Coordination and Cooperation in Local, Random and Small World Networks: Experimental Evidence

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Games in Networks

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Abstract

A laboratory experiment studies coordination and cooperation in games played in different networks - local, random and small-world. Coordination on the payoff-dominant equilibrium was faster in small-world networks than in local and random networks. However, in a prisoner's dilemma game, cooperation was the hardest to achieve in small-world networks. Two graph-theoretic characteristics - clustering coefficient and characteristic path length - accounted for differences in individual behavior, possibly explaining why equilibrium convergence is most rapid in small-world networks.

Keywords: Coordination, Cooperation, Experiment, Graph Theory, Network, Local, Random, Small-World

JEL Classification: C69, C72, C91, C92

1. Introduction

Many people send cards or bring chocolates to their secretaries. People desiring to adopt a child often speak to priests and teachers. These common behaviors can be viewed as everyday applications of network theory. Secretaries, teachers and priests are thought to "know everyone", thus going through them is often the best way to reach any other member of the group.

On the other hand, people are at times surprised in discovering that the stranger sitting next to them at a public event happens to be a very dear friend of their cousin. "What a small world!" Such accidental encounters are so frequent that they have inspired not only movies and plays[1], but also extensive scientific research (Milgram, 1967; Schelling, 1971). Results have seeped into the popular culture, e.g. "six degrees of separation", "Kevin Bacon" and "Erdös" numbers.

Indeed, we are all part of a tangled net of personal, work-related, community-oriented relations, which strongly affect and constrain our economic as well as personal choices. In the economy such networks are widespread. From the network of web-pages connected through hot-links to the network of international relations, from the network of overlapping claims among financial institutions to the network of "friend to friend" Herbalife sellers, these relations shape our world. In conjunction with the latest advances in analytical and computational methods, economists have finally started to incorporate a network based perspective in their analysis, finding that the particular pattern of links among individuals - network - has important and wide applications[2].

[1] E.g. the Broadway play "Six Degrees of Separation" by Guare or the homonymous movie by Schepisi.

[2] Some of these issues include: different patterns of contagion in financial crises (Cassar and Duffy, 2001; Eisenberg, 1995; Allen and Gale, 2000), bargaining outcomes (Charness, Corominas-Bosh, Frechette, 2001) contemporaneous evolution of different conventions (Young, 1993; and 1998), partial monopolistic behavior of markets for services and goods where transportation is important (Blume, 1993; and 1995), how global inefficiency might result from local efficiency (Epstein and Axtell, 1996), persistency in the business cycle from small independent agent-level shocks (Verbrugge, 1998), the variability of corruption across nations or regions (Verbrugge, 1998).

In this paper, via experimental methods, I explore the extent to which different networks influence the sustainability of cooperation and coordination. Recent works on the prisoner's dilemma and coordination games have focused on local networks to model sustainable cooperation (Samuelson, Eshel and Shacked,1998; Axelrod, Riolo and Cohen, 2000; Nowak and May, 1992 and 1993; Watts, 1999); and relatively fast coordination on the less risky equilibrium (Kandori, Mailath and Rob, 1993; Ellison, 1993; Blume, 1995; Young 1993, and 1998).

Here I compare three different networks: random, local and small-world. The small-world network, in particular, is important for economics because it replicates many social networks from the society in which we live to the World Wide Web (see Milgram, 1967; Adamic, 1999).

Following a recent work by Watts (1999), I analyze the impact of two important network characteristics: the extent to which a person's neighbors are connected with each other (the clustering coefficient) and the average distance between pairs of individuals (the characteristic path length). These concepts will be useful in explaining the results of the experiment.

The analysis below suggests that the small-world network drives a system towards equilibrium at the quickest pace. This finding is consistent with some related computational predictions by Watts and Strogatz (1998), according to which signal speed and synchronizability are higher in systems with small-world properties than in regular lattices.

In particular, for the coordination game, the experimental data show that agents on a small-world network are the most successful in achieving coordination on the payoff-dominant equilibrium. In fact, a high clustering coefficient and a short characteristic path length significantly increase the probability for an agent to choose the payoff-dominant action.

Results for the prisoner's dilemma game show that cooperation is difficult to reach on all three networks, with agents on a small-world network being the least likely to cooperate. For this game, high clustering and short length increase the probability that agents defect.

2. Background

2.1. Coordination Game

In a coordination game agents gain by choosing identical actions, such as driving on the same side of the road or switching to daylight savings time. Without a previous agreement, it is often hard to predict the outcome.

With only two players, the Harsanyi and Selten (1988) criterion predicts the selection of the less-risky (risk-dominant) equilibrium, provided each player chooses the action which maximizes his payoff given the distribution of choices of the other (i.e. plays best-reply). Only when the costs of miscoordination are equal across actions, can agents coordinate on the better (payoff-dominant) outcome.

When the game is extended to several players, a frequent assumption has been uniform matching[3]. For this non-spatial context, Kandori, Mailath, and Rob (1993) finds that the risk-dominant criterion can still be applied, and predicts the less risky outcome when small stochastic shocks are present among players using myopic best-reply.

Moving to a spatial context, one in which agents are directly connected to only a subset of other agents, the number of possible equilibria increases. Now, best-reply to the distribution of choices in one's neighborhood results in the ability to support other equilibria which are characterized by the coexistence of different actions. Ellison (1993), comparing the dynamics of systems with uniform matching to systems with local matching, concludes that the evolutionary argument of Kandori, Mailath, and Rob (1993) may be applied to a social system only if interactions are local. In the local model, in fact, the random events that produce a transition to the risk-dominant equilibrium are much more likely than under the uniform matching rule.

Recent experimental results show that coordination games played on local networks

[3]Uniform matching is a non-spatial structure in which either each player is matched with each of the remaining players exactly once, or there is a mean matching within a period.

present indeed more coordination on the risk-dominant equilibrium when compared to closed groups with the same number of neighbors, but less then when players are located on a lattice, which instead allows for the establishment of several equilibria (Berninghaus, Ehrhart and Keser, 1997, 1998a, and 1998b; Berninghaus and Schwalbe, 1996).

The problem with these results is that the comparisons are among systems differing in terms of the total number of players, and not only in terms of the matching process as analyzed by theory. In fact, van Huyck, Battalio and Beil (1990) and Berninghaus, Ehrhart and Keser (1997) found that the number of players may affect equilibrium selection, leading to coordination on risk-dominant equilibrium in large groups, and on payoff-dominant equilibrium in small groups[4].

Regarding individual behavior, Bouchez and Cassar (2002), Berninghaus, Ehrhart and Keser (1997, 1998a, and 1998b) and Berninghaus and Schwalbe (1996) found that subjects in spatial networks have a significant tendency to play best-reply to the distribution of their neighbors' decisions in the previous period, and to react with inertia. See Table 1 for a summary of these theoretical and empirical results.

2.2. Prisoner's Dilemma

The problem of cooperation, abstractly formulated as the prisoner's dilemma, is that individuals realize the existence of an overall benefit from cooperation, but their private incentives draw them away from it, locking them into sub-optimal actions.

When we assume local best-reply, stage game behavior in a spatial context does not differ from non-spatial contexts. Individuals will immediately adopt the dominant strategy of defection regardless of the network structure.

When we relax the assumption of best-reply, spatial contexts have the opportunity to

[4] In van Huyck, Battalio and Beil's experiment the number of iterations is only 10. Increasing the number of periods, the probability of coordinate on the payoff-dominant equilibrium is actually higher, as found also by Berninghaus, Ehrhart and Keser (1997) and Berninghaus and Ehrhart (1998).

provide different predictions. Other equilibria are now possible in which some of the agents choose to cooperate and others choose to defect, thus forming clusters of cooperators coexisting with clusters of defectors (see the theoretical model by Samuelson, Eshel and Shaked, 1998; and the computational works by Nowak and May, 1992; 1993; and Nowak et al., 1994). Two assumptions are necessary to obtain this result: myopic imitation and a local structure for both the interactions between agents and their information. However, this appealing idea is not supported by experimental data (Bouchez and Cassar, 2002).

A computational comparison among local, random, and small-world networks by Watts (1999) shows weak evidence that cooperation tends to do worse in poorly clustered networks. In fact, once a few free-riders are present, cooperation can deteriorate quickly also in highly clustered networks.

An alternative prediction comes from the simulations of Axelrod, Riolo and Cohen (2000). They found that the important element for cooperation to survive is the preservation of the same neighbors for the entire game, not locality per se, so that local or random networks may end up supporting similar amounts of cooperation.

The experimental results of Kirchkamp and Nagel (2000) do not seem to support the theoretical prediction that local interactions support more cooperation than neighborless interactions. With respect to individual behavior, they found that players imitate more in circles than in groups, where instead they seem to reciprocate more. This comparison is actually between systems which differ in terms of total number of players, and an alternative explanation (verified in many other contexts) is that small groups cooperate more than larger ones.

3. Games in Networks

A game in a network is a symmetric normal-form game in which each player chooses a single action and interacts with a specified subset of players, his neighbors in the network.

The network is specified as a graph $\mathcal{G}$ consisting of a set of nodes, $\mathcal{N} = \{n_1, n_2, ..., n_N\}$, used to represent players, and a set of lines between pairs of nodes, $\mathcal{L} = \{l_1, l_2, ..., l_L\}$, used to represent the neighbor relations between players. Since we are interested here only in symmetric relations, each line is an unordered pair of distinct nodes, $l_l = \{n_i, n_j\}$, $n_i \neq n_j$. The set $\mathcal{K}_i$ of neighbors of player i, $\mathcal{K}_i \subset \mathcal{N}$, $|\mathcal{K}_i| = k_i$, specifies his given neighborhood structure, and can be found in the subset of lines which include n_i. Note that the neighborhood relation is symmetric but irreflexive, $j \in \mathcal{K}_i \Leftrightarrow i \in \mathcal{K}_j$, but $i \notin \mathcal{K}_i$.

A game in a network can then be defined as a population $\mathcal{N}$ of $|\mathcal{N}| = N$ players, $2 \leq N < \infty$, and an underlying 2-player game, G. Player i's payoff function in the network game is the average payoff in G over his k_i neighbors in $\mathcal{G}$. Note that each player chooses a single strategy, σ_i, that is applied to all neighbors. For example, consider a symmetric 2×2 bimatrix game G with payoff function $P_i(\sigma_i, \sigma_j)$ given by:

		Neighbor j's choice	
		A	B
Player i' choice	A	a	b
	B	c	d

where a, b, c, $d \in \mathsf{R}$ are the payoffs for the row player (payoffs for the column player are symmetric). The average function that determines agent i's payoff in the network game is then given by:

$$\Pi_i = \frac{\sum_{j \in \mathcal{K}_i} P_i(\sigma_i, \sigma_j)}{k_i}$$

Depending on the values assumed by a, b, c, and d we obtain different games. For the coordination game, we assumed $a > c$, $d > b$ and $(a - c) < (d - b)$ to distinguish between payoff-dominant (all-playing A) and risk-dominant (all-playing-B) equilibrium. For the prisoner's dilemma game, $(a-c)(d-b)<0$ ensures that all-playing A is the Pareto efficient behavior, all-playing B the non-cooperative equilibrium.

Three network structures are analyzed: local, random, and small-world. They share the same number of nodes N and the same number of links $\frac{Nk}{2}$, but differ in terms of the pattern of connections.

Local Network. Here (Figure 1.a) N individuals are arranged on a circle[5] and may interact only with the k most immediate neighbors, so $|\mathcal{K}_i| = k_i = k \; \forall \; i \in \mathcal{N}$, for a total of $\frac{Nk}{2}$ connections. In this way, each player is connected with the $\frac{k}{2}$ most immediate players on the right and the $\frac{k}{2}$ most immediate players on the left, as if they were all seated around a table.

Random Network. Here (Figure 1.b) individuals form random relations between themselves so that each pair has an equal probability to become connected. By rewiring each of the $\frac{Nk}{2}$ relations of the local network exactly once, each agent is now connected with an average of k other individuals which could be located anywhere on the circle. While the local network is unique once N and k are specified, random networks can take a variety of shapes.

Small-world Network. A small-world network (Figure 1.c) has properties of both local and a random networks. To obtain a small-world network, we apply the same procedure used to create a random network, but this time we rewire each of the $\frac{Nk}{2}$ connections of the local network with only a very small probability. In this way, most of the agents are still connected to their closest neighbors, but now a very small number of new links can directly connect two agents otherwise far apart on the circle.

[5] This can easily extend to any d-dimensional lattice.

4. Graphs Structural Properties

In this paper, the graph structural properties are analyzed both at the individual and group level (see Wasserman and Faust, 1994). The first statistic to be considered is the *nodal degree*, $d(n_i)$, the number of nodes adjacent to n_i:

$$d(n_i) = k_i$$

It is the agent's number of neighbors, and it represents a measure for individual activity. In the local network all agents have the same nodal degree, while on the random and small-world networks some agents are more active than others.

Averaging the degree of a node over all individuals gives the *mean nodal degree:*

$$\overline{d} = \frac{\sum_{i=1}^{N} d(n_i)}{N} = \frac{2L}{N}$$

which stays unchanged among the three networks under study.

Another important graph characteristic is the proportion of lines in some particular subgraphs or in the graph as a whole. Consider, first, the subgraph made of the k_i neighbors connected to n_i. This subgraph can have at most $\binom{k_i}{2} = k_i(k_i - 1)/2$ lines connecting its nodes. Consider the number of these lines that are actually present. Then, the density C_i of this subgraph is the proportion of possible lines that are actually present. C_i shows the extent to which a person's neighbors are connected to each other. Averaging C_i over all i gives the clustering coefficient C (see Watts, 1999). In a social network, the clustering coefficient represents a measure of the overlapping present in a group of individuals. It ranges from 0 (when no neighbors are neighbors to each other) to 1 (when everyone is connected to everyone else). For the local network, it is possible to find the clustering coefficient exactly by enumeration:

$$C_{local} = \frac{3(k-2)}{4(k-1)} \approx \frac{3}{4} \text{ for large } k$$

For the random network, instead, each configuration has its own clustering coefficient. When $N \gg k \gg \ln(N) \gg 1$, (where $k \gg \ln(N)$ guarantees that a random graph will be connected) such measure is approximately:

$$C_{random} \approx \frac{k}{N} \ll 1$$

The last measure analyzed is the average number of links in the shortest path, L_i , between agent n_i and all the other N agents. It measures how distant a member is from everybody else. This distance is finite for connected graphs. Averaging L_i over all agents, we obtain the characteristic path length - the average distance between all pairs of individuals. For the local network:

$$L_{local} = \frac{N(N+k-2)}{2k(N-1)} \approx \frac{N}{2k} \gg 1$$

While for the random network:

$$L_{random} \approx \frac{\ln(N)}{\ln(k)}$$

Clustering coefficient and characteristic path length are particularly helpful in describing differences between networks. Among our three social structures, the clustering coefficient is highest in the local network, and is lowest in the random network (Watts, 1999). The path length is longest in the local network, and is shortest in the random network[6].

The local network represents a world in which neighbors tend to overlap and are clustered. Nonetheless, each individual remains relatively isolated from individuals far away in the network. A random network, instead, represents a world of little overlapping of neighbors and fast connections between each member and every other.

[6]Keeping constant the average number of individual connections k, an increase in the population N decreases the clustering coefficient of a random network, while leaving it unchanged for the local network. The same increase in N, causes the path length to grow linearly in a local world, and only logarithmically in a random one.

The small-world network can then be characterized as a graph whose clustering coefficient is almost as high as that of a local network, while its characteristic path length is almost as short as in a random network. It represents a situation in which the individuals, even if divided into groups of neighbors, can nonetheless communicate with every other agent through a small number of connections. The small-world network results from the introduction of a few long distance links (so called "shortcuts") in a local network that cause an immediate drop in the path length, while leaving the clustering almost unchanged. Such shortcuts have great impact on the length because they not only connect two distant individuals but also their most immediate neighbors, and their neighbors's neighbors, and so on.

5. Predictions on How Network Affects Play

The works closest related to what follows are Watts and Strogatz (1998) and Watts (1999). They report that models of dynamical systems with small-world properties display enhanced signal-propagation speed, computational power, and synchronizability. For example, application to contagion of infections show that infectious diseases spread more easily in small-world networks than in regular lattices. However, for coordination and prisoner's dilemma games, local, random, and small-world networks have not been appreciably explored. Moreover, analytical solutions to these systems are only now being developed; laboratory experiments are thus a promising way to conduct such exploratory research.

For the coordination game, it seems reasonable to expect the clustering coefficient to affect (positively) an agent's decision to choose the payoff-dominant action, and the length of the characteristic path to decrease the speed towards any equilibrium.

When the clustering among neighbors is high, agents may feel as if they were playing in a small group instead of on a much larger network. This is because they observe their neighbors responding to similar local conditions. The neighbors' future actions seem more predictable, so it seems less risky to choose payoff-dominant[7]. In this environment, there should be more chances for coordination on the better outcome.

When instead agents play on a network with little clustering, the situation in their neighborhood becomes more representative of the entire world. Neighbors react to different environments. As a result, so their future actions appear less predictable, and choosing payoff-dominant seems more risky.

Using the payoffs of the experiment (see Table II), the payoff-dominant action is a best-response only if $2/3^{rds}$ of the neighbors have chosen it. In a random network, on average $2/3^{rds}$ of the entire population has to choose payoff-dominant for an agent to play it. For players in local or small-world networks, however, even if less then $2/3^{rds}$ of the population selected payoff-dominant, it is still advantageous to choose it if in their neighborhoods the critical proportion has been reached. As a result, coordination on payoff-dominant has more chance to be successful in some neighborhoods, and, given its local success, it may spread to the entire system.

The effect of the path length is more intuitive: the shorter the characteristic path length, the faster the speed of diffusion and, therefore, of coordination.

To summarize, in going from a local to a small-world network, the path length decreases significantly while the clustering coefficient stays similar. This should imply faster coordination, since a signal starting anywhere on the circle can reach all other agents in a very short number of steps. Going instead from a small-world to a random network, the clustering coefficient decreases significantly but not the length. In this case we should expect less coordination on the payoff-dominant equilibrium.

For the prisoner's dilemma game, the works surveyed above suggest that the higher the clustering, the better should be the chance for cooperation. In fact, one possibility for cooperation to thrive is for cooperators to bond together, thus getting higher benefits.

[7] This could help explain the known empirical fact that small groups coordinate on the payoff-dominant equilibrium more than larger ones.

According to this view, a longer path length should contribute to cooperation by slowing down the velocity at which defection travels, giving time for cooperation to root.

But what happens when high clustering is associated with short length? If the path effect is stronger, a shorter path would impose more obstacle on cooperation. It would make it easier for infiltrators to enter a cluster and destroy cooperation, this especially in presence of high clustering, where the incentive to rat are even higher.

Summarizing, in going from a local to a small-world network, cooperation should decrease, since the path length becomes much shorter leaving the clustering coefficient only slightly decreased. Going instead from a random to a small-world network, a world with similarly short path length but higher clustering, cooperation could increase (decrease) if the clustering effect (short path length) is stronger.

6. Design of the Experiment

The experiment was designed to contrast the three types of networks, keeping constant the number of players, the total number of connections, and, therefore, the mean nodal degree. A summary of the design is reported in Table II; the details, including the instructions for the participants, are posted at http://econ.ucsc.edu/grads/cassar.

Each session of the experiment involved 18 subjects playing alternating games and networks. Overall, we obtained data for 21 games/networks: three runs for each game per network, plus a forth run for the prisoners' dilemma in the local and random networks and for the coordination game in the small-world network (to maintain the alternating order design).

The 2×2 payoff matrix for the coordination game is indicated in Table II. In order to separate between equilibria, the costs of miscoordination are assumed different for action A and B. In particular, the all-playing-A equilibrium was the payoff-dominant, the all-playing-B equilibrium was the risk-dominant, and $p = \frac{2}{3} > \frac{1}{2}$ was the probability with which action

A is chosen in the mixed strategy equilibrium.

The 2×2 payoff matrix for the prisoner's dilemma is presented in Table II, where all-playing A was the Pareto efficient behavior, all-playing B the non-cooperative equilibrium.

Each game ran for 78 to 84 periods, with the exact number unknown to the subjects to prevent backward induction. Each period consisted of one choice per player[8]. When the same game was played more than once in a session, the payoff matrix was transposed to keep the subjects interested and not respond to boredom.

Each period's payoff was the average of the payoffs gained playing a single action against each neighbor. The final compensation was obtained converting each experiment point into dollars at a specified conversion rate. The subjects, UCSC undergraduate students, typically earned \$9 to \$16 plus \$5 for arriving on time, for an average of \$20 for a two hour session.

In the local runs, players were matched with exactly 4 neighbors, 2 on each side; the only difference among runs of local games being the subject identity. The latter because for the local network, once N and k are specified, there is a unique overlapping structure, and clustering coefficient and path length are constant measures (see Table III).

The random and small-world networks, instead, come in a multitude of variations. For a given N, each player is connected with k other players *on average*. Links can now exist between any players on the circle. Thus, each network specification has its own clustering coefficient and characteristic path length. To be sure that the results were not due to a particular specification, three different realizations of small-world and random networks were used. As shown in Table III, the clustering coefficient ranged from 0.061 to 0.5 across networks, and the characteristic path length from 2.026 to 2.647[9].

The information available to the subjects were the payoff matrix, a short running history

[8]Since periods advance only after all subjects choose, an interesting signalling mechanism came about: some subjects were waiting and waiting before selecting an action to slow down the experiment and induce (or punish) in this way unidentified uncooperative neighbors to cooperate.

[9]This range may seem narrow. To obtain a wider one many more than 18 subjects should have been involved, but this was not allowed by my budget.

of both their own past actions and payoffs, and of their neighbors' actions. Subjects were not informed of the particular network[10], but they knew that their neighbors were randomly assigned to them at the beginning of each game, and were to stay the same for the entire duration of a game.

7. Results

7.1. Equilibrium Selection

7.1.1. Coordination game

Results from the coordination game experiment show that the majority of the players preferred the payoff-dominant action to the risk-dominant action (see Figure 2 and Table IV). After a few initial choices for which the different networks share similar frequencies, the three systems show significantly different tendencies (using the Mann-Whitney test[11]). In particular, the small-world network supports an overall level of coordination on the payoff-dominant equilibrium 7.5 percent higher than the local network, which in turns supports a level of coordination on the payoff-dominant equilibrium 22 percent higher than the random network.

Table V reports the number of runs that were successful in reaching either the payoff-dominant or the risk-dominant behavioral equilibrium, the average time to reach it, and the average number of periods for which the system stayed in equilibrium once attained. Players arranged on a small-world network achieved coordination on the payoff-dominant equilibrium faster, and once there, stayed with a retention rate higher than the local network. The short time to threshold and the high retention of the random network is due to the fact that the

[10] Not knowing one's own network served to avoid the introduction of the subjects' preconceived ideas about the effect of different networks. The result that networks are significantly different can then be properly attributed to the graph-caracteristics.

[11] The samples are not strictly independent, but I am being pretty conservative in other respects, and more rigorous testing will follow.

means are calculated only between successful runs, and the only run with random network that achieved a stable payoff-dominant equilibrium did so quickly.

These results suggest that local interactions do indeed cause faster coordination than random interactions (e.g. Ellison, 1993), but do so on the payoff-dominant equilibrium rather than on the risk-dominant equilibrium expected by Kandori, Mailath, and Rob (1993).

7.1.2. Prisoner's Dilemma

Results from the prisoner's dilemma experiment indicate that cooperation was hard to achieve. In all three networks, cooperation declined with repeated play, with the small-world network decreasing at the fastest rate (see Figure 3). By the end of the games (see Table VI), cooperation is at most half its initial level, with agents on the small-world network ending with approximately 10 percent less cooperation less than on the other two networks. The Mann-Whitney test confirms that the differences among networks are statistically significant.

Players on the small-world network achieve a defection equilibrium more often, reach this threshold more quickly, and, once attained, stay there more than when they are on the other two networks (Table VI).

These data seem to support the prediction of Samuelson, Eshel and Shaked (1998) that local interactions offer a better ground for cooperation than other networks. On the other hand, they are not favorable to the Axelrod, Riolo and Cohen (2000) idea that what matters is neighborhood preservation; or we would not have found significantly less cooperation on the small-world network which preserves neighborhoods as the other two networks.

7.2. Network Characteristics and Individual Behavior

7.2.1. Coordination Game

As indicated in Table VIII, the frequency of payoff-dominant decisions increases with the percentage of neighbors who played payoff-dominant the period before (except for the lower frequencies, for which this measure indicates agents' tentative to induce coordination on the better outcome). Under identical conditions in their neighborhoods, player reactions vary greatly depending on the network. Players on small-world networks play mostly payoff-dominant, even when half or more of their neighbors play risk-dominant. Those on the local networks are more reluctant to play payoff-dominant. They seem either less willing to elicit coordination for the better outcome or less forgiving of occasional miscoordination. Players on the random network play payoff-dominant with even more resistance.

To test whether the network characteristics matter for individual behavior, I examine four possible decision models. When observations are correlated across time, e.g. when the same subject plays for several periods, it is common practice to estimate logit models with individual fixed-effects. With the present network data, however, without a balanced panel (where each subject plays under all possible networks/treatments), this procedure is problematic. In such a model the individual fixed effect would capture the home-grown preferences individuals have, as well as the network effect - the behavior due to the particular position a subject occupies in the network. For this reason, I estimate the models both with and without fixed effects, bearing in mind that in this way the network effect may be washed out.

In all models presented in Table X, the dependent variable (PayoffDominantAction) is the current action chosen by the player: 1 if the player chooses payoff-dominant, 0 if she chooses risk-dominant. The independent variables of the first model (CO1) test for an overall network effect on individual choices (NetworkClustering and NetworkLength), in addition to inertia in one's behavior (LagOwnAction), the payoff difference between the actions given neighbors' choices last period (PayoffAdvantage[12]), and centrality (NeighborsNumber).

In the second model (CO2), everything is the same except that the overall network characteristics are substituted by IndividualClustering and IndividualLength, which are the clustering coefficient and the path length measured at the individual level.

According to the data, the overall network characteristics are better than the individual level characteristics in explain coordination. Individual behavior can be described in terms of best-reply and inertia, as assumed by theory. In addition, as expected, high network clustering and short path length increase the probability with which agents coordinate on the payoff-dominant equilibrium. The number of neighbors does not seem to play a significant role for coordination.

To understand the reason for these network effects, I test the interaction of best-reply with both the clustering coefficient and the path length for affecting a player strategy (using individual fixed-effects). Again, we will consider the overall network characteristics (PayoffAdv.×NetworkClustering, PayoffAdv.×NetworkLength), as well as the characteristics specific to the individual (PayoffAdv.×IndividualClustering, PayoffAdv.×IndividualLength).

The results are reported on the last two columns of Table IX. Again, the group characteristics are better in explaining coordination. As in the previous models, inertia and best-reply maintain significant explanatory power in player behavior. In addition, the third model tells us that a high clustering coefficient or a short path length strengthen best reply, increasing the probability for a player to choose payoff-dominant if last period that was best-reply. This helps understand why the small-world network is the fastest to achieve coordination on the payoff-dominant equilibrium.

[12] PayoffAdvantage is the expected advantage to the payoff-dominant action. It depends on the expected proportion (π) of players in one's neighborhood choosing payoff-dominant. Here π is assumed equal to the frequency of payoff-dominant choices in the previous period. Therefore, the difference in expected payoffs of playing payoff-dominant is $PayoffAdvantage(\pi) = (1, -1)P(\pi, 1-\pi)'$, where P is the payoff matrix. The larger the (positive) value of the responsiveness to the perceived payoff advantage, the more likely a player is to apply best response to last period local choices.

7.2.2. Prisoner's Dilemma

Table IX shows that players on the small-world network cooperate the least for all levels of cooperation in the neighborhood. Instead, consistent with most of the local interactions literature, agents on the local network are more willing to elicit cooperation when no-one else does; to sustain such cooperation when everyone else cooperates; and to take advantage of the defection payoff once everyone else cooperates much less then agents on the other two networks.

Also for the prisoner's dilemma game we estimate four models to test how individual behavior is affected by the overall and individual network characteristics (see Table XI). The dependent variable is Cooperate, with value 1 if the player chooses to cooperate, 0 if he defects. The independent variables of the first model include the agent's action in previous period (LagOwnAction), the previous period percentage of cooperation in the neighborhood (Lag%NeighCoop), the number of neighbors (NeighborsNumber), and the overall network characteristics (NetworkClustering, NetworkLength). Here, we can no longer use PayoffAdvantage because in this game that variable would constantly indicate defect. Instead, we use Lag%NeighCoop. A significant and positive responsiveness to Lag%NeighCoop would support at least two hypotheses on individual behavior: agents apply reciprocation, like tit-for-tat, or they imitate the most popular action. A second model is estimated with the overall network effects substituted by the individual ones.

As indicated in Table XI, both models yield similar results: in addition to reciprocity and inertia, high clustering and short length encourage defection. Interestingly, those characteristics that helped coordination are now weakening cooperation. Here, high clustering seems to induce a bigger temptation to defect, and when coupled with short path length, destroys group cooperation.

With the inclusion of the interaction variables, we can test whether clustering and path affect reciprocity. Adding these variables along with individual fixed-effects, does not yield better results. The individual network characteristics seem to explain slightly better individual behavior, showing that high clustering increase the probability with which agent reciprocate cooperation. Most often, the effect of the interaction variables on cooperation is not significant. In addition to the individuals fixed-effect, only LagOwnAction remains largely significant.

8. Conclusion

This study offers experimental results on the effect of networks on cooperation and coordination. The data suggest that networks have important economic effects. Local, random, and small-world networks support significantly different amounts of cooperation and coordination. In particular, in line with the results of Watts and Strogatz (1998) and Watts (1999), the small-world network is the pattern of relations that allows a group to reach its equilibrium at the fastest pace.

In the coordination game experiment, individuals preferred the payoff-dominant action to the risk-dominant action in all three networks, but agents in the small-world reached coordination more successfully than agents in the local network, who in turn were more successful than agents in the random network.

In the prisoner's dilemma experiment, cooperation was difficult to achieve in all three networks, with agents in the local network more likely to cooperate than agents in the random network, and agents in the small-world network being the least likely.

Individual behavior was significantly affected by the network characteristics. For the coordination game, higher clusterings and shorter lengths increased the probability that players choose the payoff-dominant action. For the prisoner's dilemma, the effect of the network's characteristics were more difficult to analyze, even if, as expected, the long length of the local network supported the highest level of cooperation.

It is important to note that these results are exploratory, because a theory linking network characteristics to individual behavior is yet not available. It is hoped that these empirical findings stimulate such theoretical development.

These results do have, however, important practical implications. Many human networks (e.g. the society in which we live or the World Wide Web) tend to have small-world characteristics. What this study suggests is that this "natural" pattern of links is fertile ground for achieving coordination on Pareto superior outcomes, but might not be the best ground for cooperation to thrive.

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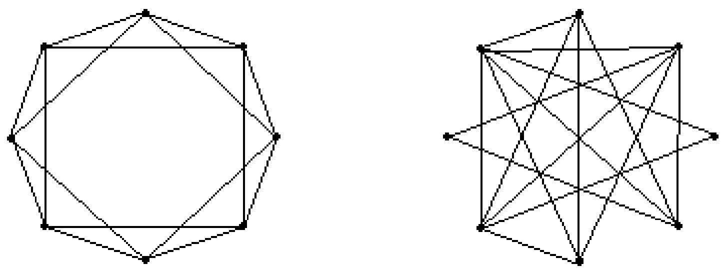
Figure 1. Local, Random, and Small-World Networks



a) Local Network

b) Random Network

c) Small-World Network

Figure 2. Coordination Game: Average Network Coordination

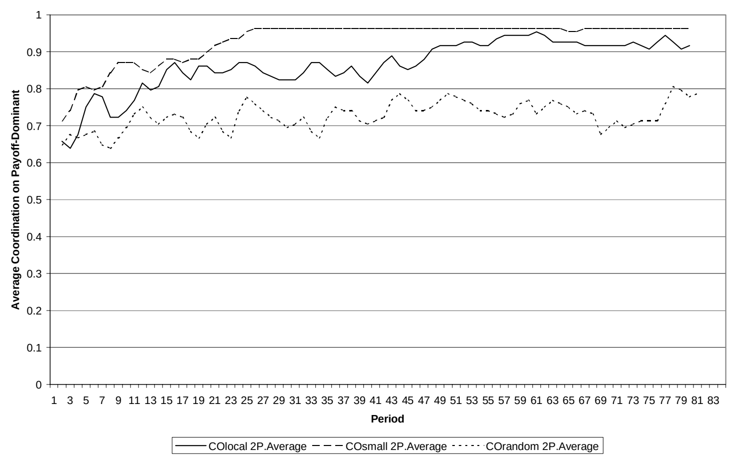


Figure 3. Prisoner's Dilemma Game: Average Network Cooperation

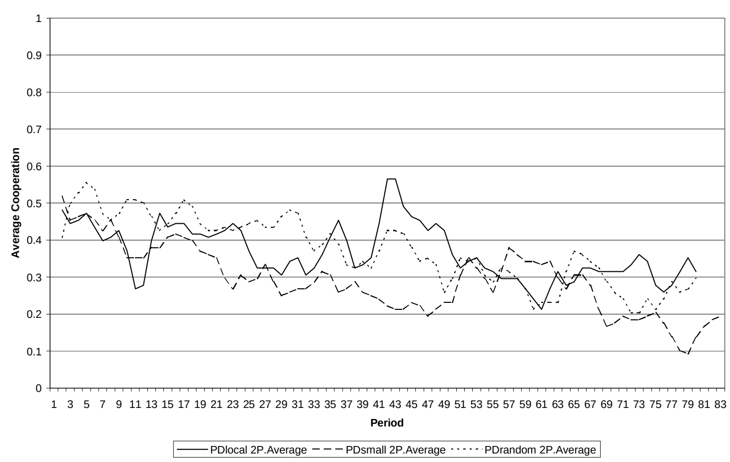


Table I. Summary of Theoretical and Empirical Results

	Theory Expectations		Empirical Evidence	
Local vs. Group	CO-Risk-dom. if U.M.	KMR(93)	CO-L.I. more coord.	BEK(98)
	CO-L.I. speeds up	Y(93)	on Risk-dom. than	KEB(98)
	conv. to Risk-dom.	E(93)	closed G.I. with=neigh.	BEK(97)
	PD-L.I. moore coop.	SES(98)	PD-L.I. less coop.	KN(00)
	than R.I. or G.I.	W(99)	than G.I. with=neigh.	
	PD-L.I. equal coop to	ARC(00)		
	R.I. if neigh. preserved			
Circle vs. Lattice	CO-Unclear: Lattice	E(93)	CO-L.I. more coord.	BEK(98)
	less overlapping		on Payoff-dom.	BS(96)
	PD-Circle moore coop.	SES(98)	than Lattice	
	than Lattice		CO-Several conventions	
Neighb. Size	CO-L.I. bigger size	E(93)	CO-No effect	BEK(98)
	decreases conv.		CO-Destabilize Risk-dom.	BS(96)
	to Risk-dom.			
	PD-L.I. bigger size	SES(98)		
	less coop.			
Num. of Players	CO-L.I. no effect	E(93)	CO-Large Groups coord.	HBB(90)
	CO-Slower conv.	KMR(93)	on Risk-dom.	
	with U.M.		PD-Large Num. less coop.	KN(00)
Num. of Periods	CO-L.I. less periods to	E(93)	CO-with time higher	BE(98)
	conv. to Risk-dom.		coord. on Payoff-dom.	BEK(97)
	PD-More coop. if long			
Behavior	CO-Myopic BestReply	KMR(93)	CO-Local BestReply	BS(96)
		E(93)	and Inertia	BEK(97)
		Y(93)		BEK(98)
				BC(02)
	PD-Imitation	SES(98)	PD- Reciprocity in Group	KN(00)
	PD-Evolutionary	W(99)	Imitation on Circle	
		ACR(00)	PD-No Imitation on Circle	BC(02)

Legend:

CO = Coordination Game; PD = Prisoner's Dilemma Game

L.I = Local Interactions; R.I.= Random Interactions; U.M. = Uniform Matching

G.I.=Group Interactions

Table II. Experimental Design Summary

Session	Run	Game	Network	Neighbors	Players	Iterations
small-01	1	CO	local	4 (exact)	18	79
	2	PD	smallworld1	4 (average)	18	82
small-02	1	COI	random1	4 (average)	18	81
	2	PD	local	4 (exact)	18	80
	3	CO	smallworld1	4 (average)	18	79
	4	PDI	random1	4 (average)	18	79
	5	COI	local	4 (exact)	18	82
	6	PD	random2	4 (average)	18	79
small-03	1	PD	smallworld2	4 (average)	18	83
	2	CO	random2	4 (average)	18	79
	3	PDI	local	4 (exact)	18	78
	4	COI	smallworld3	4 (average)	18	78
	5	PD	random3	4 (average)	18	80
small-04	1	CO	smallworld2	4 (average)	18	80
	2	PDI	local	4 (exact)	18	82
	3	COI	random3	4 (average)	18	81
	4	PD	smallworld3	4 (average)	18	84
	5	CO	local	4 (exact)	18	80
	6	PDI	random1	4 (average)	18	83
	7	COI	smallworld1	4 (average)	18	80
	8	PD	local	4 (exact)	18	82

Legend:

CO = Coordination Game Payoff Matrix

	A	B
A	5	-1
B	4	1

COI = CO Inverted Matrix

	A	B
A	1	4
B	-1	5

PD = Prisoner's Dilemma Payoff Matrix

	A	B
A	4	0
B	5	1

PDI = PD Inverted Matrix

	A	B
A	1	5
B	0	4

Table III. Network Characteristics

		Network Characteristics	
		Clustering Coefficient	Characteristic Path Length
	Local 1	0.5	2.647
	Local 2	0.5	2.647
	Local 3	0.5	2.647
	Small 1	0.406	2.301
Network	Small 2	0.472	2.458
	Small 3	0.354	2.366
	Random 1	0.181	2.033
	Random 2	0.061	2.026
	Random 3	0.180	2.078

Table IV. CO - Frequency of Coordination on Payoff-Dom. Behavioral Eq.

		Period				
		1-20	21-40	41-60	61-end	1-end
Percentage	Small Network	86.7%	96.0%	97.2%	97.2%	94.3%
Payoff-Dom.	Local Network	78.4%	84.6%	90.8%	92.7%	86.8%
Decisions on	Random Network	69.5%	71.9%	75.3%	73.2%	72.5%
	P(small=local=random)	0	0	0	0	0

Table V. CO - Equilibrium Selection

Network	Num. Runs in Eq.*		Av. Time to Eq.**		Av. Retention Eq.**	
	Payoff-D.	Risk-D.	Payoff-D.	Risk-D.	Payoff-D.	Risk-D.
Small	3 out of 4	0 out of 4	9 among 3	-	98%	-
			(s.d.$\pm$11.3)		(s.d.$\pm$1.9)	
Local	3 out of 3	0 out of 3	26 among 3	-	64%	-
			(s.d.$\pm$30.7)		(s.d.$\pm$51.5)	
Random	1 out of 3	0 out of 3	2	-	95%	-
			-		-	

*Payoff-D. (Risk-D.) behavioral equilibrium was considered reached if at least 17 of the 18 players choose action A (B) at least once in CO Payoff Matrix

	A	B
A	5	-1
B	4	1

.

**Averages are evaluated only among runs which reached equilibrium.

Table VI. PD - Frequency of Cooperation

		Period				
		1-20	21-40	41-60	61-end	1-end
Percentage	Small Network	41.2%	28.2%	27.7%	20.8%	29.1%
of Coop.	Local Network	49.9%	40.7%	37.1%	31.7%	39.7%
Decisions on	Random Network	50.7%	41.5%	34.9%	28.0%	38.6%
	P(small=local=random)	0	0	0	0	0

Table VII. PD - Equilibrium Selection

Network	Num. Runs in Eq.*		Av. Time to Eq.**		Av.Retention Eq.**	
	Coop.	Def.	Coop.	Def.	Coop.	Def.
Small	0 out of 3	2 out of 3	-	35 among 2	-	25%
				(s.d.$\pm$4.24)		($\pm$24)
Local	1 out of 4	2 out of 4	1 among 1	36 among 2	1%	4%
			(-)	(s.d.$\pm$34.6)	(-)	($\pm$2)
Random	0 out of 4	1 out of 4	-	54	-	11%
				(-)		(-)

*Cooperation (Defection) behavioral equilibrium was considered reached if at least 17 of the 18 players choose action A (B) at least once in PD Payoff Matrix

	A	B
A	4	0
B	5	1

.

**Averages are evaluated only among runs which reached equilibrium.

Table VIII. CO - Frequency of Payoff-Dominant Decisions

		Percentage of Neighbors playing Payoff Dominant Previous Period				
		0%	25%	50%	75%	100%
Percentage of	Small Network	-	76.2%	74.6%	91.0%	95.8%
Payoff-Dominant	Local Network	46.8%	41.6%	54.7%	79.7%	96.9%
Decisions on	Random Network	31.3%	29.5%	42.7%	68.0%	93.8%

Table IX. PD - Frequency of Cooperative Decisions

		Percentage of Neighbors playing Cooperate Previous Period				
		0%	0.25%	0.5%	0.75%	1%
Percentage of	Small Network	17.1%	30.1%	33.0%	39.3%	60.2%
Cooperative	Local Network	25.7%	30.9%	39.1%	56.8%	86.9%
Decisions on	Random Network	21.9%	29.5%	39.8%	50.2%	64.1%

Table X. CO Logit

Model:	CO1	CO2	CO3	CO4
Intercept	1.87*	-3.11*	fixed-eff.	fixed-eff.
	(0.93)	(0.37)		
LagOwnAction	4.14*	4.13*	2.38*	2.41*
	(0.08)	(0.08)	(0.09)	(0.09)
PayoffAdvantage	1.02*	1.03*	6.66*	0.89
	(0.05)	(0.05)	(1.81)	(0.65)
NetworkClustering	3.63*			
	(0.78)			
NetworkLength	-1.80*			
	(0.50)			
IndividualClustering		-0.34		
		(0.25)		
IndividualLength		0.90*		
		(0.15)		
NeighborsNumber	-0.03	-0.02		
	(0.04)	(0.05)		
PayoffAdv.×NetworkClustering			8.07*	
			(1.81)	
PayoffAdv.×NetworkLength			-3.56*	
			(1.01)	
PayoffAdv.×NeighborsNumber			-0.06	-0.08
			(0.08)	(0.08)
PayoffAdv.×IndividualClustering				1.59*
				(0.47)
PayoffAdv.×IndividualLength				-0.12
				(0.30)

Legend:

* = Significant at 5%

Prob(PayoffDominantAction)=$\frac{1}{1+e^{-x'\beta}}$=

CO1: =F(Int.,LagOwnAct.,PayoffAdv.,NetworkClust.,NetworkLength,Neigh.Num.)

CO2=F(Int.,LagOwnAct.,PayoffAdv.,Ind.Clust.,Ind.Length,Neigh.Num.)

CO3=F(Ind.Int.,LagOwnAct.,PayoffAdv.,PayoffAdv.×NetworkClust.,
PayoffAdv.×NetworkLength,PayoffAdv.×Neigh.Num.)

CO4=F(IndInt.,LagOwnAct.,PayoffAdv.,PayoffAdv.×Ind.Clust.,
PayoffAdv.×IndividualLength,PayoffAdv.×Neigh.Num.)

Table XI. PD Logit

Model:	PD1	PD2	PD3	PD4
Intercept	-4.57*	-2.90*	fixed-eff.	fixed-eff.
	(0.51)	(0.20)		
LagOwnAction	2.58*	2.58*	1.95*	1.95*
	(0.04)	(0.04)	(0.04)	(0.04)
Lag%NeighCoop	1.33*	1.37*	2.05	2.55*
	(0.08)	(0.08)	(2.34)	(0.88)
NetworkClustering	-1.99*			
	(0.46)			
NetworkLength	1.19*			
	(0.28)			
IndividualClustering		-0.28*		
		(0.13)		
IndividualLength		0.22*		
		(0.08)		
NeighborsNumber	0.07*	0.07*		
	(0.03)	(0.03)		
Lag%NeighCoop×NetworkClustering			0.13	
			(2.09)	
Lag%NeighCoop×NetworkLength			-0.02	
			(1.28)	
Lag%NeighCoop×NeighborsNumber			-0.12	-0.14
			(0.11)	0.11
Lag%NeighCoop×IndividualClustering				1.00**
				(0.54)
Lag%NeighCoop×IndividualLength				-0.32
				(0.37)

Legend:

* = Significant at 5%

** = Significant at 7%

Prob(Cooperate)=$\frac{1}{1+e^{-x'\beta}}$ =

PD1=F(Int.,LagOwnAct.,Lag%NeighCoop,NetworkClust.,NetworkLength,Neigh.Num.)

PD2=F(Int.,LagOwnAct.,Lag%NeighCoop,Ind.Clust.,Ind.Length,Neigh.Num.)

PD3=F(Ind.Int.,LagOwnAct.,Lag%NeighCoop,Lag%NeighCoop×NetworkClust.,
Lag%NeighCoop×NetworkLength,Lag%NeighCoop×Neigh.Num.)

PD4=F(Ind.Int.,LagOwnAct.,Lag%NeighCoop,Lag%NeighCoop×Ind.Clust.,
Lag%NeighCoop×Ind.Length,Lag%NeighCoop×Neigh.Num.)