advocating to reduce help for others has a negative effect on subsequent helping rates. Compared to GPT-4, the statistical significance of the coefficient is slightly stronger with GPT-4o and slightly weaker with GPT-4o-mini.

Table A7. Descriptive statistics of the textual analysis variables using different GPT models

Note: Means and standard deviations (in parentheses) of the variables coded by ChatGPT based on the content of the chat messages. Panel A corresponds GPT-4o and Panel B to GPT-4o-mini. Emotional valence ranged from −1 to 1. All other variables ranged from 0 to 1. The *p*-value corresponds to the F-test evaluating whether there are differences between network structures based on linear regressions clustering standard errors on organizations.

	Network structure				
	Two clusters	C.-P. star	Circle	Complete	*p*-value
Panel A: GPT-4o					
Emotional valence	0.31	0.36	0.38	0.55	0.061
	(0.25)	(0.24)	(0.21)	(0.32)	
Reaching consensus	0.51	0.53	0.54	0.42	0.138
	(0.22)	(0.21)	(0.21)	(0.30)	
Coordination	0.59	0.61	0.61	0.55	0.055
	(0.13)	(0.12)	(0.13)	(0.23)	
Advocating to receive help	0.17	0.18	0.17	0.14	0.513
	(0.19)	(0.19)	(0.14)	(0.21)	
Advocating to reduce help to others	0.16	0.13	0.09	0.10	0.122
	(0.13)	(0.12)	(0.08)	(0.19)	
Panel B: GPT-4o-mini					
Emotional valence	0.44	0.51	0.53	0.65	0.102
	(0.26)	(0.24)	(0.22)	(0.28)	
Reaching consensus 0.55	0.56	0.62	0.55	0.401	
	(0.17)	(0.16)	(0.32)	(0.23)	
Coordination	0.61	0.61	0.64	0.59	0.708
	(0.09)	(0.10)	(0.31)	(0.17)	
Advocating to receive help	0.40	0.40	0.36	0.35	0.321
	(0.17)	(0.18)	(0.16)	(0.23)	
Advocating to reduce help to others	0.30	0.24	0.19	0.18	0.016
	(0.16)	(0.14)	(0.09)	(0.21)	

Table A8. Helping rate depending on lagged variables from the textual analysis using different GPT models

Note: Linear regressions with the mean helping rate over three-period blocks per organization as the dependent variable. The independent variable in each regression corresponds to the lagged value of one of the textual analysis variables. All regressions include network fixed effects and robust standard errors clustered on organizations. Panel A corresponds to GPT-4o and Panel B to GPT-4o-mini. **, *, $^{+}$ indicate statistical significance at 0.01, 0.05, and 0.10.

	Textual analysis variable				
	Emotional valence	Reach consensus	Coor-dination	Receive help	Reduce others' help
Panel A: GPT-4o					
Coefficient	3.58^{*}	2.35^{**}	2.51^{**}	1.24^{+}	-2.64^{*}
Standard error	(1.40)	(0.77)	(0.86)	(0.73)	(1.26)
Panel B: GPT-4o-mini					
Coefficient	4.31^{*}	2.38^{+}	1.68	1.25^{+}	−1.93
Standard error	(1.60)	(1.27)	(1.30)	(0.70)	(1.54)
Observations	136	136	136	136	136
Clusters	34	34	34	34	34