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Coordination and cooperation in local, random and small world networks: Experimental evidence

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Received 12 February 2002

Abstract

A laboratory experiment has been designed to study coordination and cooperation in games played on local, random and small-world networks. For the coordination game, the results revealed a tendency for coordination on the payoff-dominant equilibrium in all three networks, but the frequency of payoff-dominant choices was significantly higher in small-world networks than in local and random networks. For the prisoner's dilemma game, cooperation was hard to reach on all three networks, with average cooperation lower in small-world networks than in random and local networks. Two graph-theoretic characteristics—clustering coefficient and characteristic path length—exhibited a significant effect on individual behavior, possibly explaining why the small-world network, with its high clustering coefficient and short path length, is the architecture of relations that drive a system towards equilibrium at the quickest pace.

JEL classification: C69; C72; C91; C92

Keywords: Local network; Random network; Small-world network; Coordination; Cooperation; Experiment; Prisoner's dilemma; Graph theory

1. Introduction

Much of the scientific research of last century has been guided by reductionism: the idea that we can understand a system by understanding all the subsystems it is composed of. As a result, tremendous progresses were achieved in several fields by studying atoms, molecules, genes and, in economics, individual agents. Many disciplines, economics included, are now trying to re-

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0899-8256/$ – see front matter
doi:10.1016/j.geb.2006.03.008

assemble all the parts to understand the whole; studying the complex systems which result when all the elements are linked back together (see Barabasi, 2002), and networks—the ways in which the elements of a system are linked to each other—are becoming an important research area.

In the social sciences, social network theorists have developed formal measures of network characteristics that facilitate the development of testable models (see Wasserman and Faust, 1994) and economists are increasingly incorporating a network-based perspective in their analyses with the finding that the particular pattern of links among individuals, the network, has important and wide applications. 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 et al., 2004), employment and inequality in labor markets (Calvo-Armengol and Jackson, 2004), contemporaneous evolution of different conventions (Young 1993, 1998), partial monopolistic behavior of markets for services and goods where transportation is important (Blume 1993, 1995), how global inefficiency might result from local efficiency (Epstein and Axtell, 1996), provision of trust when contract enforcement is weak or nonexistent and transmission of information about profitable trade opportunities in markets with networks (Rauch and Casella, 2001; Cassar et al., 2004; and, for a critical overview, Zuckerman, 2003).

In this paper I explore via experimental methods 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 et al., 1998; Axelrod et al., 2002; Nowak and May, 1992, 1993; Watts, 1999); and relatively fast coordination on the less risky equilibrium (Kandori et al., 1993; Ellison, 1993; Blume, 1995; Young 1993, 1998). In view of these theories, I designed a laboratory experiment to compare the performance of games played on three different networks: local (links form a simple lattice structure such as a circle or grid), random (links are equally likely between each pair of agents), and small-world (local with a few links substituted by long-distance links). This last network, the small world network,[1] is particularly important for economics because it has the properties of many human networks from the society in which we live to the World Wide Web (see Milgram, 1967; Adamic, 1999).

The results of the experiment revealed a tendency for coordination on the payoff-dominant equilibrium in all three networks, but the frequency of payoff-dominant choices was significantly higher in small-world networks than in local and random networks. For the prisoner's dilemma game, cooperation was hard to reach on all three networks, with average cooperation lower in small-world networks than in random and local networks.

Following a recent work by Watts (1999), I analyzed the impact of two 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). The significant effect that these two network characteristics exhibited on individual behavior suggests that the small-world network, with its high clustering coefficient and short path length, is the architecture of relations that drive a system towards equilibrium at the quickest pace.

[1] Milgram (1967) was the first to discover that the pattern of links among people is different from the one widely used by theorists, the random network, and can be described as a small-world network. The origin of the term comes from the common experience of discovering acquaintances and friends of friends even in the most unusual locations. Experience that make us sigh: "What a small world!"

Milgram's results have stimulated extensive scientific research across fields (e.g. Schelling, 1971), and have even seeped into popular culture with the Broadway play "Six Degrees of Separation" by Guare or the homonymous movie by Schepisi, and the "Kevin Bacon" or "Erdös" numbers.

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, the agents can coordinate on the better (payoff-dominant) outcome.

When the game is extended to several players there is no agreement on how to generalize the risk-dominance equilibrium criterion (e.g., Goeree and Holt, 2001), and numerous experimental studies have found evidence of both risk-dominance and payoff-dominance as equilibrium criteria depending on the number of players, the number of rounds or the payoff structure (see for example, van Huyck et al., 1990; Berninghaus et al., 2002).

In theoretical models a frequent assumption has been uniform matching.[2] For this non-spatial context, Kandori et al. (1993) find 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,[3] concludes that the evolutionary argument of Kandori et al. (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 present more coordination on the risk-dominant equilibrium when compared to closed groups with the same number of neighbors, but less than when players are located on a lattice, which instead allows for the establishment of several equilibria (Berninghaus et al. 1997, 1998, 2002; 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 et al. (1990) and Berninghaus et al. (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]

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[2] 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.

[3] Under local matching the players are located on a lattice of any order—for example, on a circle—and are matched with a specified number of neighbors positioned to their right and left.

[4] In van Huyck et al.'s experiment the number of iterations is only 10. By increasing the number of periods, the probability of coordinating on the payoff-dominant equilibrium is actually higher, as found also by Berninghaus et al. (1997) and Berninghaus and Ehrhart (1998).

Regarding individual behavior, Cassar (2003), Berninghaus et al. (1997, 1998, 2002) 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.

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 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 et al., 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 supported only weakly by experimental data (Cassar, 2003).

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 et al. (2002). 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, $\mathcal{N} = \{n_1, n_2, \ldots, n_N\}$, used to represent players, and a set of lines between pairs of nodes, $\mathcal{L} = \{l_1, l_2, \ldots, l_L\}$, 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, $2 \leqslant N < \infty$, and an underlying 2-player game, G. Player i's payoff function in the network game is the average payoff[5] 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:

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

where $a, b, c, d \in R$ 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, I assumed $a > c$, $d > b$, $a > d$ 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, $c > a$, $d > b$ and $a > d$ ensure 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 $Nk/2$, but differ in terms of the pattern of connections.

Local network. Here (Fig. 1(a)) N individuals are arranged on a circle[6] 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 $Nk/2$ connections. In this way, each player is connected with the $k/2$ most immediate players on the right and the $k/2$ most immediate players on the left, as if they were all seated around a table.

Random network. Here (Fig. 1(b)) individuals form random relations between themselves so that each pair has an equal probability to become connected. By rewiring each of the $Nk/2$ relations of the local network exactly once, each agent is now connected with an average of k

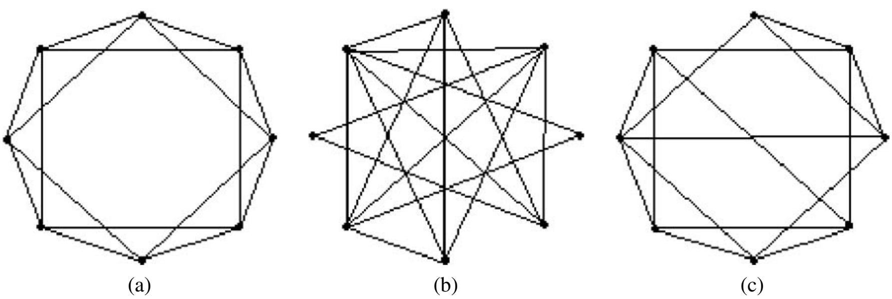

Fig. 1. Local (a), random (b), and small-world (c) networks.

[5] The games, and therefore the results, could be quite different if player i's payoff function was, instead of the average, the minimum or the maximum function. See, for example, Berninghaus et al. (2002).

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

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 (Fig. 1(c)) has the properties of both local and random networks. To obtain a small-world network, we start with a local network and randomly rewire each of the $Nk/2$ connections of the local network with 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 that are far apart on the circle.

4. Graphs structural properties

I analyze the graph structural properties 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*:

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

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—i.e., no overlapping) to 1 (when everyone is connected to everyone else). For the local network, it is possible to find the clustering coefficient exactly by enumeration:

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

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:

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

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—i.e., the average distance between all pairs of individuals. For the local network:

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

while for the random network:

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

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.[7]

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.

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' neighbors, and so on.

5. Hypotheses on how network affects play

Watts and Strogatz (1998) and Watts (1999) 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. In game theory local, random and small-world networks have not been appreciably explored yet, thus exact predictions on how these networks affect play are not available. Nevertheless, extending what we know from the literature surveyed above, we can form the following hypotheses to test in the laboratory.

H1. Coordination game: the higher the clustering coefficient, the higher the probability of agents choosing the payoff-dominant action.

When the clustering among neighbors is high, agents observe their neighbors responding to similar local conditions and play as if they were playing in a small groups instead of on a much larger network. Van Huyck et al. (1990) and Berninghaus et al. (1997) found that small groups coordinate on the payoff-dominant equilibrium more than larger ones, so environments with higher clustering should support more coordination on the better outcome.

H2. Coordination game: the shorter the characteristic path length, the faster the convergence towards any equilibrium.

[7] 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 shorter the characteristic path length, the smaller the number of steps it takes for a signal, or an action, to reach all the other members of the network. As a consequence, coordination on either the payoff-dominant or risk-dominant equilibrium should be faster in environments with shorter path lengths.

In conclusion, we expect the small-world and the local networks to exhibit more coordination on the payoff-dominant equilibrium than the random network, since both share higher clustering coefficients. In addition, coordination on the payoff-dominant equilibrium should be faster in the small-world network than in the local network since the path length of the first is shorter. For similar reasons, we expect the random network to support the least amount of coordination on the payoff-dominant equilibrium, given its low clustering associated with short path.

H3. Prisoner's dilemma game: the higher the clustering coefficient, the higher the probability of agents choosing to cooperate.

The reported works of Watts (1999), Samuelson et al. (1998) and Nowak and May (1992, 1993) 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 thereby getting higher benefits than defectors, making cooperation sustainable.

H4. Prisoner's dilemma game: the longer the characteristic path length, the higher the probability of agents choosing to cooperate.

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 present more obstacles to cooperation. It would make it easier for infiltrators to enter a cluster and destroy cooperation, especially in the presence of high clustering, where the incentive to "rat" is even higher.

In conclusion, we expect the local network to be the one in which cooperation has the highest chance to thrive given its high clustering and long path length. The small-world and random networks, instead, have similarly short path lengths so cooperation is hard to achieve. Still, cooperation would be higher in the small-world if the clustering effect was stronger than the path length effect, or in the random network if the path length effect was stronger than the clustering effect.

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 1; the details, including the instructions for the participants, are available upon request.

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 fourth 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 presented in Table 1. 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

Table 1
Experimental design summary

Session[a]	Run	Game	Network	Neighbors	Players	Iterations[a]
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

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

[a] Each session lasted 2 hours (except for small01 where software difficulties forced us to finish after only 2 runs) but ended up with a different number of runs. The duration of each run was variable, depending on the actual number of periods per run (randomized and unknown to the subjects), and on the speed at which the subjects were selecting their actions (the game would go from one period to the next only after all 18 subjects made their selections).

was the risk-dominant, and $p = 2/3 > 1/2$ 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 1, 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 random and not known in advance to the subjects to prevent issues of 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.

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

Table 2
Network characteristics

Network	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
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

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 subjects' identities. In fact, 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 2).

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 2, 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 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 Fig. 2 and Table 3). Individual runs

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

[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 characteristics.

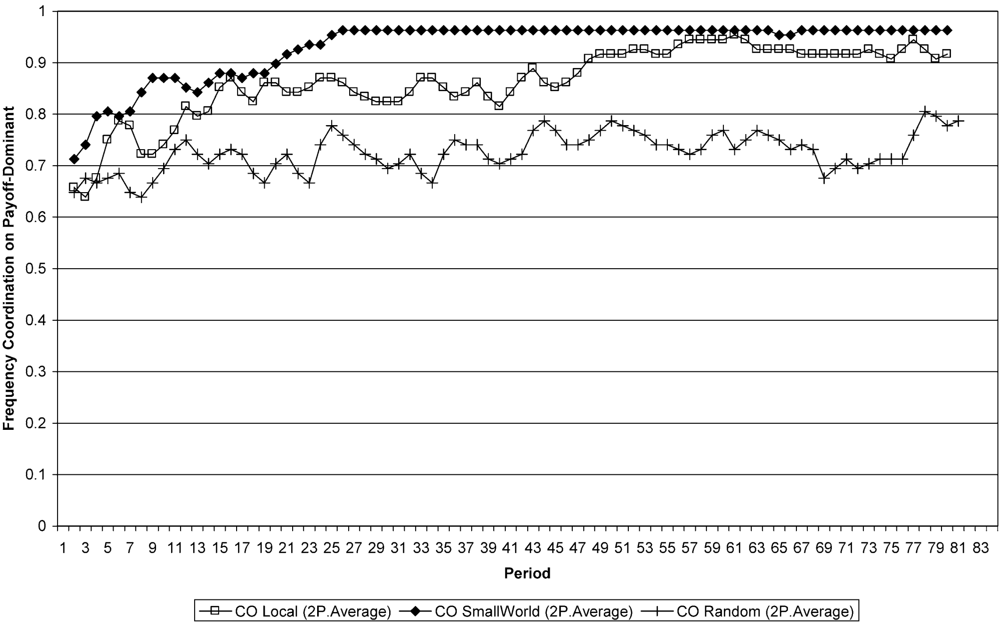

Fig. 2. Coordination game: average network coordination.

Table 3
CO frequency of coordination on payoff-dominant 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

are shown in Figs. 3, 4 and 5. After a few initial periods 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 4 reports the number of runs that were successful in reaching either the payoff-dominant or the risk-dominant behavioral equilibrium,[12] the average time to reach it, and the retention rate, i.e., 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 equi-

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

[12] Payoff-D. (Risk-D.) behavioral equilibrium was considered reached if at least 17 of the 18 players choose action A (B).

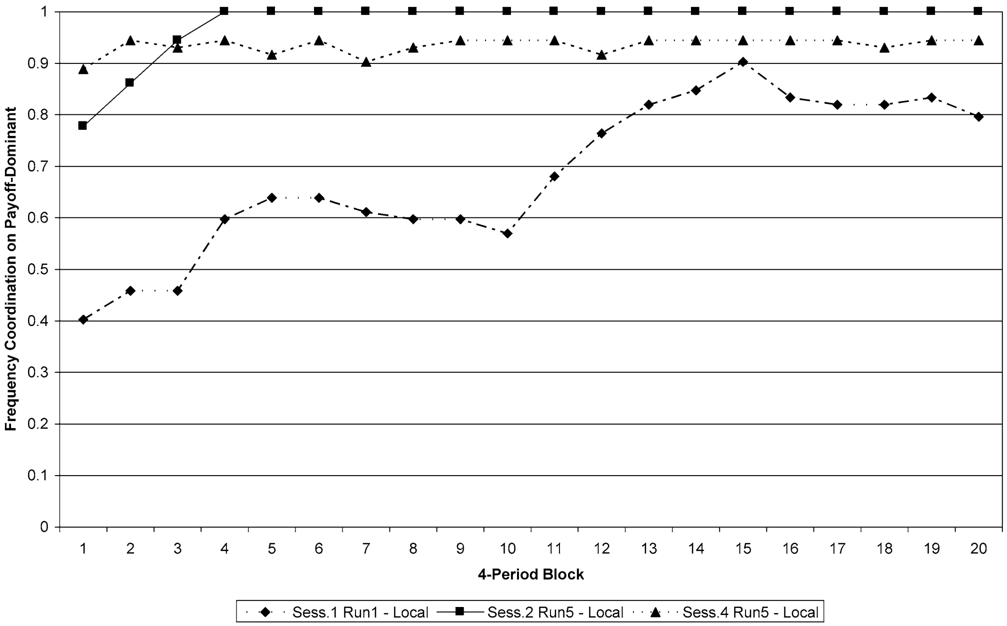

Fig. 3. Coordination game: local runs (4-period blocs).

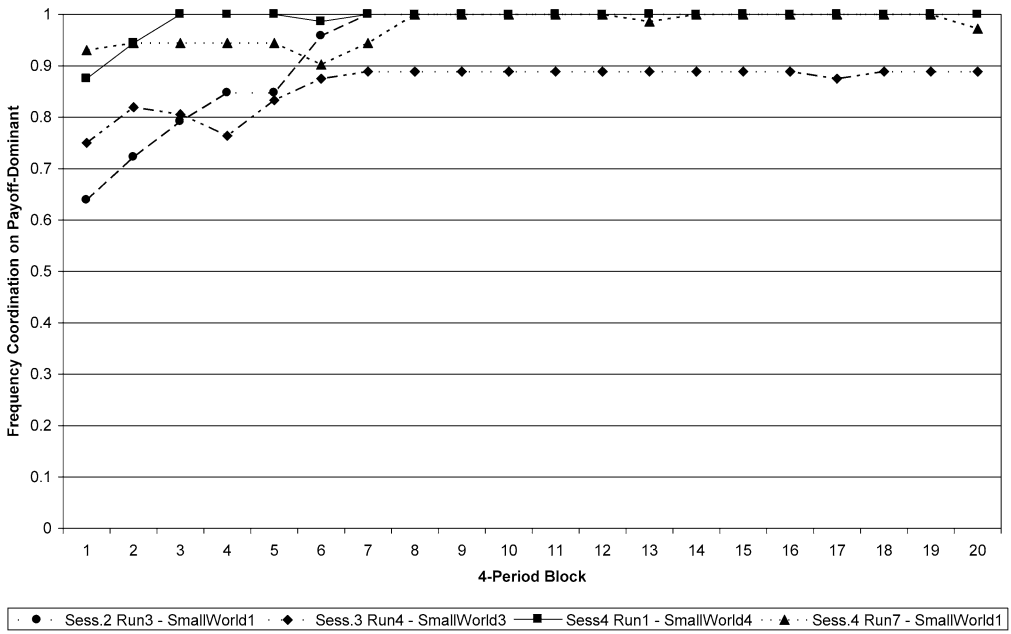

Fig. 4. Coordination game: small-world runs (4-period blocs).

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

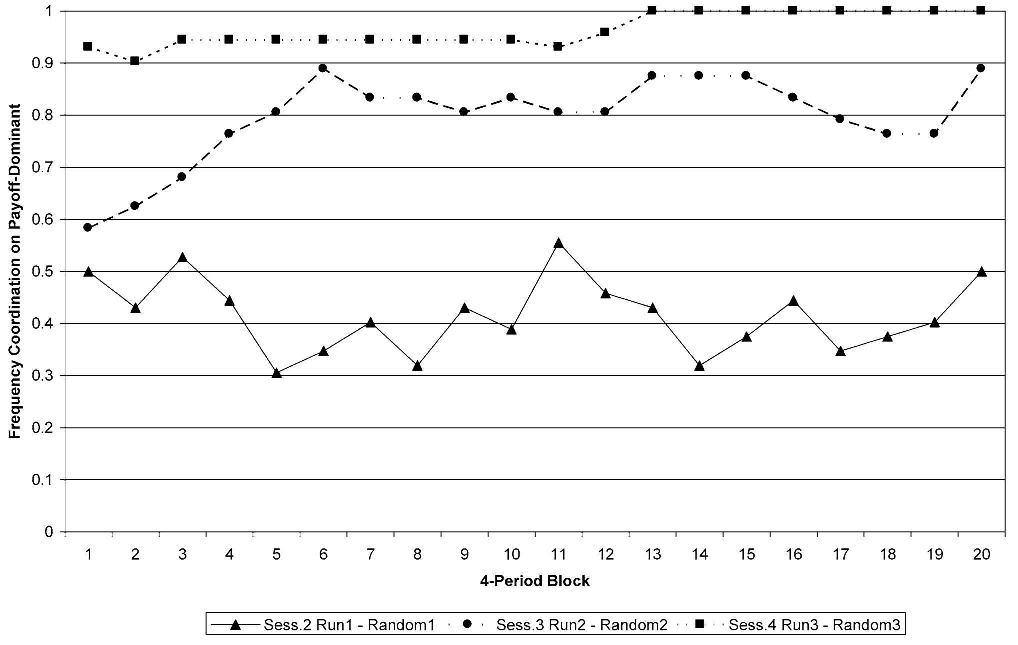

Fig. 5. Coordination game: random runs (4-period blocs).

Table 4
CO equilibrium selection

Network	Num. runs in eq.[a]		Av. time to eq.[b]		Av. retention eq.[b]	
	Payoff-D.	Risk-D.	Payoff-D.	Risk-D.	Payoff-D.	Risk-D.
Small	3 out of 4	0 out of 4	9 among 3 (s.d. ± 11.3)	–	98% (s.d. ± 1.9)	–
Local	3 out of 3	0 out of 3	26 among 3 (s.d. ± 30.7)	–	64% (s.d. ± 51.5)	–
Random	1 out of 3	0 out of 3	2 –	–	95% –	–

[a] 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 $\begin{array}{c|c|c|} & A & B \\ \hline A & 5 & -1 \\ \hline B & 4 & 1 \\ \hline \end{array}$.

[b] Averages are evaluated only among runs which reached equilibrium.

These results suggest that local interactions do cause faster coordination than random interactions (as expected e.g., by Ellison, 1993), but do so on the payoff-dominant equilibrium rather than on the risk-dominant equilibrium expected by Kandori et al. (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 Fig. 6). Individual runs are shown in Figs. 7, 8 and 9. By the end of each game (see Table 5), cooperation is at most half its initial level, with agents on the small-world networks ending with approximately 10 percent less cooperation than on the other

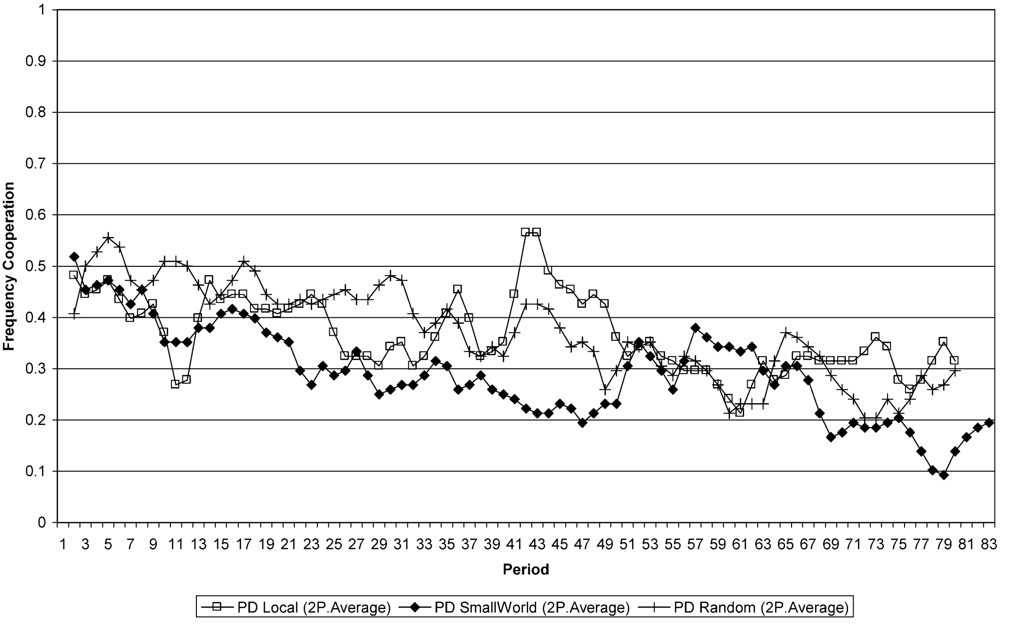

Fig. 6. Prisoner's dilemma game: average network coordination.

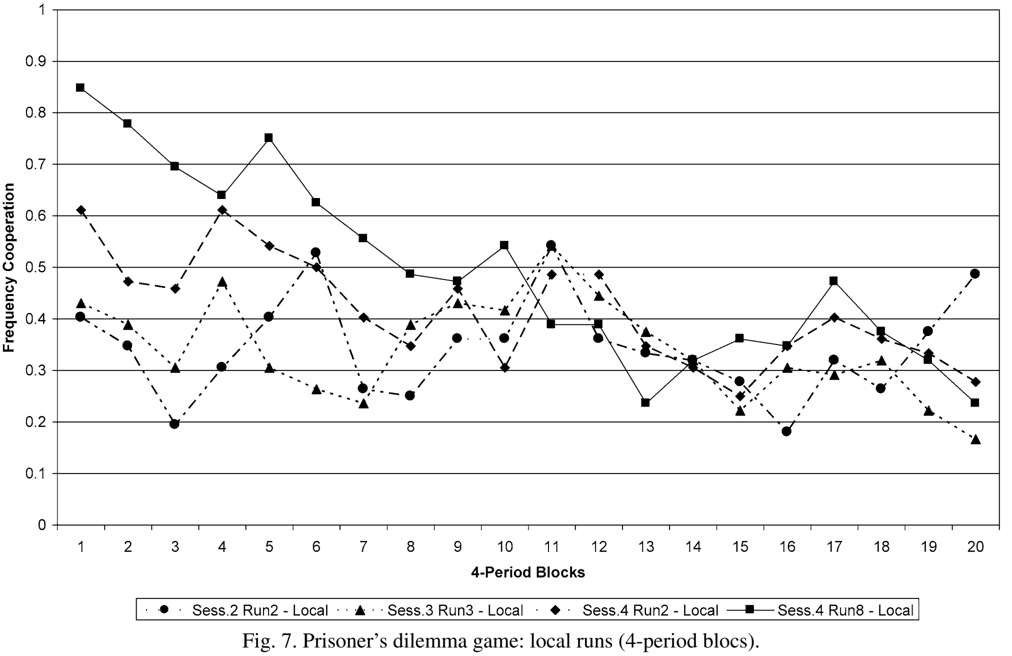

Fig. 7. Prisoner's dilemma game: local runs (4-period blocs).

two networks. The Mann–Whitney test[13] confirms that the differences among the three networks are statistically significant, even if the difference seems to be between the small-world network on one side and the local and random networks on the other.

[13] Again, the samples are not strictly independent, so more rigorous testing will follow.

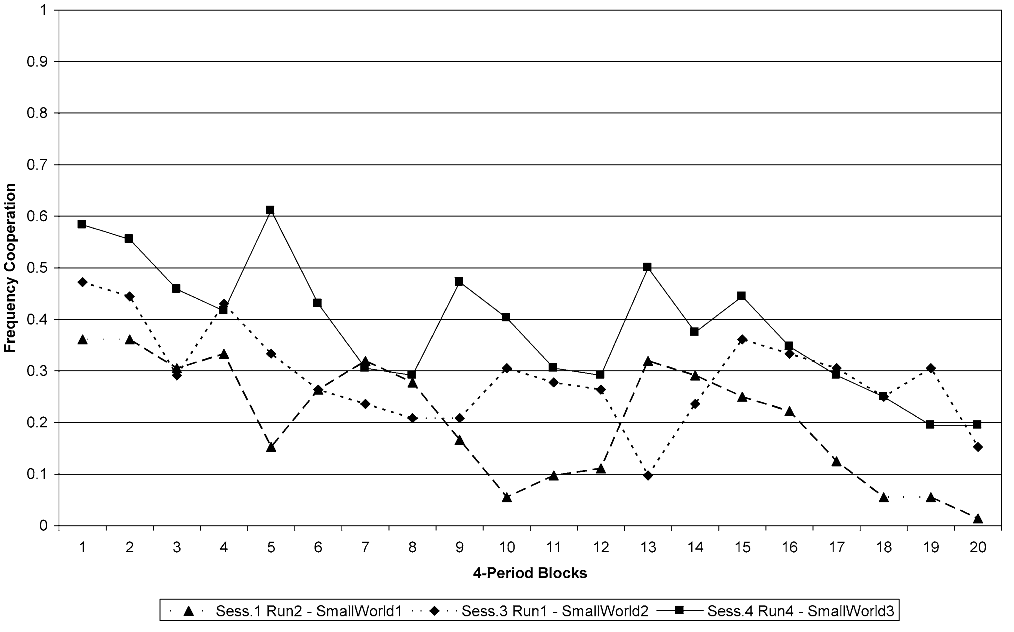

Fig. 8. Prisoner's dilemma game: small-world runs (4-period blocs).

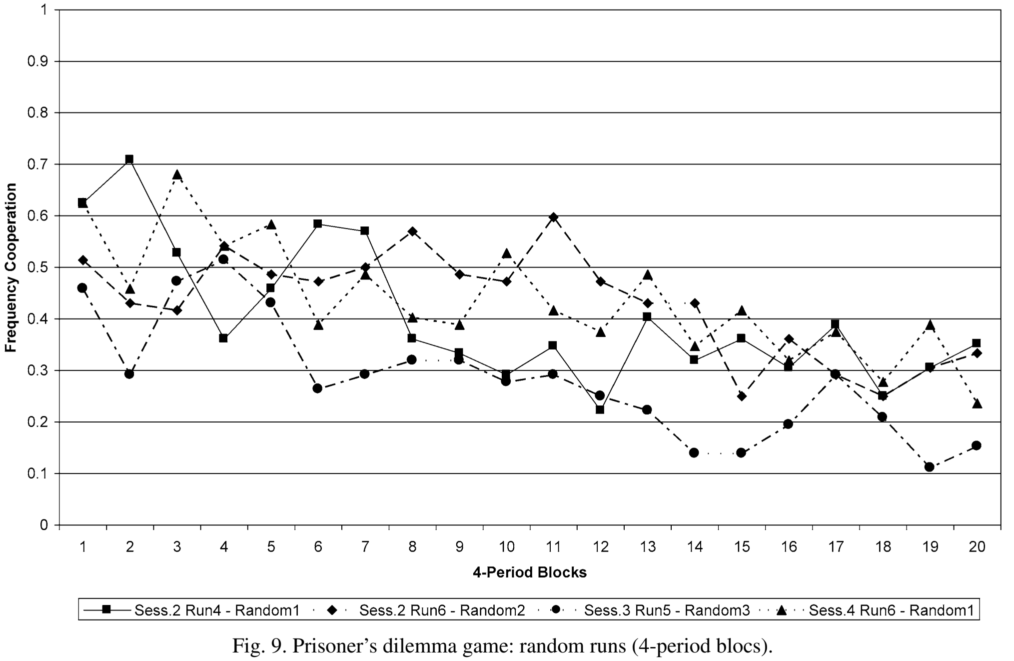

Fig. 9. Prisoner's dilemma game: random runs (4-period blocs).

Players on the small-world network achieve a defection equilibrium more often, reach this threshold more quickly, and, once attained, stay there longer than when they are on the other two networks (Table 6).

These data seem to support the prediction of Samuelson et al. (1998) that local interactions offer a better ground for cooperation than other networks. On the other hand, they are not favorable

Table 5
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 6
PD equilibrium selection

Network	Num. runs in eq.[a]		Av. time to eq.[b]		Av. retention eq.[b]	
	Coop.	Def.	Coop.	Def.	Coop.	Def.
Small	0 out of 3	2 out of 3	–	35 among 2	–	25%
				(s.d. ± 4.24)		(±24)
Local	1 out of 4	2 out of 4	1 among 1	36 among 2	1%	4%
			(–)	(s.d. ± 34.6)	(–)	(±2)
Random	0 out of 4	1 out of 4	–	54	–	11%
				(–)		(–)

[a] 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 $\begin{array}{c|c|c|} & A & B \\ \hline A & 4 & 0 \\ \hline B & 5 & 1 \\ \hline \end{array}$.

[b] Averages are evaluated only among runs which reached equilibrium.

to the Axelrod et al. (2002) idea that what matters is neighborhood preservation—i.e., keeping the same neighbors for one entire game—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 7, 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' attempts 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 five possible models. When observations are correlated across time, as 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-effects would capture not just the home-grown preferences individuals have, but also 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 with fixed-effects the network effect may be washed out.

In all the models presented in Table 8, the dependent variable (PayoffDominantAction) is the current action chosen by the player: 1 if the player chooses payoff-dominant, 0 if she chooses

Table 7
CO frequency of payoff-dominant decisions

% Payoff-dom. decisions on	% Neighbors playing payoff-dom. previous period				
	0%	25%	50%	75%	100%
Small network	–	76.2% (16)	74.6% (100)	91.0% (719)	95.8% (4491)
Local network	46.8% (22)	41.6% (77)	54.7% (220)	79.7% (578)	96.9% (2822)
Random network	31.3% (70)	29.5% (72)	42.7% (349)	68.0% (513)	93.8% (2105)

Frequencies provided in parentheses.

Table 8
CO logit—Prob(PayoffDominantAction) $= \frac{1}{1+e^{-x'\beta}} =$

Model:	CO1	CO2	CO3	CO4	CO5
Intercept	1.95*	0.94	−1.75	fixed-eff.	fixed-eff.
	(0.94)	(2.80)	(1.43)		
LagOwnAction	4.08*	6.81*	4.03*	3.24*	4.43*
	(0.08)	(0.20)	(0.08)	(0.08)	(0.22)
PayoffAdvantage	1.07*	0.62*	0.94*	1.04*	1.56*
	(0.05)	(0.21)	(0.06)	(0.06)	(0.22)
NetworkClustering	3.92*	5.10***	2.03**	1.49	10.06***
	(0.88)	(3.42)	(1.17)	(1.37)	(6.45)
NetworkLength	−3.28*	−4.54*	−1.61*	−0.19	−1.19
	(0.55)	(1.77)	(0.78)	(0.91)	(3.10)
IndividualClustering	−0.35	−0.57	−0.31	−1.11*	−9.30*
	(0.33)	(0.72)	(0.33)	(0.56)	(2.28)
IndividualLength	1.47*	1.91*	1.43*	1.64*	2.12**
	(0.20)	(0.51)	(0.21)	(0.37)	(1.28)
NeighborsNumber	−0.02	0.25	−0.01	0.29*	−0.44
	(0.05)	(0.16)	(0.05)	(0.09)	(0.38)
PreviousRun%Coord.		0.60			0.67
		(0.73)			(1.62)
DummySession2			0.60*		
			0.18		
DummySession3			0.50*		
			(0.17)		
DummySession4			0.84*		
			(0.17)		
Number of obs.	14,202	8532	14,202	12,300	4666
Log likelihood	−2441.5	−458.6	−2429.2	−2033.5	−291.3
Pseudo R^2	0.58	0.75	0.58	0.50	0.63

* Significant at the 5% level.
** Idem, 10%.
*** Idem, 15%.

risk-dominant. The independent variables of the first model (CO1) test for an overall network effect on individual choices (NetworkClustering and NetworkLength—the network clustering coefficient and the path length as reported in Table 2), an individual network characteristic effect (IndividualClustering and IndividualLength—which are the clustering coefficient and the path length measured at the individual level, whose average among all agents in a network produce NetworkClustering and NetworkLength), inertia in one's behavior (LagOwnAction), best reply measured as the payoff difference between the actions given neighbors' choices last period (PayoffAdvantage[14]), and a measure of centrality (NeighborsNumber).

The second model (CO2) adds the frequency of payoff-dominant choices in the last 10 periods from the same type of game played previously in the same session (PreviousRun%Coord.). This variable is introduced to capture sequencing or contagion effects from one round to the next. Since only 6 out of 10 runs have this variable, the number of observations in this model is greatly reduced. Still, the results are very similar to the previous model, with the exception that now the NetworkClustering is significant only at 15%, and no evidence of sequencing effects. CO3 adds to CO1 session dummies to account for session effects. While session effects are indeed significant, the results do not change much from CO1 except for, again, the decreased significance of NetworkClustering.

These three models present a similar picture: high network clustering and short network path length increase the probability with which agents coordinate on the payoff-dominant equilibrium. At the individual level, clustering is not significant, while agents located relatively more distant from the rest show a higher probability of choosing the payoff-dominant action. The number of neighbors does not seem to play a significant role. Best reply and inertia are significant for explaining individual behavior.

The last two columns of Table 8 report the results of evaluating the model with fixed-effects,[15] with and without PreviousRun%Coord. Keeping in mind the caveat mentioned above of using fixed-effects with this data set, the results now indicate that the overall network characteristics lose their significance, while the characteristics at the individual level stay or gain significance. Here, a relatively longer individual length increases the probability of playing payoff-dominant, while, surprisingly, a relatively higher individual clustering decreases this probability. As in the previous models, inertia and best-reply keep their significant explanatory power.

7.2.2. Prisoner's dilemma

Table 9 shows that players on the small-world network cooperate the least for all levels of cooperation in their neighborhoods. Instead, consistent with most of the local interaction 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.

[14] 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 $\mathit{PayoffAdvantage}(\pi) = (1, -1)P(\pi, 1-\pi)'$, 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.

[15] Session dummies are not included now because of multicollinearity with individual effects. Still many observations were discarded because of insufficient variation.

Table 9
PD frequency of cooperative decisions

% Cooperative decisions on	% Neighbors playing cooperate previous period				
	0%	25%	50%	75%	100%
Small network	17.1% (219)	30.1% (400)	33.0% (413)	39.3% (182)	60.2% (62)
Local network	25.7% (243)	30.9% (597)	39.1% (648)	56.8% (492)	86.9% (279)
Random network	21.9% (215)	29.5% (315)	39.8% (872)	50.2% (527)	64.1% (264)

Frequencies provided in parentheses.

Table 10
PD logit—Prob(Cooperate) $= \frac{1}{1+e^{-x'\beta}} =$

Model:	PD1	PD2	PD3	PD4	PD5
Intercept	−4.57*	−3.66*	−3.42*	fixed-eff.	fixed-eff.
	(0.51)	(0.82)	(0.61)		
LagOwnAction	2.58*	2.80*	2.57*	2.33*	2.47*
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Lag%NeighCoop	1.33*	1.31*	1.27*	1.39*	1.57*
	(0.08)	(0.10)	(0.08)	(0.08)	(0.11)
NetworkClustering	−1.93*	−0.47	−0.57	−0.64	0.40
	(0.48)	(0.74)	(0.64)	(0.67)	(1.35)
NetworkLength	0.95*	0.03	0.13	0.07	−0.51
	(0.30)	(0.46)	(0.38)	(0.40)	(0.74)
IndividualClustering	−0.05	−0.16	−0.05	0.10	0.25
	(0.16)	(0.19)	(0.16)	(0.20)	(0.25)
IndividualLength	0.25*	0.47*	0.26*	0.28*	0.43*
	(0.11)	(0.14)	(0.11)	(0.14)	(0.19)
NeighborsNumber	0.07*	0.07*	0.07*	0.16*	0.19*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
PreviousRun%Coop.		0.74			−0.87
		(0.48)			(1.30)
DummySession2			0.35*		
			(0.11)		
DummySession3			0.20*		
			(0.10)		
DummySession4			0.37*		
			(0.10)		
Number of obs.	15,858	10,044	15,858	15,777	10,044
Log likelihood	−7494.9	−4617.6	−7486.0	−7043.3	−4266.3
Pseudo R^2	0.28	0.31	0.28	0.23	0.27

* Significant at the 5% level.

Table 10 reports the results of five models estimated to test the effect on individual behavior of the network characteristics. The dependent variable is Cooperate, valued 1 if the player chooses to cooperate, 0 if he defects. The independent variables of the first model (PD1) include the overall network characteristics (NetworkClustering, NetworkLength—the clustering coefficient and the path length measured at the network level as reported in Table 2), the network characteristics at the individual level (IndividualClustering, IndividualLength), the number of neighbors

(NeighborsNumber), the agent's action in previous period (LagOwnAction), and the previous period frequency of cooperation one's neighborhood (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 (PD2) is estimated adding PreviousRun%Coop to capture sequencing effects, and a third one (PD3) includes session dummies.

The last two models (PD4 and PD5) estimate individual fixed-effects, with and without PrevRun%Coop (apply same caveats as using fixed-effects with the coordination game data).

As indicated in Table 10, all five models yield roughly similar results. In addition to reciprocity and inertia, there are only two network characteristics which significantly affect cooperation: the path length measured at the individual level and the number of neighbors. Agents relatively more isolated from the others (longer IndividualLength) tend to cooperate more. The higher the number of neighbors, the higher the probability for an agent to cooperate. The clustering coefficient does not seem significant either at the network or at the individual level, except in PD1 for which cooperation is encouraged by long length and, contrary to expectations, small clustering. This suggests that high clustering and short length may actually encourage defection, which we observe highest in small-world networks. Interestingly, those characteristics that helped coordination on the better outcome are here weakening cooperation.

8. Conclusion

This study offers experimental results indicating 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 system to reach equilibrium at the fastest pace.

In the coordination game experiment, in all three networks most individuals preferred the payoff-dominant action to the risk-dominant action, but players on the small-world network were faster reaching coordination than agents in the local network and random network respectively.

In the prisoner's dilemma game experiment, cooperation was difficult to achieve in all three networks, but players on the local network were the most likely to cooperate while players on the small-world network were the least likely to cooperate.

Individual behavior was significantly affected by the network characteristics. For the coordination game, higher network clusterings and shorter network lengths increased the probability of players choosing the payoff-dominant action. For the prisoner's dilemma game, the longer individual lengths of the local network supported the highest level of cooperation, while clustering did not seem significant.

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 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.

Acknowledgments

I am particularly grateful to Daniel Friedman for his continuous encouragement and support during this project. I would like to thank Steffen Huck, Rosemarie Nagel and Reinhard Selten for their comments and advice; Nicole Bouchez for help during the experiment; David Kaun for his stylistic suggestions; and two anonymous referees for constructive comments.

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