Play Locally, Learn Globally: The Structural Basis of Cooperation

Jung-Kyoo Choi

SFI WORKING PAPER: 2002-12-066

SFI Working Papers contain accounts of scientific work of the author(s) and do not necessarily represent the views of the Santa Fe Institute. We accept papers intended for publication in peer-reviewed journals or proceedings volumes, but not papers that have already appeared in print. Except for papers by our external faculty, papers must be based on work done at SFI, inspired by an invited visit to or collaboration at SFI, or funded by an SFI grant.

©NOTICE: This working paper is included by permission of the contributing author(s) as a means to ensure timely distribution of the scholarly and technical work on a non-commercial basis. Copyright and all rights therein are maintained by the author(s). It is understood that all persons copying this information will adhere to the terms and constraints invoked by each author's copyright. These works may be reposted only with the explicit permission of the copyright holder.

www.santafe.edu
Play Locally, Learn Globally:
The Structural Basis of Cooperation

Jung-Kyoo Choi

University of Massachusetts, Amherst, MA 01003

November 2002

1I would like to thank the Santa Fe Institute for the Computational Economics Workshop which initially stimulated the idea of this research, and for a Graduate Fellowship that allowed me to pursue it to completion. The paper has also benefited comments by Alan Swedlund, Scott Page, John Miller, Herbert Gintis, and Samuel Bowles as well as participants at seminars at the Santa Fe Institute and Lake Arrowhead Conference on Computational Social Science and Social Complexity (Lake Arrowhead, CA, May, 2002). Author’s email address: jkchoi@santafe.edu
Abstract

In group-structured populations, altruistic cooperation among unrelated group members may be sustainable even when the evolution of behavioral traits is governed by a payoff-based replicator dynamic. This paper explores the importance in this dynamic of two aspects of group structure: interaction in a public goods game and the cultural transmission of behavioral traits. Agents are paired with others to play the game and (independently of this) to learn from a cultural model. Where pairing is global, one’s game partners and cultural model are drawn from the entire population. Or pairing may be local, in which case one’s game partners will be the same from period to period, and one’s cultural models will be drawn from one’s game partners. To clarify the underlying dynamic I derive an extension of the Price equation for the decomposition of changes in the population frequency of a binary trait and analyze the effect of different structures of social interaction on within- and between-group variances and on the evolution of cooperation.

The simulations reported below use a genetic algorithm to explore a large strategy space for this problem, and to study the dynamics of this population. I show that of the four population structures given by global and local learning and global and local game interaction, local interaction with global learning provides the most favorable environment for the evolution of cooperation. This occurs because this combination of learning and interaction structures supports a high level of between group variance in the frequency of cooperative types, so that most cooperators benefit from being in groups composed mostly of cooperators. However neither global learning nor local interaction is sufficient by itself to support high levels of cooperation. Learning globally and playing locally are thus highly complementary: global learning in the presence of global interactions or local interaction in the presence of local learning, makes little contribution to the evolutionary success of cooperative traits.

JEL codes: B52, C72, D64
1 Introduction

Altruistic cooperation among genetically unrelated individuals is frequently observed in human societies (Boyd and Richerson, 2003). Many experimental studies of public goods games have shown that a higher degree of cooperation takes place in laboratory settings than is expected by standard economic theory (See Dawes and Thaler, 1988; Fehr and Gachter, 2000; for review). When cooperation is socially beneficial but individually costly, it is a form of altruism, the evolution of which has long been regarded as a challenging puzzle and one of the most intriguing issues in socio-biological debate. Furthermore, in social interactions in which many people are engaged, the problem becomes more puzzling because we cannot rely solely on the repetition of the game and the possibility of retaliation to explain the evolution of cooperation (Boyd and Richerson, 1988). In this regard, many studies have suggested the need to investigate various social structures that serve to attenuate the selection pressure operating against altruistic cooperators (Boyd and Richerson, 1990, 1992; Axelrod, 1986; Boyd, Gintis, Bowles and Richerson, 2002; Bowles, Choi, and Hopfensitz, 2002).

In this paper, we analyze a strategic situation involving more than two players and investigate the effect of different structures of social interaction on the evolution of cooperation. We particularly examine the effects of different structures of social interaction (global interaction vs. local interaction) and different modes of strategy-updating (global learning vs. local learning). We use an agent-based model in which agents interact with others under these different social structures to see which combination of learning and interaction structures provides favorable conditions for cooperative behavior. In the model, each agent is characterized by a strategy and culturally updates his or her strategy by using adaptive learning behavior. We also introduce a genetic algorithm technique (Holland, 1992; Miller, 1996; Albin and Foley, 2000) to evolve strategies under different social settings.

Our computer experiments identify which of these social structures of interaction and learning favors cooperative behavior. The basic insight illuminated by the model is that the group with whom one interacts either cooperatively or not (for example, in the economy) is often not the same group from whom one draws examples of alternative types of behavior, and which is therefore critical to the process of cultural transmission. Individual engaged in a very localized exchange process may nonetheless be exposed to cultural models from a much wider population. Conversely individuals whose economic activities lead them to interact with large numbers of others, may adopt their behaviors in response by copying successful member of their own small ethnic or other group while ignoring other
To clarify the underlying dynamic, in section 2 we derive an extension of the Price equation for the analysis of the effect of different social structures on within- and between-group variances and on the evolution of cooperation. In section 3, we construct an agent-based model in which agents interact with others under different social structures. In section 4, we report the simulation results and show that the combination of local interaction and global learning supports high levels of cooperation by supporting a high level of between group variance. The last part of this paper (section 5) investigates the possibility that the social structure favoring the evolution of cooperation can itself evolve along with cooperation.

2 An n-Person Public Goods Game

2.1 Playing Games, Learning Behaviors: The Price Equation Revisited

We start with the general conditions for cooperation to evolve in human societies. Consider a population where there are $N$ agents and $T$ groups with the same group size $n = N/T$ who play the following game. Each member in a group can incur a cost, $c$, to contribute one unit of effort to a public project. The total amount contributed to the public project is multiplied by $b$ ($b > 0$) and equally distributed to all members of the group. To make the game structure reflect a social dilemma, assume that making a contribution is individually costly (i.e., $-c + \frac{b}{n} < 0$) and socially beneficial (i.e., $b - c > 0$).

Consider two strategies: cooperation (contributing) and defection (not contributing). Let $p_j$ be the frequency of cooperators in the $j$th group ($j = 1, 2, \ldots, n$), and $\pi_j^C$ and $\pi_j^D$ be the payoff of a cooperator and a defector in the $j$th group, respectively. Then we have

\[
\pi_j^C = -c + bp_j \\
\pi_j^D = bp_j
\]

Now consider the following learning process. After playing the public goods game described above, each individual has a chance to update his or her strategy. To update his or her strategy, each agent copies the strategy of a cultural model (parent, teacher or religious leader) from the pool of models. Initially we
assume that the pool is globally formed in the sense that each agent can learn from model(s) selected from the whole population. Assume that when agent \( i \) selects cultural models, the probability that agent \( k \) from the pool is selected to be agent \( i \)'s teacher is equal to agent \( k \)'s relative payoff compared to the total payoff of the pool (i.e., \( \pi_k / \sum_{m=1}^{M} \pi^m \), where \( M \) is the size of the pool and, in the case of the globally-formed pool, \( M = N ) \)\(^1\). Then, without updating errors, the expected population frequency of cooperators in the next period, \( p' \) is equal to probability that cooperators are selected as cultural models, which simply becomes

\[
p' = \frac{\sum_{j=1}^{T} \pi_j^C p_j n}{\sum_{j=1}^{T} \pi_j^C n + \sum_{j=1}^{T} \pi_j^D (1 - p_j) n}
\]

(1)

Since current population frequency of cooperators \( p \) is \( \sum_{j=1}^{T} p_j / T \), we have

\[
\Delta p = p' - p = \frac{\sum_{j=1}^{T} \pi_j^C p_j}{\sum_{j=1}^{T} \pi_j^C p_j + \sum_{j=1}^{T} \pi_j^D (1 - p_j)} - \frac{\sum_{j=1}^{T} p_j}{T}
\]

(2)

It can be shown that (see Appendix A for the derivation)

\[
p' - p = \left( \frac{1}{\alpha} \right) \left[ \sum_{j=1}^{T} p_j (1 - p_j) (\pi_j^C - \pi_j^D) + \sum_{j=1}^{T} p_j \sum_{k \neq j}^{T} (1 - p_k) (\pi_j^C - \pi_k^D) \right]
\]

\[
\quad = \left( \frac{1}{\alpha} \right) \left[ \sum_{j=1}^{T} p_j (1 - p_j) (-c) + \sum_{j=1}^{T} p_j \sum_{k \neq j}^{T} (1 - p_k) (-c + b(p_j - p_k)) \right]
\]

(3)

where \( \alpha = T \sum_{j=1}^{T} \pi_j^C p_j + \pi_j^D (1 - p_j) \).

Equation (3) shows the replicator dynamic of the game. It is obvious that \( \pi_j^C - \pi_j^D \) always has a negative value, \( -c \). That is, by free-riding, non-cooperators always receive a higher payoff than cooperators within the same group. However, the sign and the magnitude of \( \pi_j^C - \pi_k^D \) depend on \( p_j \) and \( p_k \). When a cooperator happens to be assigned to a group in which there are many other cooperators, he or she receives “group benefits” (high \( b p_j \)). This group effect may be strong enough to offset the negative “individual effect” \( (-c) \). Therefore, a cooperator in

\(^1\)This process is analogous to the so-called ‘spinning roulette wheel’ in a genetic algorithm. For details, see Mitchell (1996).
a group with a high frequency of cooperators has a high chance of being a cultural model, despite the fact that the few defectors in that group have an even higher probability of being a model.

Let $a_{ij}$ be a variable which has a value of 1 if agent $i$ in group $j$ is a cooperator and 0 otherwise. Then we can decompose equation (3) into within-group variance and between-group variance terms (see Appendix B for the derivation).

$$p' - p = \left(\frac{1}{\gamma}\right) \left[(-c)E(var(a_{ij})) + (b - c)var(p_j)\right]$$

(4)

where $\gamma = (\sum_j p_j^C + \pi_j^D/(1-p_j))/T$, the average of the whole population.

Equation (4) shows that the evolution of cooperation depends on the relative magnitude of within group variance and between group variance. We call this equation the intra-demic version of the Price equation. The equilibrium condition shown in the equation (4) is $var(p_j) = E(var(a_{ij})) = 0$, or if $var(p_j) \neq 0$, $E(var(a_{ij})) \neq 0$, then

$$\frac{var(p_j)}{E(var(a_{ij}))} = \frac{c}{b-c}$$

(5)

Equation (4) and (5) show the condition for the evolution of cooperation. $var(p_j)$ is the term for between-group variance and $E(var(a_{ij}))$ represent the average of within-group variance. As the original Price equation suggested (Price, 1972), high between-group variance is essential for the selection pressure acting on groups to offset the pressure acting on individuals.

### 2.2 Within-group Variance vs. Between-group Variance

The condition represented by equation (5), however, seems very unlikely to hold. It has been suggested that “group selection” is likely to be only a minor influence on evolution because, in the absence of special conditions supporting levels of between group variance greater than that resulting from random grouping (Wilson, 1977; Wilson and Sober, 1999; Boyd and Richerson, 1990), the left hand side of equation (5) tends to become smaller than right hand side of the equation. Therefore, for group selection theory to be a plausible explanation for the evolution of cooperation, the theory should show that the ratio of between-group variance to

---

2We interpret the deme as a cultural parental pool from which all the members select their cultural model.
within-group variance should be large enough to make the left hand side of equation (5) greater than $\frac{\epsilon}{b-c}$. To resolve this theoretical limitation, researchers have identified institutions which serve as important mechanisms to slow down within-group selection. According to this line of thinking, if group competition has allowed for the evolution of cooperation throughout human history, some institutions must have played important roles in reducing the speed of within-group selection. Examples of such institutions include second-order punishment (Boyd and Richerson, 1992; Axelrod, 1986; Boyd, Gintis, Bowles and Richerson, 2002), cultural conformism (Boyd and Richerson, 1985), segmentation (Bowles, Choi and Hopfensitz, 2002), food-sharing (Kaplan and Gurven, 2003), and consensus decision-making processes (Boehm, 2002).

In this paper, we investigate another possibility. We suggest that between-group variance is also affected by social factors such as how individuals interact among one another, how they form groups, and from whom they learn. In section 3, we examine how different social structures affect the relative size of between-group variance, which, in turn, affects the outcome of the public goods game.

3 Structural Basis for the Evolution of Cooperation

3.1 Four Different Social Structures

To see the effect of social structure on the evolution of cooperation, we consider two different social interaction structures. Agents can either interact with a random group (global grouping) or with the same group (local grouping).

- **Global Interaction:** In each round, each member is randomly assigned to a group. After each round, they update their strategies and are randomly assigned to another group to play the same game.

- **Local Interaction:** Once each player is assigned to a group, he plays the game only with members of that group. Unlike under global interaction, players interact only with the same members even after playing one round. After updating their strategy, each agent returns back to his or her original group. This mode of interaction is characterized as an interaction with persistent membership.

In addition to interaction structure, we also consider different learning processes. To update strategies, agents can learn from cultural models selected from
Table 1: **Four Different Social Structures**

<table>
<thead>
<tr>
<th></th>
<th>Global Interaction</th>
<th>Local Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global Learning</td>
<td>Spot Market</td>
<td>Market without Mobility</td>
</tr>
<tr>
<td>Local Learning</td>
<td>Globalized Peer Group</td>
<td>Isolated Village</td>
</tr>
</tbody>
</table>

the whole population (global learning) or from members whom they interact with (local learning).

- Global Learning: Each individual is paired to his or her models from the whole population and learns from them (in the manner described in section 2.1).
- Local Learning: Each individual is paired to his or her models drawn from his or her game partners.

Table 1 suggests real life interactions corresponding to the social settings identified. We characterize the first combination as a “market,” since random interaction with global learning is one of the main characteristics of a social-interaction based on the market. The second pair can be seen as a “market without mobility” or “market with persistent membership.” This social setting is partly based on a market, in the sense that a global level selection pressure is still operating. However, as the name indicates, the agents in this setting play the game with the same group of members without changing membership. Many economic organizations (e.g., firms with long-term employment policies) provide structures similar to this setting. For example, individuals working in a company usually interact with the same members of the group for a long time, but they learn from others outside their group. The third pair of this combination is characterized as “globalized peer group”. This setting is characterized as globalized interaction with a narrow vision. In each period members are assigned to different groups and interact with new members. When updating their strategy, they only learn from those whom they interacted with. The last pair is termed “isolated small village” or “island without any outside interaction”. Once agents are assigned to a group, they play only with the members of that group and learn only from the members of the group.
3.2 An Agent-Based Model of The Evolution of Cooperation

In this work, we ran several computer experiments\textsuperscript{3} under the four different social settings described in the previous section in order to see which social structures favor the evolution of cooperation. Even if we could derive a general condition for cooperation to evolve (from equation (5)), we can say little more than that between-group variance should be high enough for the evolution of cooperation. After taking into account the effect of social structures and the role of chance events, the process becomes far too complex to be modelled analytically. To know which social structures favor the cooperative behaviors, or under which parameter values the answer is still relevant, agent-based modelling is helpful.

3.2.1 Strategies

Although the public goods game is an extension of the two-person prisoner’s dilemma game, there are significant differences between the two games. One of the main properties of the public goods game structure is that players have only limited information about the outcome of previous interactions; they do not know who cooperated or defected in the previous stage, but only know how many players cooperated in the group. Considering that one of the main keys to support high level of cooperation in the two-person prisoner’s dilemma game is the potential of retaliation by the partner, one can imagine that the evolution of cooperation is much less likely in a public goods game structure in which multiple players are simultaneously engaged.

Suppose each player repeats the public goods game $R$ times in his or her group with group size $n$ (We call this an $R$-stage public goods game). Also, suppose that agents have limited memory, so that they decide to cooperate or defect based only on the outcome of the previous stage.

We can represent the $R$-stage public goods game structure as an extensive form game with information sets. In $t-1$th stage, every member in a group can either cooperate or defect, which reaches one of $2^n$ possible states (or nodes). However, since they only have incomplete information (they do not know who cooperated in the previous stage, but only know how many members cooperated), the interaction in $t-1$th stage ends up with $2 \times n$ information sets (Figure 1).

\textsuperscript{3}The program was written in Borland C++ Builder by the author. The code is available upon request.
Figure 1: **Reduced Game Tree and Information Sets for Each Stage.** \( \sum y^{t-1} \) is the number of cooperators in this group at previous stage. Since each member remembers whether he or she cooperated or not and how many members cooperated in the previous stage, he or she knows that which one of \( 2 \times n \) information sets was attained in the previous stage (where \( n \) is the group size).

Therefore, at the beginning of each stage \( t \) (\( t \neq 1 \)), members know which one among \( 2 \times n \) information sets they have just reached, depending on whether they themselves cooperated or not at the \( t - 1 \)th stage and how many members cooperated. Assume that an agent has a complete plan of action that indicates which action he or she should take at any information set of the game tree. Then, a strategy consists of \( (2 \times n) + 1 \) action plans: one plan is for the first stage, and \( 2 \times n \) plans for each information set. Then each player’s strategy can be represented as a series of binary strings as follows. Let 1 indicate “cooperate” and 0 “defect.”

\[
S = \{s_1, S_c, S_d\}
\]

where \( s_1 \in \{0, 1\} \) and \( S_c \) and \( S_d \) are \((1 \times n)\) vectors whose elements are 0 or 1, respectively.

For example if the group size is 5 and an agent has \( \{1, \{0,1,1,0,1\}\} \{1,0,1,1,0\}\) (see figure 2), this agent cooperates on the first stage, as the 1 in the first element indicates. The first vector (\( S_c \)) controls this agent’s action when she cooperated on the last stage of the game. The first element of the vector is the plan of her action when the number of cooperators on the last stage was 1, the second element is for when the number of cooperators was 2, and so on. Therefore if she cooperated on the last stage, she cooperates when the number of cooperators was 2, 3, or 5, and defects when the number of cooperators was 1 or 4. By the same token, if she defected on the last stage, she refers to the second vector (\( S_d \)). The first element
Figure 2: An Example of the Strategy Make-up. \( \Sigma y^{t-1} \) is the number of cooperators in this group at the previous stage. Suppose the group size is 5. The first element of the strategy indicates whether the agent should cooperate or defect in the first stage. Each element in the first and the second vector indicates what the agent should do in each information set. The first vector in the strategy is the plan of actions when the agent cooperated in the previous stage and the second vector is the plan when the agent defected in the previous stage.

\[
\begin{align*}
\Sigma y^{t-1} = 1 & \quad \Sigma y^{t-1} = n \\
\{1, (0, 1, 1, 0, 1)\}, & \quad \{0, 1, 1, 0, 1\}
\end{align*}
\]

of this vector is the plan of her action when the number of cooperators on the last stage was 0, the second element is for when the number of cooperators was 1, and so on. Therefore if she defected on the last stage, she cooperates when the number of cooperators was 0, 2, or 3, and defects when the number of cooperators was 1 or 4.

3.2.2 The Algorithm for Computer Experiments

We assume that each agent plays the public goods game ten times in each round (We call each game a stage game). After playing the game ten times, players update their strategies. As described in section 2.1, we use a genetic algorithm to evolve strategies and interpret the process as a cultural learning process. In the learning process, we assume that the top 50% of agents who did well in the last round keep their strategy without updating and the bottom 50% of agents choose two cultural models (in the way described in section 2.1) and copy the models’ strategies. The pool can be formed either globally or locally (see section 3.1). When copying the models’ strategies, a learner divides his or her strategy into two parts and copies the first part from one model and the second part from the
Figure 3: Basic Parameter Set

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group Size</td>
<td>10</td>
</tr>
<tr>
<td>The Number of Groups</td>
<td>20</td>
</tr>
<tr>
<td>The Cost of Cooperation ((c))</td>
<td>1</td>
</tr>
<tr>
<td>The Coefficient for Benefit from Cooperation ((b))</td>
<td>3</td>
</tr>
<tr>
<td>Mutation Rate</td>
<td>0.05</td>
</tr>
<tr>
<td>Updating Frequency</td>
<td>Every One Round (After 10 Stages)</td>
</tr>
</tbody>
</table>

Figure 4: Basic Algorithm

1) Create an initial random population of 200 agents.
2) Assign each agent to one of 20 groups with group size 10.
3) Let all the agents play the public goods game within their group.
4) Form a new population of 200 agents.
   (a) Top 50% of agents keep their strategy without updating.
   (b) Bottom 50% of agents choose two cultural models and learn from them.
      (i) Select two parents from the parental pool.* The probability that agent \(k\) becomes a cultural model of agent \(i\) is \(\pi_k / \sum_j M \pi_j\) (where \(M\) is the size of the parental pool).
      (ii) Copy strategy from both cultural models.**
   (c) Apply mutation to each player’s strategy.
5) Repeat 2) through 4) (global interaction), or 2) through 3) (local interaction).

* Parental pool can be formed either globally or locally.
** This is the same process as biological crossover. A learner divides his strategy into two parts and copies the first part from one model and the second part from the other model.

other model.\(^4\) We also apply a small chance of updating error\(^5\) to newly-learned strategies. After updating strategies, agents are randomly assigned to new groups (global interaction), or they return to their previous group (local interaction). The parameter values for the computer experiments are given in figure 3, and the basic structure of the algorithm is depicted in figure 4.

\(^4\)This process is the same one as biological crossover. We applied a crossover process to our learning process to generate a wider range of strategies.
\(^5\)This is the same process as mutation in biology.
Table 2: Different Social Structures and Supporting Cooperation. Average frequencies of cooperators (%) over 30,000 rounds. High level of cooperation is observed when interaction is local and learning is global.

<table>
<thead>
<tr>
<th></th>
<th>Global Interaction</th>
<th>Local Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global Learning</td>
<td>1.71</td>
<td>95.36</td>
</tr>
<tr>
<td>Local Learning</td>
<td>0.42</td>
<td>0.59</td>
</tr>
</tbody>
</table>

4 Results

Table 2 shows the results from our computer experiments. Except for the local interaction/global learning case, each case shows the typical result of a prisoner’s dilemma game. “Defecting” appears to be always the best response and cooperation does not evolve in these cases. While mutations repeatedly impact the system, their impacts are mostly insignificant and the return to the “all-defection” equilibrium occurs very fast. Cooperation — socially beneficial behavior — simply becomes “non-adaptive” and subject to extinction.

However local interaction, when combined with global learning, has a huge effect on the evolution of cooperation. Under the parameter set we used, the average population frequency of cooperators over 30,000 rounds was 95.36 %. Local interaction/global learning appears the critical condition for the evolution of cooperation.

4.1 The Fate of Cooperation under Local Learning

That cooperation does not evolve when learning occurs locally is not surprising, because cooperators are more likely to switch their types to defection if they are always paired to cultural models drawn from their game partners among whom defectors always have higher payoff than cooperators. Defectors are less likely to switch their types for similar reasons. Therefore within a given group, the less cooperative types will tend to have a disproportional share of the payoffs and hence be overrepresented among the cultural models.

It might be interesting to see what happens if agents learn locally or globally with a certain probability. To see this, let $\lambda$ be the probability that an agent locally updates his or her strategy. That is, when agent $i$ in group $j$ updates his or her strategy, with probability $\lambda$ he or she selects cultural model(s) with whom he or she interacted (i.e., locally-formed parental pool) and with probability $1-\lambda$ from the whole population (i.e. globally-formed parental pool). The expected
population frequency of cooperators in the next period is, therefore,

\[
p' = \frac{1}{n} \sum_{j=1}^{T} n \left(1 - \lambda \right) \frac{\sum_{j=1}^{T} \pi_j^C p_j n}{\sum_{j=1}^{T} \pi_j^C n + \sum_{j=1}^{T} \pi_j^D (1 - p_j) n} + \lambda \frac{\pi_j^C p_j}{\pi_j^C p_j + \pi_j^D (1 - p_j)}
\]

\[
= (1 - \lambda) \frac{\sum_{j=1}^{T} \pi_j^C p_j}{\sum_{j=1}^{T} \pi_j^C + \sum_{j=1}^{T} \pi_j^D (1 - p_j)} + \frac{1}{T} \lambda \sum_{j=1}^{T} \frac{\pi_j^C p_j}{\pi_j^C p_j + \pi_j^D (1 - p_j)}
\]

Since \( p = \sum_{j=1}^{T} p_j / T \), we can show that (see Appendix C for the derivation)

\[
p' - p = (1 - \lambda) \left( \frac{1}{\gamma} \right) \left[ (-c) E(var(a_{ij})) + (b - c) var(p_j) \right] + \lambda \frac{1}{T} \sum_{j=1}^{T} \frac{var(a_{ij})}{\gamma_j}
\]

where \( \gamma_j = \pi_j^C p_j + \pi_j^D (1 - p_j) \), the average payoff of group \( j \), and \( \gamma = (\sum_{j=1}^{T} \pi_j^C p_j + \pi_j^D (1 - p_j)) / T \), the average payoff of the whole population.

Equation (6) shows the negative effect of local learning on the evolution of cooperation. It is obvious that cooperation cannot evolve when only within-group selection operates (i.e., when \( \lambda = 1 \)). For cooperation to evolve, between-group variance should be sustained at a higher level as \( \lambda \) becomes higher. However it becomes much harder to sustain high between-group variance when \( \lambda \) becomes higher. The right hand panel in figure 5 shows the effect of \( \lambda \) on the evolution of cooperation when interaction is completely local. The horizontal axis of the figure shows the probability of global learning (i.e. 1-\( \lambda \)). Only with a high probability of global learning (upto \( \lambda = 0.15 \)), cooperative outcome is possible. When \( \lambda \) becomes greater than 0.2, cooperation is unlikely to evolve.

### 4.2 The Effect of Local Interaction

Local interaction/global learning provides a striking result. The localization of social interaction combined with global learning successfully supports a high rate of cooperation. When a cooperator happens to be assigned to a group in which there are many cooperators, he or she receives “group benefits.” If these group
Figure 5: **Cooperation is Favored by Local Interaction and Global Learning.** Each point in the figures show the average level of cooperation (%) over 30,000 rounds. $\lambda$ is the probability that learning occurs locally and $\rho$ is the probability of local interaction. For the left figure, we set $\lambda = 0$ (i.e., global learning). We ran 10 different runs for each value of $\rho$. For the right figure, we set $\rho = 1$ (i.e., local playing) and ran 10 different runs for each value of $1 - \lambda$. Therefore, there are 10 points corresponding to each $\rho$ value and $1 - \lambda$ value, respectively. The figure shows that the evolution of cooperation becomes unlikely as interaction becomes global and learning becomes local.

![Figure 5: Cooperation is Favored by Local Interaction and Global Learning.](image)

benefits are sufficiently large to dominate the individual cost, the strategies of the cooperators in these groups are likely to be learned by the globally learning members of other groups in which members receive low payoffs due to frequent defections (see equation (3)).

Local interaction successfully supports high between-group variance, because once a group (group $j$) has many cooperators (high $p_j$), $p_j$ in the next period is also expected to be high due to persistent membership. Therefore it becomes possible for a cooperator, once assigned to a group with many cooperators, to benefit from continuous interaction with highly cooperative groups (i.e., high $p_j$) in successive periods. This situation cannot take place in the case of global interaction. In such a case, at the beginning of each period agents are randomly and newly assigned to another group, and the large group effect disappears at each round. In other words, the localization of interaction provides the condition under which between-group variance stays sufficiently high for cooperation to evolve. Figure 6 shows the movement of within- and between-group variance over time as well as the levels of between-group variance that supports cooperation. Compared to panel (a) (global interaction), panel (b) shows that between-group variance is sustained at high level in the case of local interaction. Here, we observe that the population frequency of cooperators, $p$, rose from the beginning, accompanied by the increase
Figure 6: The Evolution of Cooperation and Between-Group Variance When Learning is Global. The panel (a) (global interaction) shows that between-group variance stays near zero level while the panel (b) (local interaction) shows that the population frequency of cooperators, $p$, rose from the beginning accompanied by the increase in between-within variances ratio.

- To examine the effect of localization of social interaction more closely, we invest-
Figure 7: **Play Locally, Learn Globally** Each coordinate shows the level of cooperation corresponding to the degree of localization of interaction and learning, respectively. The horizontal axis represents the degree of local learning (from completely global ($\lambda=0$) to completely local ($\lambda=1$)), and the vertical axis represents the degree of local interaction (from completely global ($\rho=0$) to completely local ($\rho=1$)). To obtain the average level of cooperation, we ran 10 different simulations, each of which had 30,000 rounds. White squares indicate that the average level of cooperation is less than 10%; gray squares, between 10% and 70%; and black squares, higher than 70%.

To investigate another situation where the degree of localization varies continuously. Let $\rho$ be the probability of local interaction and $\lambda$ be the probability of local learning. After updating strategies, agents return to their previous group with probability $\rho$ or join a new group with probability $1 - \rho$. When agents update strategies, they are paired to cultural models from the globally-formed pool (with probability $1 - \lambda$) or from their reference groups (with probability $\lambda$). Figure 7 shows that as interaction becomes more global (random groupings), defection becomes the norm. When agents tend to stay within the same group, cooperative outcomes are much more likely to occur if selection is global. Again, local interaction with global learning turns out to provide the most favorable environment for the evolution of
cooperation.

5 Evolving Population Structure

So far, we have investigated the possibility of the evolution of cooperation under different social structures. Local interaction, when combined with global learning, appears essential for the evolution of cooperation.

The last problem we explore in this paper is whether the social structure that favors the evolution of cooperation can itself evolve along with cooperation, when the propensity of local interaction is an individual characteristic. We start from the most favorable situation, in which every agent learns globally (i.e., \( \lambda = 0 \)) and assume that \( \rho \) (the probability that agents return back to the previous group after updating) is an individual characteristic. That is, after a strategy-updating, agent \( i \) returns to the previous group with probability \( \rho_i \), and joins a new group with probability \( 1 - \rho_i \) (where \( \rho_i \in \{0, \frac{1}{15}, \frac{2}{15}, \ldots, \frac{14}{15}, 1\} \)). In addition to the strategy make-up introduced in section 3.2.1, each agent is assumed to have \( S_\rho \) vector controlling his or her propensity of local play. Now, we have the following strategy make-up.

\[
S' = \{s_1, S_c, S_d, S_\rho\}
\]

where \( s_1 \in \{0, 1\} \), and \( S_c \) and \( S_d \) are \((1 \times n)\) vectors whose elements are zero or one, respectively. \( S_\rho \) is assumed to be a \((1 \times 4)\) vector whose elements are zero.

---

6The propensity to learn globally (\( \lambda \)) does not evolve in the same way as that to interact locally. In the case of the propensity to learn globally, whether an agent learns locally or globally does not affect his or her payoff, rather it increases the probability that agents become cooperators and, hence, contribute to the expected payoff of the others with whom these agents interact. We cannot expect a certain trait to evolve based on payoff-based replicator dynamic if the trait does not affect agents’ payoffs. In this sense, the propensity of global learning is only likely to evolve as group characteristic or population characteristic, rather than individual characteristic. By contrast, in the case of the propensity of local interaction (\( \rho \)), whether an agent is a local player or a global player affects the agent’s performance (or payoff). The reason is that if a cooperator is a local player (having high \( \rho \)), when he or she is assigned to a highly cooperative group (with high \( p_j \)), he or she will play in the same group in the next round and continuously enjoy “group benefit” resulting from high \( p_j \). If he or she is a global player (having low \( \rho \)), he or she cannot enjoy the “group benefit” in the next round due to random grouping. Therefore we can assume that the selection pressure acts on different degrees of local playing and that the propensity evolves as individual characteristic.
Figure 8: The Evolution of Cooperation with Evolving Local Interaction. This figure shows the first 25,000 rounds. The population frequency, $p$, stays at 1 for another 20,000 rounds after 25,000th round.

or one. If $S_\rho = \{0, 0, 0, 0\}$, the probability of local interaction is $0/15=0$, and if $S_\rho = \{1, 1, 1, 1\}$, the probability is $15/15=1$.

In the computer experiment, agents play a ten-stage public goods game with other members of the group and update their strategy based on the global learning process described before. In the next round, each agent remains in the same group with probability $\rho$, or leaves the group and joins a new group with probability $1 - \rho$. When agents learn from their models, they learn $\rho$ (i.e., the $S_\rho$ part in the strategy) as well as the other part of the strategy ($s_1, S_c$, and $S_d$).

Figure 8 shows the result from one typical run. Until the 6,000th round, cooperation sporadically occurred, but due to the low level of localization (low $\rho$) the cooperation was not sustained for long. The change in $\rho$ during this period was basically due to drift. When the cooperation level is around zero, no selection pressure acts on agents’ strategies. Therefore $\rho$ freely fluctuates. When $\rho$ becomes sufficiently high, cooperation becomes viable in this environment (after the 6,000th round). Once the cooperation level rises above the zero level, the “group effect” appears. Since the “group effect” operates, the selection favors individuals who have high a $\rho$, that is those who have a high propensity to remain in the same group. Therefore, $\rho$ tends to be 1 (i.e., those who remain in the same group do better than those who switch groups frequently). Once $p$ goes to fixation ($p = 1$), $\rho$ begins to drift. This is because everyone gets the same payoffs, and therefore selection pressure does not act on different levels of $\rho$. Sometimes a cooperative
regime breaks down (e.g., around the 8,300th round) or is sustained for a fairly long period (e.g., after the 20,000th round).

We ran different runs with different learning modes. The result showed that the localization of interaction evolved only when learning was sufficiently global ($\lambda > 0.9$). Local learning, even with a low probability, appears fatal to the evolution of cooperation as well as to the evolution of local interaction. If a cooperator is a local learner, as we have seen, he or she is highly likely to switch his or her type. Note that if the probability of local learning ($1-\lambda$) is 0.1, on average, 5% of the cooperators are subject to switch their type in each period. Therefore, local learning (with probability higher than 10%) can prevent the emergence of cooperation. Note that the propensity of local interaction can evolve since the existence of the “group effect” makes the selection favor those who have a high propensity to play locally. Under local learning processes, cooperation hardly evolves and, therefore, local interaction does not evolve. Therefore, a global learning process appears essential to the evolution of local interaction and, by that, to the evolution of cooperation.

6 Conclusion

Our results bring us to the following conclusions: First local interaction (or persistent membership) is effective in sustaining high levels of cooperation when combined with a “market” type learning process. Second, this is mainly because local interaction is effective in sustaining sufficiently high levels of between-group variance and global learning is effective for cooperative traits to spread over the whole population. This suggests a way by which human societies can successfully avoid the “tragedy of the commons.” Third, local learning appears fatal to cooperative traits. This is for two reasons; one is that the condition for cooperation to evolve (represented in equation 5) is less likely to be satisfied under local learning processes. The other is that those who are defectors and at the same time local learners face little selection pressure since within any group they always do better than cooperators. Fourth, the contributions of local interaction and global learning to the evolution of cooperation are complementary, each enhancing the positive effect of the other. The reason that local interaction has a positive effect only in conjunction with global learning is that if learning is entirely local (as equation (6) shows) the positive effect of the between group differences sustained by local interaction vanishes. The reason why the positive effect of global updating is enhanced by local interaction is that if between group differences are absent due to
global interactions, then, local and global updating are indistinguishable, because
the fraction of total payoffs of the entire population enjoyed by cooperators is no
greater than the fraction of each group’s total payoffs gained by cooperators and so
cultural models drawn from the entire population are no more likely to be cooper-
ators than those drawn from local groups. Fifth, local interaction as an individual
characteristic may coevolve along with cooperation under global learning process.
In this case it is required that agents learn from globally-formed population with
a sufficiently high probability.

Could human behavioral traits supporting cooperation among large numbers
of non-kin have evolved through the combination of local interaction and global
learning? Any answer is bound to be somewhat speculative, but the structure of
the mobile foraging bands that made up most of human society for most of our
history could well have exhibited the structures we have identified as favorable
to the evolution of cooperation. Bands were relatively small groups of frequently
interacting members\textsuperscript{7}; but they formed part of larger ethno-linguistic units with
whom contacts, visiting, and the seasonal merging of bands into larger units was
frequent. In this setting it is highly likely that cultural models were drawn at
least to some extent from the ethno-linguistic unit as a whole. This structure
seems remarkably close to the play locally, learn globally structure identified here
as most favorable to the evolution of cooperation.

\textbf{References}


Axelrod, R. (1986), “An Evolutionary Approach to Norms”, \textit{The American Polit-

\textsuperscript{7}See the sources referred in Bowles and Choi, 2002


**Appendix A**

From equation (2), we have

\[
\Delta p = p' - p = \frac{\sum_{j=1}^{T} \pi_j^C p_j}{\sum_{j=1}^{T} \pi_j^C p_j + \sum_{j=1}^{T} \pi_j^D (1 - p_j)} - \frac{\sum_{j=1}^{T} p_j}{T}
\]

By rearranging the equation, we have

\[
p' - p = \left( \frac{1}{\alpha} \right) \left[ \sum_{j=1}^{T} \pi_j^C p_j (T - \sum_{k=1}^{T} p_k) - \sum_{j=1}^{T} \pi_j^D (1 - p_j) \sum_{i=1}^{T} p_i \right]
\]

\[
= \left( \frac{1}{\alpha} \right) \left[ \sum_{j=1}^{T} \pi_j^C p_j \sum_{k=1}^{T} (1 - p_k) - \sum_{j=1}^{T} \pi_j^D (1 - p_j) \sum_{k=1}^{T} p_k \right]
\]

\[
= \left( \frac{1}{\alpha} \right) \left[ \sum_{j=1}^{T} p_j (1 - p_j)(\pi_j^C - \pi_j^D) + \sum_{j=1}^{T} p_j \sum_{k \neq j}^{T} (1 - p_k)(\pi_j^C - \pi_k^D) \right]
\]

\[
= \left( \frac{1}{\alpha} \right) \left[ \sum_{j=1}^{T} p_j (1 - p_j)(-c) + \sum_{j=1}^{T} p_j \sum_{k \neq j}^{T} (1 - p_k)(-c + b(p_j - p_k)) \right]
\]

where \( \alpha = T \sum_{j=1}^{T} \pi_j^C p_j + \pi_j^D (1 - p_j) \).
Appendix B

Let $a_{ij}$ be a variable which has a value of 1 if agent $i$ in group $j$ is a cooperator and 0 otherwise. Then we can easily show the following:

\[
\sum_{j=1}^{T} T^2 X_j = \sum_{j=1}^{T} T^2 \text{var}(p_j) + (T - 1) \sum_{j=1}^{T} p_j (1 - p_j)
\]

\[
\sum_{j=1}^{T} p_j \sum_{k \neq j}^{T} (1 - p_k) = T^2 \text{var}(p_j) + \frac{1}{2} \sum_{j=1}^{T} \sum_{k \neq j}^{T} (p_j - p_k)^2 = T^2 \text{var}(p_j)
\]

Then we can decompose equation (3) into within-group variance and between-group variance terms.

\[
p' - p = \left( \frac{1}{\alpha} \right) \left[ -c T \sum_{j=1}^{T} \text{var}(a_{ij}) + (\alpha - c) T^2 \text{var}(p_j) + (b) T^2 \text{var}(p_j) \right]
\]

\[
= \left( \frac{1}{\alpha} \right) \left[ -c T \sum_{j=1}^{T} \text{var}(a_{ij}) + (b - c) T^2 \text{var}(p_j) \right]
\]

\[
= \left( \frac{T^2}{\alpha} \right) \left[ (-c) \sum_{j=1}^{T} \text{var}(a_{ij}) / T + (b - c) \text{var}(p_j) \right]
\]

\[
= \left( \frac{1}{\gamma} \right) \left[ ((-c) E(\text{var}(a_{ij})) + (b - c) \text{var}(p_j)) \right]
\]

where $\gamma = (\sum_{j=1}^{T} \pi_j^C p_j + \pi_j^D (1 - p_j)) / T$, the average of the whole population.

Appendix C

When agent $i$ in group $j$ updates his or her strategy, with probability $\lambda$ he or she selects cultural model(s) with whom he or she interacted (i.e., locally-formed parental pool) and with probability $1 - \lambda$ from the whole population (i.e. globally-formed parental pool). The expected population frequency of cooperators in the
next period is, therefore,

\[
p' = \frac{1}{n \times T} \sum_{j=1}^{T} n((1 - \lambda) \frac{\sum_{j=1}^{T} \pi_j^C p_j n}{\sum_{j=1}^{T} \pi_j^C n + \sum_{j=1}^{T} \pi_j^D (1 - p_j) n} + \lambda \frac{\pi_j^C p_j}{\pi_j^C p_j + \pi_j^D (1 - p_j)})
\]

\[
= (1 - \lambda) \frac{\sum_{j=1}^{T} \pi_j^C p_j}{\sum_{j=1}^{T} \pi_j^C + \sum_{j=1}^{T} \pi_j^D (1 - p_j)} + \frac{1}{T \lambda} \sum_{j=1}^{T} \left( \frac{\pi_j^C p_j}{\pi_j^C p_j + \pi_j^D (1 - p_j)} - \frac{T}{\sum_{j=1}^{T} p_j} \right)
\]

Since \( p = \sum_{j=1}^{T} p_j / T \), we have

\[
p' - p = (1 - \lambda) \left( \frac{\sum_{j=1}^{T} \pi_j^C p_j}{\sum_{j=1}^{T} \pi_j^C + \sum_{j=1}^{T} \pi_j^D (1 - p_j)} - \frac{T}{\sum_{j=1}^{T} p_j} \right) + \frac{1}{T \lambda} \sum_{j=1}^{T} \left( \frac{\pi_j^C p_j}{\pi_j^C p_j + \pi_j^D (1 - p_j)} - \frac{T}{\sum_{j=1}^{T} p_j} \right)
\]

From equation (2), (3), and (4), the first term of the right hand side equation is \((1 - \lambda) \left( \frac{1}{\gamma} \right) [(-c)E(var(a_{ij})) + (b - c)var(p_j)]\). And the second term in the right hand side equation becomes

\[
\frac{1}{T \lambda} \sum_{j=1}^{T} \frac{\pi_j^C p_j (1 - p_j) - \pi_j^D p_j (1 - p_j)}{\pi_j^C p_j + \pi_j^D (1 - p_j)} = \frac{1}{T \lambda} \sum_{j=1}^{T} \frac{(\pi_j^C - \pi_j^D) p_j (1 - p_j)}{\pi_j^C p_j + \pi_j^D (1 - p_j)}
\]

Therefore we have

\[
p' - p = (1 - \lambda) \left( \frac{1}{\gamma} \right) [(-c)E(var(a_{ij})) + (b - c)var(p_j)] + \frac{1}{T \lambda} \sum_{j=1}^{T} (-c) \frac{var(a_{ij})}{\gamma_j}
\]

where \( \gamma_j = \pi_j^C p_j + \pi_j^D (1 - p_j) \), the average payoff of group \( j \), and \( \gamma = (\sum_{j=1}^{T} \pi_j^C p_j + \pi_j^D (1 - p_j)) / T \), the average payoff of the whole population.

23