Core–periphery segregation in evolving prisoner’s dilemma networks

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Dense cooperative networks are an essential element of social capital for prosperous societies. These networks enable individuals to overcome collective action dilemmas by enhancing trust. In many biological and social settings, network structures evolve endogenously as agents exit relationships and build new ones. However, the interplay between game strategy and interaction structure by which evolutionary dynamics leads to self-organization of dense cooperative networks has not been understood. Our prisoner’s dilemma experiments with exit and partner choice options show that core–periphery segregation of cooperators and defectors drives the emergence of cooperation. Cooperators’ Quit-for-Tat and defectors’ Roving strategy lead to a highly asymmetric core and periphery structure. Densely connected to each other at the core, cooperators successfully isolate defectors at the periphery and earn larger payoffs.

Keywords: economic experiment; dynamic network; evolution; core-periphery structure; quit-for-tat; roving.

1. Introduction

Biological and social agents achieve cooperation through a variety of mechanisms [1–4]. Preferential association is one of the mechanisms in settings where agents are not forced to interact with fixed partners [5–8] Preferential association characterizes a wide range of domains from coauthorship among researchers and joint ventures among business firms to free-trade agreements among nation states in which agents can build and break interaction links with other agents [9]. Several theoretical studies show that partner selection promotes cooperation by allowing cooperators to interact with other cooperators [10, 11]. Available evidence from experiments using human subjects [6, 12] also supports the optimistic scenario.

However, the coevolutionary process between agents’ strategic behaviour and network structure is not fully understood. Despite the fact that many real-world networks consist of agents with extremely
heterogeneous topological traits [9], previous experimental studies were not able to trace the macroscopic coevolution of strategies due to the fixed number of links per subject [13]. While recent experimental studies aim to reveal the coevolution of individual level networking and gaming strategies experimental research with networking option [12, 14] was not successful at reproducing the emerging payoff advantage of cooperators, thus failing to explicate the only biologically relevant criterion for the evolution of cooperation, the comparative fitness advantage of cooperation [2]. Finally, the process of macroscopic structural evolution of networks between individuals, driven by the interactions between strategic and structural benefits, accompanying diversification of individual positions in the networks has not been addressed.

To fill this gap in knowledge, we ran experiments in which agents can break existing relationships and build new ones, enter multiple relationships and play cooperatively with some partners but opportunistically against others. We used groups of 35–40 subjects per session and allowed subjects to freely re-establish relationships. The experiments were conducted in two different link cost settings in order to examine the robustness of the evolving network patterns.

2. Methods

2.1 Experimental setup and procedure

In our experiments, multiple subjects played 2-person prisoner’s dilemma (PD) games with real monetary stakes. Potential partners and ego-centric game-networks were visually presented on individual computer screens. Subjects played 20 rounds of the experimental game, in which a round consisted of a partner selection stage and a PD game stage. Two individuals were paired if and only if both proposed to each other during the partner selection stage (Fig. 1). Subjects played the 2-person PD game for each established link. A subject could differentiate his or her PD game strategies in games with different partners. Subjects paid link costs of $4.4(k - 1)^2$ in the low-cost setting and $8.8(k - 1)^2$ in the high-cost setting for $k > 1$, and 0 otherwise, where $k$ denotes the number of established links. The link cost limited the number of links a subject could profitably maintain. We conducted four sessions in total, of which two for each cost setting.

The experiments were conducted in a computer lab at Korea University, Seoul, Korea in June and July of 2010. Paid volunteer subjects were recruited via web advertisements posted on university websites. A total of 150 subjects participated in the experiments, 35 and 40 in two high-cost sessions and 36 and 39 in two low-cost sessions (see the Supplementary information for detailed information).

![Fig. 1](https://academic.oup.com/comnet/article/8/1/cnz021/5523025)

**Fig. 1.** The PD game with partner choice and exit options. Two subjects play the PD game only when they both propose to play with each other at the partner selection stage of a given round. After a link is formed, each dyadic pair plays the PD game. See Methods for detailed description of the procedure.
2.2 Statistical and graph theoretical analysis

To characterize the modular structure in each network, we utilized a modularity-based community detection method. The benefit function, modularity $Q$, is defined as follows [15–17]:

$$Q = \sum_{s=1}^{N_M} \left( \frac{l_s}{L} - \left( \frac{d_s}{2L} \right)^2 \right)$$

where $N_M$ is the number of modules, $l_s$ is the number of links within module $s$, $L$ is the total number of links in the network and $d_s$ is the total number of links that are connected with nodes belonging to module $s$. We employed an iterative greedy algorithm to find an optimal division corresponding to the maximum modularity value ($Q_{\text{max}}$) of the interaction network for a given round [15]. The corresponding modularity value ($Q_{\text{max}}$) for that particular division was used to indicate the level of natural clustering in the network (see the Supplementary information for details).

To obtain random reference networks for each round’s interaction network while preserving its degree distribution, we used link swapping method [18]. For each step of link swapping, two links with non-overlapping nodes were selected. Suppose the first link was a connection between nodes $a$ and $b$ and the second link was a connection between nodes $c$ and $d$. Then, these links swapped their neighbours so that after the swapping, links $a$–$b$ and $c$–$d$ were eliminated and new links $a$–$d$ and $c$–$b$ were formed without loss of generality. We repeated this procedure at least five times for each link to obtain each of the 1000 random networks for a given round.

Finally, modularity $Z$-score for a given round was computed as follows:

$$Q_{Z{-}\text{score}} = \frac{Q_{\text{max}} - Q_{\text{rand}}}{\sigma(Q_{\text{rand}})}$$

where $Q_{\text{max}}$ is the maximum modularity value of the optimal division for the network of a given round, $Q_{\text{rand}}$ is the average and $\sigma(Q_{\text{rand}})$ is the standard deviation of maximum modularity values of 1000 random reference networks respectively.

In each round, coreness values ($k_s$) were assigned to nodes according to whether they were located at the densely connected core or the sparsely connected periphery (Fig. 3B) [19, 20]. The iterative pruning process began by eliminating all nodes with degree $k = 0$. This process was repeated until there was no node left with $k = 0$. Nodes pruned in this round were assigned the $k$-shell layer $k_s = 0$. Next, remaining nodes with $k \leq 1$ were pruned and assigned with $k_s = 1$. This process was repeated by sequentially ($+1$) increasing the number of maximum degree ($k$) and $k_s$ until all of the nodes were removed.

3. Results

Cooperation evolved in all sessions, with high levels of cooperation in most rounds. The proportion of cooperative choices ($%C_{\text{total}}$) from round 1 to round 19 was 59.89 ($\pm 11.26$) % in the low-cost setting and 76.37 ($\pm 9.66$) % in the high-cost setting (Fig. 2A). The $%C_{\text{total}}$ in the first rounds ($53.89 \pm 9.46$%) was similar to those in the fixed-matching PD experiments [21, 22]. In our experiments, however, cooperation gradually increased, in contrast to the decreasing patterns found in most fixed-matching experiments [21, 22]. Only in the very final round did the $%C_{\text{total}}$ plunge to 21.21 ($\pm 6.73$) %, showing a strong end-game effect (see the Supplementary information).
The high level of cooperation is associated with an increasing level of positive assortment, a well-known driver of the evolution of cooperation [10, 11, 23–27]. To measure the degree of positive assortment, we compared the observed proportions of cooperation–cooperation pairs and defection–defection pairs with the proportions that would be obtained from random interactions. Furthermore, individuals with higher rates of cooperation were more likely to interact with each other as indicated by the increasing Pearson correlation coefficient between paired players’ %C (Fig. 2B).

The degree of modularity observed in our experiments was significantly lower than that of the random benchmark (see the Supplementary information) [17] (Fig. 3A). The presence of positive assortment without a significant modular structure suggests core–periphery segregation, in which cooperators occupy a highly connected, cohesive core and defectors scatter on the sparse, intransitive periphery [28].

To quantify the location of cooperators and defectors in the core–periphery spectrum, we adopted the $k$-shell decomposition method (Fig. 3B), which outputs an integer index of coreness ($k_s$) for each node [20]. The method takes into account not only the number of links a node has but also the number of links each of its neighbours has. For example, a node with $k_s = 3$ has at least three neighbours each of whom has at least three neighbours and so on. The coreness metric better elucidates the structural position of a node compared with ego-centric measures such as simple degree ($k$) or clustering coefficient which does not discount connections to peripheral nodes (see the Supplementary information).

Cooperators formed a stable and dense cluster at the structural core of the network, whereas defectors loosely and unstably connected to this core. Pearson correlation coefficients between the %C and the $k_s$ of nodes steadily increased until near the end (Fig. 3C). Figure 3D and E provide graphical illustrations of the core–periphery segregation. The core–periphery segregation was robust across all four sessions (see the Supplementary information).

The driving force behind the core–periphery segregation was the subjects’ networking strategies (i.e., partner selection) rather than their PD game choices for given partners. The subjects’ choices in PD games rarely changed between rounds (Supplementary Fig. S7 and Table S4). The %C profile vectors of subjects in two adjacent rounds were significantly correlated with each other ($r = 0.85 \pm 0.09$). The core–periphery segregation was robust across all four sessions (see the Supplementary information).
Fig. 3. Core–periphery segregation. (A) Z-scores of modularity value of each interaction network per round compared with one thousand random networks preserving the degree distribution of a given round (see the Supplementary information). (B) A toy network consisting of nodes with different coreness \(k_s\). Nodes are assigned with \(k_s\) indicating whether they are located at the densely connected core or the sparsely connected periphery [20]. The iterative pruning process begins by eliminating all nodes with degree \(k = 0\). This process is repeated until there is no node left with \(k = 0\). Nodes pruned in this round are assigned the \(k\)-shell layer \(k_s = 0\). Next, remaining nodes with \(k \leq 1\) were pruned and assigned with \(k_s = 1\). This process was repeated by sequentially (+1) increasing the number of maximum degree \(k\) and \(k_s\) until all of the nodes were removed. (C) Correlation between a player’s coreness \(k_s\) and %C. High cooperators were more likely to be located at the core as rounds repeated. (D) and (E) Graphical illustration of core–periphery segregation in two representative rounds of a low-cost session. The colour of each node indicates %C of the depicted player in the corresponding round. A blue arc with arrow indicates its originator’s cooperative decision to its receiver, whereas an arc in red represents defection. Nodes are distributed in a spring-embedded layout that locates transitively connected nodes at proximal distances. The larger node indicates higher \(k_s\).

Segregation resulted from the subjects’ networking strategies: cooperators used Quit-for-Tat [24, 29] and defectors used Roving [30]. Cooperators never left cooperative partners, but they unforgivingly cut relationships with defectors (Fig. 4A). Defectors, in contrast, frequently left current partners to search for new victims even when the partners were cooperators (Fig. 4B). Due to these networking strategies, CC (cooperation–cooperation) links remained as the only stable link type, whereas (cooperation–defection) and DD (defection–defection) links were likely to vanish (Fig. 4C).

As a consequence of the networking strategies used by cooperators and defectors, the cooperative dyads continued through next rounds with high probabilities (95.91 ± 5.89%), whereas mutual defection and mixed (CD) dyads were unlikely to continue (13.54 ± 12.38% and 21.00 ± 10.09%, respectively) (Fig. 5A). As rounds repeated, deeper cores with higher \(k_s\) values were formed. At the same time, the probability of link maintenance at the core grew larger, whereas the links at the periphery became increasingly unstable (Fig. 5A). Defectors had difficulty in connecting to others. Even though defectors made much more proposals than cooperators did, defectors had much smaller number of proposals actually accepted as indicated by the increasing level of correlations between the number of accepted proposals and %C (Supplementary Fig. S9).

Cooperators enjoyed payoff-advantages. In earlier rounds, defectors gained more than cooperators did. Over time, however, cooperators’ earnings grew larger than those of defectors did (Fig. 5B). Cooperators had large numbers of mutually cooperative links, whereas defectors had fewer links and defectors’ links
mostly ended up with mutual defection outcomes. This result suggests that the experimental conditions of partner choice and exit served as a mechanism for the evolution of cooperation. The proportion of cooperation increased as some players’ cooperative behaviour created incentives for others to behave
likewise [4]. But the early defectors often failed to join the cooperative core when they tried to convert in a later time, because many cooperators were already locked in with each other.

4. Discussion

Combining behavioural experiments and social network analysis, we examined the generative mechanism of dense cooperative clusters as the structural correspondence of social capital. Dense networks of cooperators emerged as a consequence of preferential partner choice even without mechanisms for social reputation or indirect reciprocity. Cooperators organized a closed network of their own, stably occupying the structural core of the evolving network. This result supplements the concept of spatial [26] and network reciprocity [27] by specifying the topological characteristics of type clusters and their locations in the core–periphery spectrum of the global network. The structural stratification produced inequality by providing a large material advantage to players located at the cooperative core, thus suppressing the revival of defectors. In other words, the collective pattern of network formation served as a self-organized punishment mechanism towards defection. We also note the possibility that our results depend on the specific design parameters, such as the link cost function and cardinal values of the PD game payoffs [31]. Future studies could test the robustness of the present results in different experimental settings.

Our experiment shows the feasibility and characteristics of self-organized network solutions for the dilemma of cooperation. Our experiment raises several questions for future research. If endogenous network formation is a common characteristic of contemporary human interactions, why do some communities and groups fail to evolve dense cooperative clusters while the others succeed? Many societies suffer from low levels of social capital, which lead to distrust among individuals, malfunctioning institutions and failure in providing public goods [32, 33]. In contrast to such negative scenarios, under what conditions could the defectors at the periphery change their strategies, and join the cooperators’ cluster? Research on these questions will provide a more comprehensive picture of the interplay between strategic
choices, network structures and the evolution of cooperation, ultimately leading to insights for policy design.

Supplementary data

Supplementary data are available at COMNET online.

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REFERENCES

1. AXELROD, R. & HAMILTON, W. (1981) The evolution of cooperation. Science, 211, 1390–1396.
2. NOWAK, M. A. (2006) Five rules for the evolution of cooperation. Science, 314, 1560–1563.
3. TRIVERS, R. L. (1971) The evolution of reciprocal altruism. Q. Rev. Biol., 46, 35–57.
4. CAMERER, C. F. & FEHR, E. (2006) When does “economic man” dominate social behavior? Science, 311, 47–52.
5. HAMMERSTEIN, P. (2003) Why is reciprocity so rare in social animals? A protestant appeal. Genetic and Cultural Evolution of Cooperation (P. Hammerstein ed.). Cambridge, MA, USA: MIT Press.
6. ORBELL, J. & DAWES, R. M. (1991) A “cognitive miser” theory of cooperators’ advantage. Am. Political Sci. Rev., 85, 515–528.
7. THORNDIKE, E. L. & BRUCE, D. (1911) Animal Intelligence: Experimental Studies. New York: Macmillan.
8. TULLOCK, G. (1985) Adam Smith and the prisoners’ dilemma. Q. J. Econ., 100, 1073–1081.
9. BARABÁSI, A. L. & ALBERT, R. (1999) Emergence of scaling in random networks. Science, 286, 509–512.
10. SANTOS, F. C., PACHECO, J. M. & LENAERTS, T. (2006) Cooperation prevails when individuals adjust their social ties. PLoS Comput. Biol., 2, e140.
11. SKYRMS, B. & PEMANTLE, R. (2000) A dynamic model of social network formation. Proc. Natl. Acad. Sci. USA, 97, 9340–9346.
12. FEHL, K., VAN DER POST, D. J. & SEMMANN, D. (2011) Co-evolution of behaviour and social network structure promotes human cooperation. Ecol. Lett., 14, 546–551.
13. GRACIA-LÁZARO, C., FERRER, A., RUIZ, G., TARANCÓN, A., CUESTA, J. A., SÁNCHEZ, A. & MORENO, Y. (2012) Heterogeneous networks do not promote cooperation when humans play a Prisoner’s Dilemma. Proc. Natl. Acad. Sci. USA, 109, 12922–12926.
14. RAND, D. G., ARBESMAN, S. & CHRISTAKIS, N. A. (2011) Dynamic social networks promote cooperation in experiments with humans. Proc. Natl. Acad. Sci. USA, 108, 19193–19198.
15. BLONDEL, V. D., GUILLAUME, J. L., LAMBIOTTE, R. & LEFEBVRE, E. (2008) Fast unfolding of communities in large networks. J. Stat. Mech. Theory Exp., 2008, P10008.
16. GUIMERA, R., SALES-PARDO, M. & AMARAL, L. A. N. (2004) Modularity from fluctuations in random graphs and complex networks. Phys. Rev. E, 70, 025101.
17. NEWMAN, M. (2011) Communities, modules and large-scale structure in networks. Nat. Phys., 8, 25–31.
18. MASLOV, S. & SNEPPEN, K. (2002) Specificity and stability in topology of protein networks. Science, 296, 910.
19. CARMI, S., HAVLIN, S., KIRKPATRICK, S., SHAVIT, Y. & SHIR, E. (2007) A model of internet topology using k-shell decomposition. Proc. Natl. Acad. Sci. USA, 104, 11150–11154.
20. KITSAK, M., GALLOS, L. K., HAVLIN, S., LILJEROS, F., MUCHNIK, L., STANLEY, H. E. & MAKSE, H. A. (2010) Identification of influential spreaders in complex networks. Nat. Phys., 6, 888–893.
21. ANDREONI, J. & MILLER, J. H. (1993) Rational cooperation in the finitely repeated prisoner’s dilemma: experimental evidence. Econ. J., 103, 570–585.
22. COOPER, R., DEJONG, D. V., FORSYTHE, R. & ROSS, T. W. (1996) Cooperation without reputation: experimental evidence from prisoner’s dilemma games. Games Econ. Behav., 12, 187–218.
23. APICELLA, C. L., MARLOWE, F. W., FOWLER, J. H. & CHRISTAKIS, N. A. (2012) Social networks and cooperation in hunter-gatherers. Nature, 481, 497–501.
24. HAYASHI, N. & YAMAGISHI, T. (1998) Selective play: choosing partners in an uncertain world. Pers. Soc. Psychol. Rev., 2, 276–289.
25. MACY, M. W. & SKVORETZ, J. (1998) The evolution of trust and cooperation between strangers: a computational model. Am. Sociol. Rev., 63, 638–660.
26. NOWAK, M. A. & MAY, R. M. (1992) Evolutionary games and spatial chaos. Nature, 359, 826–829.
27. OHTSUKI, H., HAUERT, C., LIEBERMAN, E. & NOWAK, M. A. (2006) A simple rule for the evolution of cooperation on graphs and social networks. Nature, 441, 502–505.
28. BORGATTI, S. P. & EVERETT, M. G. (2000) Models of core/periphery structures. Soc. Networks, 21, 375–395.
29. MORESI, S. & SALOP, S. (2003) A few righteous men: imperfect information, quit-for-tat, and critical mass in the dynamics of cooperation. Economics for An Imperfect World: Essays in Honor of Joseph E. Stiglitz (R. Arnott, B. Greenwald, R. Kanbur & B. Nalebuff, eds). Cambridge, MA, USA: MIT Press.
30. DUGATKIN, L. A. & WILSON, D. S. (1991) Rover: a strategy for exploiting cooperators in a patchy environment. Am. Nat., 138, 687–701.
31. WANG, Z., KOKUBO, S., JUSUP, M. & TANIMOTO, J. (2015) Universal scaling for the dilemma strength in evolutionary games. Phys. Life Rev., 14, 1–30.
32. OSTROM, E. (1990) Governing the Commons: The Evolution of Institutions for Collective Action. Cambridge, UK: Cambridge University Press.
33. PUTNAM, R. D., LEONARDI, R. & NANETTI, R. Y. (1994) Making Democracy Work: Civic Traditions in Modern Italy. Princeton, NJ, USA: Princeton University Press.