An Experimental Study on the Effects of Communication, Credibility, and Clustering in Network Games[*]

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Abstract: We examine how pre-play communication and clustering affect play in a challenging hybrid experimental game on networks. Free-form chat is impressively effective in achieving the non-equilibrium efficient outcome, but restricted communication has little effect. We support this result with a model about the credibility of cheap-talk messages. We also offer a model of message diffusion that correctly predicts more rapid diffusion without clustering. We show an interaction effect of network structure and communication technologies. A remarkable result is that restricted communication is quite effective in a network Stag Hunt, but not in our extended game.

JEL Codes: C71, C91, D03, D85

Keywords: Networks, Clustering, Communication, Credibility, Cheap talk, Experiment

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[*] We thank Ramon Cobo-Reyes, Sanjeev Goyal, Brit Grosskopf, Erik Kimbrough, Arthur Robson, three referees, and seminar participants at the ASSA meetings, University of Bonn, CESifo, UCSB, Simon Fraser University, Stanford Institute for Theoretical Economics, the University of Cologne, Columbia University, University of East Anglia, University of Exeter, LBEG at LSE, the EEG-inaugural conference at MPI Bonn, the III BiNoMa workshop in Bilbao on economic networks, and the University of Portsmouth for helpful comments. We gratefully acknowledge funding: Ministerio de Ciencia, Innovación y Universidades, Spain (ref. RTI2018-097620-B-I00), Junta de Andalucía - FEDER (P18-FR-3840 and UMA18-FEDERJA-243), and the University of Cologne (through the Hans Kelsen Prize).

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1. Introduction

In many field environments, agents must coordinate their actions to achieve success. For example, collective action may only be effective when a threshold number of parties participate in an action that is potentially risky. Think of hunting together or defending one's territory against potential invaders, coordinating on a ceasefire in military conflict, or imagine companies coordinating on a new technological standard when competing platforms are available.

Naturally, communication amongst the parties may occur; yet it might need to be covert and so restricted to those people with whom one is directly linked. This creates a network setting in which individuals can interact only with other individuals who share a connection or link. Such networks – a bridge between bi-lateral interactions and full-fledged markets in which all agents can interact with all other agents – are ubiquitous and important for many domains in one's life. Jackson (2010) states (p. 512) that one's social network "influences patterns of decisions regarding education, career, hobbies, criminal activity, and even participation in micro-finance."

There is even evidence (Parker, 2014; Cantoni *et al.*, 2019) that social-media networks have had a crucial role in the effectiveness of protest movements. People might participate in such movements if enough others also participate, so that the information flow in one's network may be decisive. Another example is whether to go on strike, which might depend upon the willingness of co-workers to also go on strike. These examples do have a local effect, since one's utility can be significantly affected by one's neighbors' choices (e.g., to go on strike or join a protest).[1]

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[1] An alternative approach would have been to have population games, where the most frequent choice is implemented. However, we wished to make this difficult for free-form communication to have an effect in our challenging game, and we felt that randomly choosing one of four neighbors from a larger network created more uncertainty.

The real-world examples, however, are too complex to carefully control the network structure and the communication between parties, making it very difficult to causally identify the influence of specific network structures and communication technologies on the actions taken in a network. Thus, we study these situations in an abstract and controlled laboratory setting. Such a setting allows us to examine how network characteristics such as clustering and different forms of pre-play communication – and the interaction between network structure and communication forms – affect coordination in a challenging network game that has multiple equilibria.

Our research makes an original contribution to the field of experimental economics by considering two dimensions that have been rarely investigated until now (and never jointly) despite their important role in understanding today's online interactions: communication technologies (especially free-form chat) and social networks. While there are many open questions associated with this kind of complex environment, this work provides a first step towards answering them, and illustrates the value of experimentally studying this type of problems in the lab.

We form 8-person networks in which each person is linked to exactly four others. Only linked players can communicate with each other (two forms of communication) and then play an extended stag-hunt game in which we select (at random) one of the four neighbors as the interaction partner. This challenging hybrid game builds on the classic Stag Hunt with two actions per player. We add a third action that is strictly dominated by both other actions and so does not change the pure-strategy equilibria of the game. Yet, when played jointly, this action leads to the highest social payoffs (but one receives zero when the other player doesn't choose it).[2] This game

[2] Our game has some similarity to the Cooper *et al.* (1992; see their Figure I) *cooperative coordination game*, where the third action – if played mutually – yields the highest social payoffs. Yet, there the third action is not strictly dominated by both other actions. Hence, our extension makes it more challenging to reach the social optimum.

is a stylized representation of economies with multiple (Pareto-ranked) equilibria, in which the most efficient equilibrium is not socially optimal due to the presence of positive externalities. Bank runs, public-good environments, and team-production problems are classic examples of such games with positive externalities leading to socially efficient non-equilibrium outcomes.

Our experimental design varies two factors, and the unique combination separates our paper from previous work. First, we allow communication and permit either simple letter messages (*bare*), free-form chat messages (*rich*), or no (*no*) messages to linked parties. Second, clustering is a critical element of network structure and measures the extent to which an individual's neighbors in a network are linked. A *cluster* is a triple of subjects in which each member is linked to every other member. Our networks have either zero or positive clustering.

Note that none of our communication technologies should be sufficient to achieve the socially-efficient (but dominated) outcome in our game, since standard theory doesn't consider that messages will be credible when they advertise a dominated strategy. However, we present two behavioral models that address how communication might affect play in the network game, and we then derive predictions from these models for our experiment. For both models, we assume that there is a taste for efficiency (Charness and Rabin, 2002). We start with a model of the diffusion of messages within the network, which yields predictions about the effects of our treatment variation with respect to the clustering coefficient of the two networks. We then proceed with a model of the credibility of messages that will help us to form predictions about different effects of rich and bare communication. The latter is a novel feature, demonstrating why rich and bare communication could yield different effects on actual play.

Although the rich-communication protocol is representative of the most usual form of communication, especially in a social-media environment, there are also many real-world situations in which communication is restricted to a pre-specified set of messages. For example, in Facebook, when an "event" is created, individuals can only choose to click "I will participate" or "I am interested" (or not click); choices becoming visible by all their *friends* (neighbors).

We know of only one experimental paper on the topic of networks and communication: Choi and Lee (2014) studies coordination in networks in a four-player battle of the sexes, investigating the trade-off between the efficiency and equity of coordination outcomes and its link to the network structure of communication. They find that their bare communication tends to induce coordination on the equilibrium preferred by the best-connected players. Nevertheless, we are the first to introduce free-form (*rich*) communication to a network environment. Moreover, in comparison to Choi and Lee (2014), we also consider a second factor by varying the degree of clustering in the network, while keeping all other elements of the network structure identical.

Of course, the pure effects of clustering in networks have been addressed previously. Theoretical models by Eshel *et al.* (1998), Vega-Redondo *et al.* (2005), and Assenza *et al.* (2008) all predict that a higher degree of clustering will lead to better coordination of actions in networks. In fact, experimental work by Berninghaus *et al.* (2002), Cassar (2007), Charness *et al.* (2014), and Melamed *et al.* (2018) all find that higher clustering leads to more efficient outcomes. Yet, none of these features communication, and no research has considered how clustering in networks interacts with different forms of communication.

We are particularly interested in how messages to play cooperatively diffuse across the two different networks, as this might crucially depend on the degree of clustering in the network. For this purpose, we build on an idea used in Kearns *et al.* (2009).[3] In our design, we let subjects exchange (and change) messages for 90 seconds; they then make simultaneous choices in the game. This extended period allows us to examine how messages diffuse through the network and how this affects actual play, contingent on the network structure.

There is little experimental work (but see Charness and Dufwenberg, 2006; Brandts *et al.*, 2016) investigating the critical issue of what makes a message credible. We present a model on the credibility of messages that predicts free-form messages will be more credible than restricted ones (our bare-communication treatment). Then we test this prediction by constructing a credibility indicator that measures credibility in a principled way.

Our experimental results regarding communication are quite striking and arguably the most important finding of our paper. In our extended stag hunt game, we find attempts at coordinating on the socially-efficient-but-risky non-equilibrium outcome in the early periods of every treatment. Yet the rate of cooperative play to achieve the socially-efficient outcome rapidly deteriorates to almost nothing without communication and does so just a bit more slowly with bare communication. To the contrary, the socially-efficient outcome dominates and continues to be well over 90% with rich communication (compared to less than 20% otherwise).

Supporting the theoretical predictions of our model, the success of rich communication is higher in the non-clustered network, perhaps reflecting the quicker diffusion of messages that strive for the socially-efficient outcome. Messages with rich communication are more credible than messages with only bare communication again in line with our theoretical predictions. While

[3] Kearns *et al*. (2009) gave participants time to indicate their intended action. They see in real time the other messages and can change their own at any time. The last message before the period ends is the action played in their game. Since not all members can react to other members' last (implemented) messages, communication is not cheap talk.

rich communication has been shown to increase cooperation in bilateral interactions (e.g., Charness and Dufwenberg, 2006; Ben-Ner *et al.*, 2011; Brandts *et al.*, 2016), we are the first to demonstrate such a strong effect in a challenging game with a complex network structure.

Bare communication is almost completely ineffective in the network case, in stark contrast to earlier work in simpler (one-to-one) *non-network* settings. Sending messages about intended actions has been frequently found to increase efficiency in coordination games (also see Cooper *et al.* (1992), Blume and Ortmann (2007) and Cason *et al.* (2012). The failure of bare communication to increase cooperation and efficiency in our environment might be due to the network setting. To test this, we conduct an extended-stag-hunt game with bilateral matching. Here bare communication is quite effective in raising the level of cooperative play.

We also have a robustness treatment using the standard 2x2 stag-hunt game with bare communication, again finding considerable coordination on the efficient equilibrium. Perhaps curiously, adding a row and column to this game greatly *decreases* the average payoffs achieved! In principle, having an extra option should only improve matters. Both games have the same equilibria. And yet, people play the efficient equilibrium dramatically more often with bare communication in the standard 2x2 game than in the extended 3x3 game. Furthermore, average earnings with bare communication are considerably higher in the 2x2 game than in the 3x3 game.

Summarizing our experimental findings: 1) rich communication is very successful in achieving the socially-efficient and non-equilibrium outcome in a difficult network environment, 2) bare communication is ineffective in networks, but quite effective in the standard Stag Hunt, 3) message diffusion is contingent on the degree of network clustering, 4) messages credibility depends on the communication type, 5), adding a dominated-but-efficient action to our stag-hunt game with bare communication reduces payoffs and coordination at the efficient equilibrium and 6) there is a negative effect of clustering on efficiency when communication is rich.

The reminder of the article is organized as follows. We describe the experimental design and implementation in Section 2. Section 3 presents two models on diffusion and credibility of messages in networks and our hypotheses for the experiment. The experimental results are described in detail in Section 4, and Section 5 concludes.

2. Experimental design and implementation

2.1. Experimental design

Subjects are arranged on an 8-node symmetric network to play a game with one neighbor. Each subject in the network is linked to four *neighbors* and communication is only possible with one's neighbors. Each subject plays the game shown in Figure 1 with one randomly-selected neighbor. Figure 1 shows our extended Stag Hunt game; (A,A) is the risk-dominant equilibrium, (B,B) is the payoff-dominant equilibrium and (C,C) is the socially-efficient outcome. (C,C) is clearly not an equilibrium, since strategy C is strictly (weakly) dominated by strategy A (B).

Subjects play this game for 40 periods, with this timing in each period:

1. At the beginning of each period, subjects are randomly assigned to a group of 8 and to one node of the network. Each node has links to four neighbors.
2. Prior to playing the game, players can send messages (where feasible) during a 90-second period. During that period, players can change their prior messages by sending new ones if desired. Players continuously observe the messages of all neighbors, together with their network positions. The final message stands.
3. Each subject chooses one action (either A, B, or C).

4. Subjects are randomly paired with one of their neighbors. For each pair the chosen actions define the individual payoffs. Players are informed about the action of the paired player and the monetary outcome.

Figure 1: The extended 3x3 Stag Hunt game (about here)

Treatment variation 1: Degree of clustering in the network.

Using a between-subjects design, players are arranged in one of the two networks shown in Figure 2, and they are told their position in the network and the network structure. The two networks differ with respect to clustering, one of the features considered important in terms of network structure, but both networks are identical regarding connectivity, diameter, and assortativity, having eight players and homogeneity of degree 4 (all players have four links). Both networks are also symmetric (immune to permutations) and have diameter 2 (in each network any two players can reach each other by a path not greater than two links: 4 players at distance one and 3 players at distance two). As mentioned earlier, a *cluster* is a triple of subjects that satisfy the condition that each person in the *cluster* is connected to the other two members of the cluster.

Figure 2: The networks (about here)

The two networks in Figure 2 are characterized as follows:

- *Clust*: In the network on the left-hand side of Figure 2, each one of a subject's neighbors is linked to at least another one of his neighbors. This network has a positive clustering coefficient of 0.5. The clustering coefficient is defined as the ratio of the number of such clustered triplets to the number of all triplets.
- *NoClust*: Here, on the right-hand side of Figure 2, none of a subject's neighbors is linked to another one of his neighbors. This network has therefore zero clustering.

Treatment variation 2: Communication within the network

We also vary the form of communication permitted in a session (between-subjects design):

- *No communication*: Subjects play the game without any communication.
- *Bare communication* (Simple letter messages): Participants send messages by marking an option A, B or C. Messages are immediately visible to all one's neighbors and one could change (but not simply repeat) the marked option at any time during the period.
- *Rich communication* (Free-form chat messages): Messages via chat immediately visible to all neighbors. One can send as many messages as desired during this stage (of 90 seconds).

Our design is one of local payoffs with local communication.[4] One's payoffs depend on the decisions made by one's neighbors, since *ex post* (once the actions are already chosen) each player is randomly paired with one neighbor, and the payoffs in a pair are determined by the actions chosen by the two players. This random pairing is strategically equivalent to a *playing-the-field* game (one's total payoff is the average of one's payoffs in each bilateral interaction). The random pairing, however, constitutes the most challenging environment, since participants face the added uncertainty regarding the neighbor with whom they will play, making coordination on C difficult.[5] This uncertainty is not present in a playing-the-field game, making it easier to play action C. Hence in some sense our design is deliberately biased against finding high rates of C-play.

2.2. Implementation

Table 1 shows information about our sessions. There were 32 mutually-anonymous people in each session (except for one session in treatment *Bare_Clust*), each with two separate matching groups of 16. In each period the 16 participants of a matching group were randomly assigned to

[4] Note that one can only observe some of the messages (those sent by common neighbors) received by one's neighbors.

[5] Random pairing with bi-lateral matching normally has messages only from the matched player-to-be.

one of two 8-person groups. Positions in the network were randomly distributed in each 8-person group. A sample of our (translated) instructions is shown in Online Appendix E.

Since one is linked to four players in terms of messages, but only is matched with one of them in the game, our network environment introduces considerable uncertainty regarding the behavior of the to-be-matched player; furthermore, this uncertainty is compounded by the unseen messages received by one's neighbors (although there is diffusion of messages). To remove this uncertainty, we ran treatment *Bare_Bilateral*, where we have bare communication involving bilateral matching rather than the four-link network format. We kept other features the same to facilitate a clean comparison. We suspected the uncertainty in the network environment was an obstacle to efficient coordination of actions and so ran treatment *Bare_Bilateral* as a control.

Table 1: Treatments, sessions, and participants (about here)

In total, we had 432 people in our sessions that were run at the University of Cologne in 2015 and 2016. The average duration was about 80 minutes without communication and 120 minutes with communication. We paid for four randomly-selected periods out of the 40 total, with 100 Experimental Currency Units worth 6€. The average earnings were 19.1 Euro and 22.8 Euro, respectively (without or with communication), including a show-up payment of 4 Euro.[6]

3. Theoretical models and experimental hypotheses

We consider two models that shed light on the effect of communication on play in the network game. For both models, we assume that there is a taste for efficiency: players like to achieve the efficient outcome (C, C).

3.1. A model of message diffusion

[6] The issue of how to best pay subjects is not settled empirically. Charness *et al*. (2016) offers an extensive discussion.

Assume that the communication stage is divided into a finite number of intervals $t \in \{1, 2, \dots T\}$. In $t = 1$ one player (the *seed* player) sends a C-message (motivated by a possible increase in own payoffs and by a desire for efficiency; see Charness and Rabin, 2002). Her four neighbors receive this message. Then, in each interval $t \geq 2$ each player sends a C-message with probability $P \in (0, 1)$ if she received a C-message in any previous interval and with probability zero otherwise. We assume that messages sent in interval t are received in interval $t + 1$.

> **Proposition 1.** *In each interval $t \geq 3$ of the chat period, for each $P \in (0, 1)$ the probability distribution of the number of subjects that have sent a C-message up to interval t (included) in network NoClust first-order stochastically dominates (FOSD) the distribution of the number of subjects that have sent a C-message in network Clust.*

The proof is in Online Appendix A. Our Proposition 1 leads to our first hypothesis.

> **Hypothesis 1.** *At the end of the chat period the observed distribution of the number of subjects that sent a C-message in network NoClust first-order stochastically dominates (FOSD) the distribution in network Clust.*

The distribution of messages, however, need not affect actual play, which may instead depend on their credibility. If messages remain pure cheap talk, no difference is expected across the different networks or between treatments without communication and treatments with communication.

3.2. A model of the credibility of messages

This model is based on forward-induction reasoning. The concept, introduced by Kohlberg and Mertens (1986), is based on the idea that players delete (weakly) dominated strategies when determining which action to play. There is mixed support that people will be able to follow the kind of logic that forward induction involves. Brandts and Holt (1995) support forward induction in a simple game where it is equivalent to eliminating dominated strategies, but not in two more demanding environments. Huck and Müller (2005) find experimental support for forward induction in games shown in extensive form, but not for games in strategic form. Brandts *et al.* (2007) find support for the presence of forward-induction logic in simpler settings, but less in more complex settings. Blume and Gneezy (2010) and Evdokimov and Rustichini (2016) also find support for the presence of forward-induction logic in their experiments.

Yet there is also evidence that suggests that forward induction is not an important behavioral force. Schotter *et al*. (1994) and Nagel (1995) study experimental games for which the application of iterated dominance selects one outcome and obtain results inconsistent with the predictions of the iterated dominance argument. Still, on balance, it does not seem unreasonable to presume some awareness of forward-induction logic amongst the subjects.

Our model of the credibility of messages also assumes (like the model on message diffusion) a taste for efficiency, represented by a utility bonus $b > 0$ that players receive if they achieve the efficient outcome. We assume that players are averse to lying (Gneezy *et al.*, 2018). We model lying aversion by a cost of lying, x, that players incur if they don't play what they announced. Given previous experimental evidence of more lying aversion with endogenous messages (Lundquist *et al.* 2009), we assume the lying cost is higher with rich communication, i.e., $x^{rich} > x^{bare} > 0$.[7] While we know of no direct evidence on this point, it seems intuitive that elaborating on a lie has costs beyond merely stating it. Relatedly, the media-richness literature (e.g., Rockmann and Northcraft, 2018) suggests that people are more likely to honor a self-formulated claim or promise than a pre-formulated one (as in the bare-communication treatments).

[7] In principle this lying cost could depend on the message sent and could include motivations such as guilt aversion.

Second, for simplicity and ease of illustration, we consider a two-player game in which one player (player 1) can send one message (M) or not (NoM), and then, the extended-stag-hunt game presented in Figure 1 is played. We will assume that the message represents the intention to play the efficient action (i.e., the message is "to play C" in our game).

Proposition 2. *For each communication protocol $i \in \{bare, rich\}$ and $b > \overline{b}$ there is a threshold $\bar{x}$ where the message to play efficiently is credible if and only if $x^i > \bar{x}$. There is a set of parameters where rich (but not bare) communication leads to credible messages on efficient play.*

The proof is in Online Appendix A. Our Proposition 2 leads to our second hypothesis:

Hypothesis 2. *Rich communication will significantly increase the rate of cooperation on C, and much more so than bare communication. Since bare communication may not be credible, it may not induce higher rates of C-play than seen with no communication.*

The presumed higher credibility of C-messages in rich communication and the faster diffusion of such messages in the non-clustered network leads to our third hypothesis:

Hypothesis 3. *With rich communication, C-play is more likely in NoClust than in Clust. Given previous experimental results, there will be a higher rate of C-play in Clust than in NoClust without communication.*[8]

4. Experimental results

4.1. Descriptive statistics of actions

[8] Recall that treatment *Bare_Bilateral* is a robustness check to see whether bilateral matching – rather than play in networks – leads to more frequent C-play by removing the uncertainty concerning with whom one is matched..

Table 2 shows summary statistics of chosen actions over all 40 periods.[9] Subjects are overwhelmingly likely to make the safe choice of A when communication is not feasible, and this is largely unchanged with bare communication. The rates of choosing action A range from 80.6% to 89.1% across the first four columns, which show data for no communication and bare communication, separately for both networks. We see very little B-play, even though (B,B) is an equilibrium in standard theory. It is played in less than 5% of cases in the first four columns.[10]

The results with rich communication are dramatically different. Even in this complex game played on a network, the cooperative play of C is remarkably frequent: 92.5% in the clustered network and a spectacular 99.1% in the non-clustered network.

Table 2: Likelihood of actions A, B and C, by treatment (about here)

Conservative non-parametric tests (using each 16-person matching group as one observation) show clear statistical significance in the difference in the rate of cooperative C-play between rich communication and each of the other communication protocols. Each matching-group with rich-communication had a higher C-rate than any of the other groups. A one-tailed ranksum test indicates the differences between bare and rich communication are significant for each network ($p = 0.017$ in network *Clust*, $p = 0.010$ in network *NoClust*). Likewise, the difference between rich and no communication is significant in each network ($p = 0.021$ for *NoComm_Clust*

[9] Table B1 in Appendix B breaks down the aggregate data into blocks of ten periods each.

[10] The rarity of B-play with bare communication is the consequence of extending the traditional stag-hunt game with a third, dominated, option. To show this, we ran additional treatments with the traditional stag-hunt game where subjects can only choose between option A and option B (Figure 1 with the row and column for action C deleted). While without communication, option A is chosen in almost 90% of cases, bare communication raises the frequency of B-play to 75% of cases. Thus, our additional control treatments largely replicate former results. See Section 4.5.

versus *Rich_Clust* and $p = 0.020$ for *NoComm_NoClust* versus *Rich_NoClust*). However, there is no significant difference in C-play between bare and no communication ($p = 0.289$ for *NoComm_Clust* versus *Bare_Clust* and $p = 0.248$ for *NoComm_NoClust* versus *Bare_NoClust*). These findings provide strong support for our Hypothesis 2, according to which C-play should be most frequent with rich communication, and significantly lower otherwise.

Figure 3: Frequencies of actions across periods, by treatment (about here)

One might imagine that people are initially optimistic about reaching the (C,C) outcome, but that this is soon tempered by receiving zero after failing to coordinate. In fact, we see such a time trend in Figure 3 (Table B2 and Figure B1 in Appendix B breaks this out by matching groups). We see many choices of C (about half) initially in both the no-communication and bare-communication treatments, but this drops quickly in both cases (more so without communication). On the contrary, C is played almost 100% of the time with rich communication, apart from slightly lower frequencies in the first period and the last few periods (in which the modest unravelling is not surprising, since this is not a simple coordination game).

We next consider average payoffs. Without communication, people play A almost exclusively, with some losses due to a lack of coordination, so the average payoffs of 67.61 (clustered network) and 67.49 (non-clustered network) are not surprising and very close to the payoff of 70 per person in case of the (A,A)-outcome. Bare communication only very slightly increases the respective average payoffs in the network setting, to 68.86 and 68.54. Payoffs increase significantly only with rich communication, to 94.14 in *Clust* and 99.32 in *NoClust.*[11]

[11] Ranksum two-tailed tests – using a matching group's (16 subjects) average over 40 periods as unit of observation – gives $Z = 2.309$ and 2.323, $p = 0.021$ and 0.020, for the differences in profits between *NoComm_Clust* and *Rich_Clust*

This reflects the very high frequency of C-play with rich communication, even though playing C bears the risk of no payoff if the matched player plays A or B. Yet, coordination seems to work well. To see this, we can consider the likelihood of successful coordination on (A,A), (B,B), or (C,C). It is not straightforward to define coordination in our framework; whether it should be at the pair level – but pairs are randomly chosen –, at the neighbors' level, at the network-group level, or at the matching-group level. In Table 3, we show the rate of coordination at both the network-group level (reflecting the conservative assumption that a network group is coordinated if and only if all eight participants play the same action) and the level of the realized action-pairs.

The rate of complete coordination on A in the no- and bare-communication treatments ranges from 50% to 58%, while the coordination rate at the realized-pair level ranges from 79% to 83%; there is little difference across treatments or clustering. No consensus coordination (i.e., on the network level) on B or C was ever observed without rich communication, although there is a tiny amount (less than 1%) of pairwise coordination on B and a small amount (two to seven percent) of pairwise coordination on C. Matters are very different with rich communication, where there is a high rate of consensus coordination on C, remarkably so in the no-cluster case (with 95.6%). It is clear from these findings that only rich communication seriously affects behavior, so we summarize our findings on actions played in our first result.

Table 3: Frequencies of coordination on outcomes, by treatment (about here)

Result 1. *There is a very high likelihood of cooperative C-play with rich communication, while the safe play (of A) is chosen overwhelmingly both without communication and with*

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and between *NoComm_NoClust* and *Rich_NoClust*. Similarly, these tests give $Z = 2.121$ and 2.323, $p = 0.034$ and 0.020, for the differences in profits between *Bare_Clust* and *Rich_Clust* and between *Bare_NoClust* and *Rich_NoClust*. The difference between *Rich_Clust* and *Rich_NoClust* is also significant ($Z = 2.033$, $p = 0.042$).

bare communication, particularly after the first few periods. There is no significant difference in play across the no-communication and bare-communication conditions.

4.2. Analysis of messages

To classify the content of messages in rich communication, we first went through roughly 20% of the chat messages and defined different categories of contents (see Online Appendix C). Two RAs blind to the hypotheses independently coded (Cronbach's alpha of 0.98) whether a particular message fell into a specific category (using a binary measure of zero or one).

A. Message classification

We present a simplified scheme in Table 4; a more detailed one, with examples for each category, is shown in Online Appendix C. We consider clustered and non-clustered networks separately in Appendix C (see Tables C1 and C2), showing little difference. For completeness, we also present Tables for the messages in the *Bare* treatment in Appendix D (see Tables D1 to D3).

Table 4: Likelihood of categorized messages over successive 5-period ranges (about here)

Promise indicates a statement of intent to play C. *Social efficiency* involves statements about playing C that reflect a social norm of efficiency. *Admonition* involves admonishing the receiver to play C. *Don't choose C* means that the message was A or B or pointed out that C could give a zero payoff. *Conversational* messages had little or nothing to do with the experiment, often simply being social or friendly. Coding conflict shows a rare coder disagreement.

Overall, promises are made in about 15% of the messages overall, with a gradual decline in this rate.[12] On the other hand, the probability that a message appeals to social efficiency drops

[12] This is less prevalent than in Charness and Duwenberg (2006), perhaps due to a difference in message technology (a single one-way message on paper versus written chat on a computer).

sharply from 46% in periods 1-5 to 12% in the last 20 periods. Over 65% of all messages in the first five periods were to play C. But this falls to 25% by the end of the experiment, with *Conversational* messages reaching over 70% in the last 15 periods. This pattern is consistent with people having commonly grasped the social attractiveness of everyone playing C, so that it becomes more important to attempt to forge social ties with congenial messages. This is also likely related to the fact (see below) that fewer C messages are sent over time with rich communication.[13]

What seems important is to mutually identify the important issue (here social efficiency versus a possible zero payoff) and to establish goodwill among the linked participants

B. Diffusion of messages

We begin the analysis of the diffusion of messages by showing first that receiving a C-message affects the likelihood of sending a C-message, meaning that C-messages are propagated through the network. We show that this propagation depends on clustering, which then leads to differences in the distribution of C-messages between clustered and non-clustered networks.

Table 5: Estimated probability of sending a first C-message with rich communication, conditional on having received a C-message or not (about here)

We estimate the probability of sending the first C-message in a time interval (i.e., one second) for those that have already received at least one C-message in previous time intervals and for those that have not yet received any C-message. In Table 5 we report these estimates for different subsets of periods, since the probability of sending a C-message could be affected by the experience gained in the repetition of the game. In fact, we show below that there is a downward

[13] A similar phenomenon was observed in Brandts *et al.* (2016).

trend across the 40 periods in the likelihood of sending a message. Thus, it may be that the first period is the best for properly analyzing the propagation of messages.

The upper part of Table 5 indicates that the probability of sending a first C-message is significantly higher when one has already received a C-message. This holds true for the first period and for the first five periods (but not over all 40 periods).[14] In the lower part of Table 5 we report estimates where we remove observations for people who have not sent a C-message if no one or everyone in their group has received a C-message. The reduced sample yields the same main result: people who receive C-messages are more likely to send them. This result is consistent with the assumption on P in the diffusion model presented in subsection 3.1.

Table 6: Rates of final sent C-message, by # C-messages received (Rich Comm) (about here)

Another approach to diffusion is to examine whether the number of C-messages that one receives affects how likely one is to send a final C-message. Table 6 shows that this is true with clustered networks.[15] Hence, there is some contagion present. In the non-clustered network, one's rate of sending a final C-message is fairly constant at around 70%, compared to an overall likelihood of 60% in the clustered network. This difference in behavior provides a first clue regarding the clustering effect with rich communication (examined in more detail below).

Finally, to test Hypothesis 1, we examine the distribution of final messages at the end of the communication phase. This means that for each subject we consider the last message sent before taking an action. Given the predominance of and our interest in the determinants of a C-message, we focus on the distributions of C-messages. Figure 4 shows the cumulative distribution

[14] We provide similar estimates for the treatments with bare communication in Table D5 in Appendix D.

[15] This holds for both clustered and non-clustered networks with bare communication (see Table D4 in Appendix D).

function: on the left (right) for bare (rich) communication, showing that there are more C-messages in the 8-person networks with rich communication.

Figure 4: Cumulative distribution functions of the number of C-messages (at the 8-person network level), by treatment, and at the end of the communication stage (about here)

This gives us our second result, which supports our Hypothesis 1:

Result 2. *The cumulative distribution of C-messages with the non-clustered network first-order stochastically dominates the distribution with the clustered network. Rich messages also first-order stochastically dominate bare messages in this respect.*

C. Messages and actions

To examine how messages relate to actions, we begin by seeing which messages are actually the most credible in each of our treatments. Table 7 shows the relation between messages and actions.

Senders of A-messages played A nearly 99% of the time in bare communication, so A-messages should be very credible. B-messages are not, since at most 15% of senders choose B after a B-message. C-messages are common in all cases, but they are not credible with bare communication (C-message senders play C 25% of the time). But C-messages are highly credible given rich communication, with sender consistency at 90% in *Clust* and nearly 100% in *NoClust*.

Table 7: Messages and actions (about here)

We see that, overall, messages were sent 75.2% of the time that they were feasible.[16] With bare communication, messages were sent with probability 76.9% (*Clust*) and 93.6% (*NoClust*). These frequencies are larger than in rich communication, at 61.0% (*Clust*) and 69.8% (*NoClust*).

[16] Note that, to calculate the percentage of messages sent as a fraction of the number of times that they were feasible, we use the absolute frequencies in column "Sent" of Table 7.

One question is why more messages weren't sent with rich communication. The analysis suggests that groups appear to reach consensus quickly even without multiple messages in later periods. In fact, the percentage of people who send messages drops steadily over time in treatments *Rich_Clust* and *Rich_NoClust*, while there is no corresponding decrease in C-play.

Result 3. *Messages are sent more frequently with bare communication than with rich communication. In the latter case, groups reach consensus quickly without multiple messages in later periods. The proportion of people who send messages drops steadily over time with rich communication, but, without a corresponding decrease in C-play.*

Richer communication seems more valuable when the meaning of bare communication is more ambiguous. In bare communication, one cannot explain why she is recommending C, but with rich communication, one can do so. However, there is no possible ambiguity in the basic stag hunt in the motive for recommending B, and so no additional explanation is needed.

In addition, there may be normative uncertainty about the preferred outcome in our extended game, but not in the basic stag hunt. Rich communication may ameliorate this uncertainty in a manner that bare communication cannot. Table 8 provides some evidence for the effects of such uncertainty. It shows for the treatments with bare communication the likelihood with which a player chose a specific action, conditional on having sent only C-messages (bottom row) or – prior to a final C-message – at least one other message. We see that subjects who had sent another message before ending with a C-message are 10 percentage points less likely to play C than those subjects that only sent C-messages, which shows that uncertainty created from conflicting messages decreases the likelihood of cooperative play.

Table 8: Messages and actions in *Bare*, contingent on switching messages (about here)

4.3. Econometric analysis of the reliability and credibility of C-messages and C-play

In this section we estimate the determinants of the reliability and credibility of C-messages. We can look at this from both an *ex-post* and an *ex-ante* perspective. *Ex-post*, we focus on sent messages: a C-message is classified as *reliable* if the player that has sent it plays action C. *Ex-ante*, we focus on received messages and here we talk of credibility: a C-message is *credible* if the player that receives it believes that the sender intends to play C. We assume that the credibility of received messages reflects two factors: social norms and the experience of past reliable messages. By social norms we mean what one feels "should" be done in this game (i.e., play C by appealing to efficiency and equity, or play C because one promised to do so).

We estimate the probability of generating a reliable message to investigate the determinants of playing action C conditional on having sent a C-message. The appropriate econometric model is a probit model with sample selection (Heckman 1979), in which we jointly estimate the *selection equation* (i.e., the probability of sending a C-message) and the *action equation* (i.e., the probability of playing action C given that one has sent a C-message). We pool all data from treatments with bare and rich communication and correct standard errors at the matching-group levels. In both equations we use these explanatory variables:

- *Period* (from 1 to 40),
- *Rich* (= 1 if communication is Rich, 0 otherwise),
- *Net_NoClust* (= 1 if the network is not clustered, 0 otherwise),
- *Rich # Net_NoClust* (interaction of variables *Rich* and *Net_NoClust*)
- *Rich # Period* (interaction of variables *Rich* and *Period*)

In the *action equation* we also include the variables *Mess_C_rec* and *Credibility*. *Mess_C_rec* is the number of neighbors sending a final C-message. *Credibility* is the (expected) credibility of neighbors' messages and whose specification is explained below. A determinant of one's intention to play C (after sending a C-message) is the number of C-messages received from one's neighbors; the expected credibility of such messages may also play an important role. The *selection equation* uses the alternative regressor *Mess_C_rec2* (the number of neighbors sending a C-message when one has sent one's last message). In order to ensure identification, it includes the additional regressor *Mess_C_sent_1* (= 1 if the subject sent a C-message at the end of the last period's communication stage) measures inertia in the sending of C-messages.

Consider *Credibility*, a function of a subject's past experiences of the messages received and the actions observed. It also has an inertia component, which weights the initial beliefs on the reliability of others' messages (i.e., on the internalized social norm). Let $Credibility_\tau \in [0,1]$ be the credibility of received C-messages at period $\tau \geq 1$. Then, for each subject, the credibility that he ascribes to neighbors' C-messages evolves according to the following dynamics:

$$Credibility_{\tau+1} = \gamma \cdot Credibility_\tau + (1-\gamma) \cdot \big((1-M_\tau) \cdot Credibility_\tau + M_\tau \cdot I_\tau\big)$$

where M_τ and I_τ are indicator functions with value 1 if the subject's counterpart sent message C at t (0 otherwise) and chose action C at t (0 otherwise), respectively, and $\gamma \in [0,1]$ is the inertia parameter. This measures the weight of the prior on the credibility of messages. Then $(1-\gamma)$ is the weight assigned to the new experience. We have estimated our model once for each possible value of $\gamma \in \{0, 0.1, 0.2, \ldots, 1\}$. From this set, we have chosen the value of γ that provides the best estimation, by looking at the value that maximizes the likelihood function ($\gamma = 0.9$).

In Table 9 we report, for both equations, the estimated marginal effects of all the variables (full estimates are in Table B3 in Online Appendix B). In column (1) we report the marginal effects on the probability of sending a C-message (Selection equation), in column (2) we report the marginal effects on the reliability of C-messages (Action equation), and in column (3) we report the marginal effects on the estimated probability of playing C.

Attending first to the marginal effects for the *selection equation* (i.e., the effects of the variables on the probability of sending a C-message), we see that received C-messages have a positive (but insignificant) effect on the probability of the receiver then sending a C-message in both communication protocols. We also see that rich communication has a positive (but insignificant) effect on the probability of sending a C-message. Moreover, the network *NoClust* has a modest positive effect on the probability a C-message is sent. Finally, the probability of sending a C-message significantly decreases over periods in both communication protocols, and we observe that there is a significant inertia effect on sending C-messages (the marginal effect of *Mess_C_sent_1* is positive and significant at the 1% level both with bare and rich communication).

We now attend to the marginal effects corresponding to the *action equation* (i.e., the effects of the variables on the probability C is played, conditional on having sent a C-message). In other words, they measure the effects on the *reliability* of sent messages. The C-messages received have a significant effect on the reliability of one's sent C-message for both communication protocols.

Table 9: Marginal effects on the probability of sending C-messages, the reliability of C-messages, and the probability of playing C (about here)

The credibility of received C-messages also has a positive and significant effect in both scenarios. Rich communication has a strong effect on the reliability of sent C-messages in both networks. The network has a significant effect only with rich communication, in which network *NoClust* increases the reliability of sent C-messages by 17%. Period has no significant effect. Finally, we consider the marginal effects on the (unconditional) probability of playing C, derived from our estimation. We (qualitatively) observe the same patterns as in the *action equation*.

We summarize the main findings as follows:

Result 4. *The reliability of sent C-messages and C-play is higher without clustering than with clustering with rich communication, confirming Hypothesis 3. Rich communication significantly increases the reliability of sent C-messages & C-play, as conjectured in Hypothesis 2. Also, having no clustering has a positive effect (significant only with bare communication) on the probability of sending C-messages, in line with Hypothesis 1. Overall, the reliability of messages is much higher with rich communication.*

Since the positive effects of received messages are larger for bare communication, one may wonder why cooperation collapses in bare communication. Figure B2 (reported in Online Appendix B) provides useful evidence for answering this question, showing the evolution of reliability of C-messages. The reliability of C messages in the bare-communication treatments converges to zero and drops below 50% before period 10. Hence, while messages would work better in bare communication (if credible), the quick drop for reliability with bare communication also allows C-play to erode quickly, thus driving the network members to play A (see also Figure 4). The situation is quite different with rich communication, where reliability stays close to 100% throughout the entire experiment. This marked difference between bare and rich communication strongly supports our Hypothesis 2. A rationale for this reflects our model of credibility. Under the assumption of high lying costs in rich communication, the dominant strategy is to play according to the sent message. This explains the stability of our reliability measure during the 40 periods of play. But if lying costs are not that high (as with bare communication), responding in a different manner could be optimal for some beliefs.

4.4. Robustness checks

One hypothesis about the failure of bare communication to increase cooperation and efficiency is that the network environment introduces some level of uncertainty in the behavior of the matched player. To remove this uncertainty, we conduct a control treatment with bare communication involving bi-lateral matching (reported in Online Appendix F), and we find support for the hypothesis that we should observe more C-play in the setting with bi-lateral matching, with an overall rate of C-play of 30.5% (see Figure F1).

We also have a robustness treatment using the standard 2x2 stag-hunt game, formed by deleting row and column C from the game in Figure 1, with bare communication (reported in Online Appendix F – see Table F1 for treatment details). We find considerable coordination on (B, B), i.e., the efficient equilibrium (see Tables F2-F3 and Figure F2). Hence, adding a row and column to this game greatly *decreases* the average payoffs achieved (the average earnings with bare communication are considerably higher in the 2x2 game than in the 3x3 game).

5. Conclusion

We investigate behavior in a novel experimental game played in a network setting. We vary two dimensions: 1) the type of feasible communication and 2) the degree of clustering. No previous paper has considered this combination. Individuals can only interact with a subset of other people in the network (and, of course, in the overall population). Our hybrid game features two pure-strategy Nash equilibria and a socially-efficient, but non-equilibrium, outcome.

We find major differences in behavior across communication technologies. While there is some initial optimism without communication, play rapidly devolves to the safe risk-dominant action, with a rate of 96.4% in the last 20 of the 40 periods. There is little difference with bare communication, where only a message indicating (without words) the intended action can be transmitted; the rate of the risk-dominant play is 95.6% in the last 20 periods. However, matters change dramatically with rich communication (free-form chat with those people with whom one is linked), where the socially-efficient play is observed nearly all of the time (95.2%) in the last 20 periods and the risk-dominant play is hardly ever (4.5%) observed in the last 20 periods.

The degree of effectiveness for rich communication is remarkable, particularly since the network environment is a much more difficult one for successful coordination and cooperation. An analysis of the content of these messages indicates raising the topic of social efficiency (in this case, high mutual payoffs) seems crucial initially. A second factor is establishing credibility that they will indeed choose the actions that lead to this outcome. This is accomplished through endogenous statements of intent (promises) and congenial (friendly) chat conversation. Having a positive chat relationship appears to be more important in later periods.

Regarding the effect of clustering, theoretical and experimental work that does not incorporate communication has indicated that a higher degree of clustering leads to more efficient outcomes. We do confirm this result without communication, but we find that rich communication reverses the direction of the effect. There is a trade-off between having more repeated (and presumably deeper) interaction with the same people (with positive clustering) and reaching more individuals less frequently (with zero clustering). The first seems to be more useful when communication is not feasible, but the latter is more important when rich communication is a feature of the environment. We consider this interaction effect to be another key finding, as it deepens our understanding of the conditions under which restricted or free-form communication may – or may not – be effective in promoting efficient coordination and cooperation in networks.

We develop a theoretical model that addresses the issue of diffusion of messages across the network, given that there is duration to the communication phase in our game; we are the first to consider this factor. In fact, the prediction is that diffusion will be more rapid without clustering, which is consistent with our data. A second theoretical model considers credibility and once again our data support the model's conclusion that credibility will be higher with rich communication than with bare communication. So, our experimental and theoretical evidence shows that clustering will not necessarily lead to more efficient play when free-form communication is possible.

Interestingly, people do not play B in the 3x3 game with bare communication, even though (B,B) is an equilibrium that leads to higher payoffs than (A,A). This is sharply different than the high rate of B-play in the standard 2x2 stag-hunt game. While in principle adding a dominated strategy to the game should not adversely affect matters, adding a (strictly-dominated) row and column decreases average payoffs and coordination on the efficient equilibrium. The failure to initially achieve coordination at the efficient (but non-equilibrium) outcome (C,C) drives play to the risk-dominant (safe) choice, instead of the more efficient but riskier equilibrium (B,B). Our results indicate that such a failure erodes credibility and trust. This finding suggests that it would be interesting to study games transformed by adding choices, to identify the conditions under which this helps or hurts players. Given the varied contemporary communication technologies available, it would be useful to understand the underlying factors present and perhaps to identify the minimal information required to make communication effective.

There is certainly more work to be done to advancing our understanding of how different forms of communication combine with different network characteristics. Given the fact that communication is ubiquitous in the field and that network interaction is quite common, we feel that this is an important area for future research. We hope that others join us in this quest.

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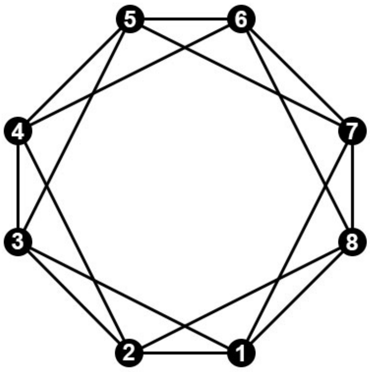
Figures and Tables

Figure 1: The extended 3x3 Stag Hunt game

		Player 2		
		A	**B**	**C**
	A	70, 70	80, 0	110, 0
Player 1	**B**	0, 80	90, 90	110, 0
	C	0, 110	0, 110	100, 100

Figure 2: The networks

Network *Clust* (Positive Clustering)



Network *NoClust* (No Clustering)

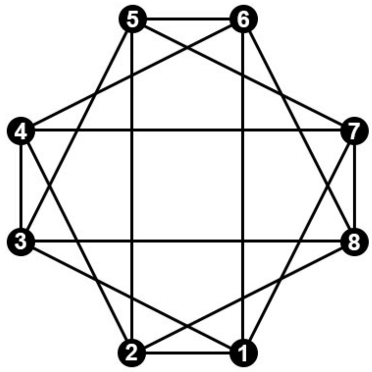


Figure 3: Frequencies of actions across periods, by treatment

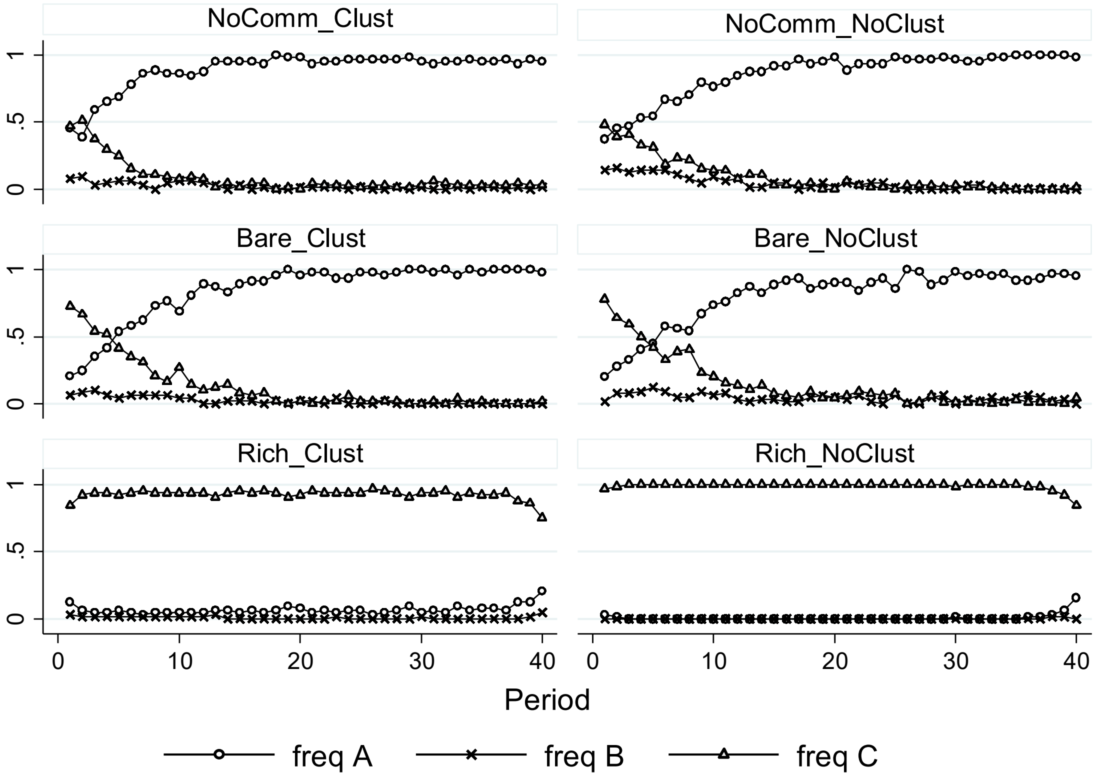


Figure 4: Cumulative distribution functions of the number of C-messages (at the 8-person network level), by treatment, and at the end of the communication stage

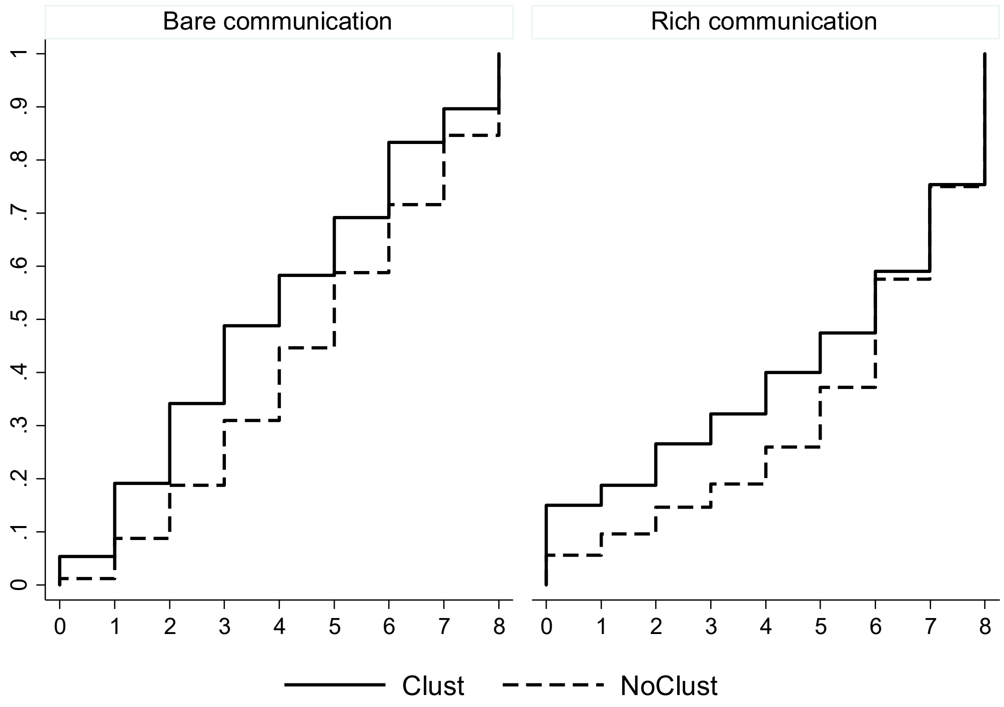


Table 1: Treatments, sessions and participants

Description of treatment	Treatment abbreviation	Sessions	Participants
No communication, clustered network	*NoComm_Clust*	2	64
No communication, non-clustered network	*NoComm_NoClust*	2	64
Bare communication, clustered network	*Bare_Clust*	2	48
Bare communication, non-clustered network	*Bare_NoClust*	2	64
Rich communication, clustered network	*Rich_Clust*	2	64
Rich communication, non-clustered network	*Rich_NoClust*	2	64
Bare communication, bilateral	*Bare_Bilateral*	2	64

Table 2: Likelihood of actions A, B and C, by treatment

	No Communication		*Bare Communication*		*Rich Communication*	
	Clust	*NoClust*	*Clust*	*NoClust*	*Clust*	*NoClust*
A	89.10% (2281)	86.13% (2205)	84.64% (1625)	80.55% (2062)	6.68% (171)	0.86% (22)
B	2.23% (57)	4.41% (113)	2.19% (42)	4.26% (109)	0.82% (21)	0.08% (2)
C	8.67% (222)	9.45% (242)	13.18% (253)	15.20% (389)	92.50% (2368)	99.06% (2536)
Total	100% (2560)	100% (2560)	100% (1920)	100% (2560)	100% (2560)	100% (2560)

The bottom number in each cell (in parentheses) is the number of observations.

Table 3: Frequencies of coordination on outcomes, by treatment

		Coordination at the network level:			
Treatment	**Total**	**on A**	**on B**	**on C**	**Obs.**
NoComm_Clust	0.556	0.556	0.000	0.000	320
NoComm_NoClust	0.563	0.563	0.000	0.000	320
Bare_Clust	0.583	0.583	0.000	0.000	240
Bare_NoClust	0.503	0.503	0.000	0.000	320
Rich_Clust	0.669	0.000	0.000	0.669	320
Rich_NoClust	0.956	0.000	0.000	0.956	320
		Coordination at the pair level			
Treatment	**Total**	**on A**	**on B**	**on C**	**Obs.**
NoComm_Clust	0.825	0.805	0.000	0.020	1280
NoComm_NoClust	0.819	0.779	0.005	0.035	1280
Bare_Clust	0.821	0.759	0.002	0.059	960
Bare_NoClust	0.794	0.712	0.009	0.073	1280
Rich_Clust	0.877	0.015	0.000	0.862	1280
Rich_NoClust	0.987	0.002	0.000	0.984	1280

Table 4: Likelihood of categorized messages over successive 5-period ranges

Category	P1-5	P6-10	P11-15	P16-20	P21-25	P26-30	P31-35	P36-40	All
Promise	0.171	0.166	0.176	0.167	0.172	0.137	0.141	0.084	0.149
	(228)	(250)	(292)	(263)	(261)	(220)	(211)	(172)	(1,897)
Social efficiency	0.435	0.256	0.178	0.152	0.124	0.121	0.110	0.108	0.178
	(581)	(387)	(295)	(240)	(188)	(195)	(165)	(221)	(2,272)
Admonition	0.052	0.036	0.025	0.018	0.020	0.017	0.016	0.029	0.026
	(70)	(55)	(41)	(28)	(30)	(28)	(24)	(59)	(335)
Don't chose C	0.004	0.002	0.004	0.002	0.001	0.004	0.001	0.002	0.003
	(5)	(3)	(6)	(3)	(2)	(7)	(2)	(5)	(33)
Conversational	0.257	0.484	0.591	0.632	0.661	0.704	0.716	0.742	0.610
	(343)	(731)	(981)	(998)	(1,005)	(1,134)	(1,075)	(1,516)	(7,783)
Coding conflict	0.082	0.056	0.028	0.030	0.022	0.017	0.016	0.034	0.035
	(110)	(84)	(46)	(47)	(34)	(28)	(24)	(69)	(442)
Periods/subject with	0.028	0.044	0.050	0.066	0.075	0.108	0.103	0.088	0.070
no message	(18)	(28)	(32)	(42)	(48)	(69)	(66)	(56)	(359)

Note: Each cell shows the probability of this type of message within the period range. The absolute number of each type of message is shown in parentheses. The last row shows the frequency of periods per subject in which no message at all was sent.

Table 5: Estimated probability of sending a first C-message with rich communication, conditional on having received a C-message or not

	C-message received	Period=1	Period<6	All Periods
Full Sample	Yes	0.040***	0.045***	0.020
	No	0.008	0.018	0.010
Reduced Sample	Yes	0.029***	0.044*	0.020*
	No	0.014	0.027	0.017

Sign test (two tails) of differences between rows, separately for full sample (rows 1 and 2) and reduced sample (rows 3 and 4). Significance at *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Rates of final sent C-message, by # C-messages received (Rich Communication)

# C messages received	Network *Clust*	Network *NoClust*
0	0.352	0.683
1	0.605	0.684
2	0.649	0.716
3	0.731	0.670
4	0.822	0.727
Total	0.607	0.694

Table 7: Messages and actions

			Sender Action			
Treatment	**Message**	**Sent**	**A**	**B**	**C**	**Consistency**
Bare_Clust	A	392	390	1	1	.995
	B	143	130	12	1	.084
	C	941	669	26	246	.261
	No	444	436	3	5	-
Bare_NoClust	A	531	519	5	7	.977
	B	327	275	50	2	.153
	C	1538	1107	52	379	.246
	No	164	161	2	1	-
Rich_Clust	A	5	0	0	5	.000
	B	2	0	0	2	.000
	C	1554	145	14	1395	.898
	No	999	26	7	966	-
Rich_NoClust	A	6	1	1	4	.167
	B	4	0	0	4	.000
	C	1777	7	0	1770	.996
	No	773	14	1	758	-

Note: "Consistency" means the likelihood that the sender's action and message are the same. To calculate this, we divide the number of times a message was sent by the number of times the corresponding action was taken by the sender. 'Sent' simply refers to all final messages in the corresponding category and treatment.

Table 8: Messages and actions with bare communication, contingent on switching messages

	Clust			NoClust			All		
	A or B	C	Total	A or B	C	Total	A or B	C	Total
Switched messages	87.04	12.96		80.11	19.89		82.65	17.35	
	94	14	108	149	37	186	243	51	294
Only C messages	72.12	27.88		74.7	25.3		73.72	26.28	
	600	232	832	1,010	342	1,352	1,610	574	2,184
Total	73.83	26.17		75.36	24.64		74.78	25.22	
	694	246	940	1,159	379	1,538	1,853	625	2,478

Note: "Switched messages" means that a subject whose final message in the communication phase was C had sent another message (A or B) previously. Actually chosen actions are denoted in the columns.

Table 9: Marginal effects on the probability of sending C-messages, the reliability of C-messages, and the probability of playing C

		(1) Selection eq. Pr(message C)	(2) Action eq. Pr(act. C|mess. C)	(3) Overall Pr(action C)
Period with:	Rich=0	-0.005***	-0.001	-0.002
		(0.001)	(0.002)	(0.002)
	Rich=1	-0.004***	-0.002*	-0.003***
		(0.001)	(0.001)	(0.001)
Net_NoClust with:	Rich=0	0.045**	-0.003	0.007
		(0.019)	(0.025)	(0.027)
	Rich=1	0.040	0.157***	0.172***
		(0.078)	(0.058)	(0.061)
Mess_C_rec with:	Rich=0		0.059***	0.058***
			(0.022)	(0.019)
	Rich=1		0.039***	0.041***
			(0.013)	(0.015)
Mess_C_rec2 with:	Rich=0	0.013		
		(0.015)		
	Rich=1	0.013		
		(0.016)		
Credibility with	Rich=0		0.955***	0.933***
			(0.057)	(0.121)
	Rich=1		0.625***	0.658***
			(0.074)	(0.061)
Mess_C_Sent_1 with:	Rich=0	0.552***		
		(0.031)		
	Rich=1	0.547***		
		(0.039)		
Rich with	Net_NoClust =0	0.047	0.227***	0.246***
		(0.072)	(0.074)	(0.070)
	Net_NoClust =1	0.042	0.387***	0.411***
		(0.051)	(0.086)	(0.086)
Observation		9,360	9,360	9,360

Marginal effects evaluated at means of other variables unless otherwise specified. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (1) Selection equation: Probability of sending a C-message; (2) Action equation: Probability of playing action C conditional on having sent a C-message; (3) Overall: Probability of playing action C.