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NETWORK DEPENDENCE OF STRONG RECIPROCITY

R. VILELA MENDES
Complexo Interdisciplinar, Universidade de Lisboa,
Av. Gama Pinto 2, 1649-003, Lisboa, Portugal
vilela@cii.fc.ul.pt

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Experimental evidence suggests that human decisions involve a mixture of self-interest and internalized social norms which cannot be accounted for by the Nash equilibrium behavior of Homo Economicus. This led to the notion of strong reciprocity (or altruistic punishment) to capture the human trait leading an individual to punish norm violators at a cost to himself. For a population with small autonomous groups with collective monitoring, the interplay of intra- and intergroup dynamics shows this to be an adaptive trait, although not fully invasive of a selfish population. However, the absence of collective monitoring in a larger society changes the evolution dynamics. Clustering seems to be the network parameter that controls maintenance and evolution of the reciprocator trait.

Keywords: Social networks; strong reciprocity; altruistic punishment.

1. Homo Economicus versus Homo Reciprocans

The assumption of rationality as a motivation for social and economic behavior is widely used as a guiding principle for social modeling. In a game theory context the idea of maximization of objective functions leads to the notion of (noncooperative) Nash equilibrium. A strategy is a Nash equilibrium if no player can improve his payoff by changing his strategy, when the strategies of the other players are fixed.

Given any environment situation, in a Nash equilibrium solution each player tries to maximize his gains assuming as fixed the other players' strategies. It is the rational expectations attitude of what has been called the *Homo Economicus*, a notion which is at the basis of many theoretical economics constructions. Whether this is a realistic notion when applied to human societies is an important issue. Experiments have been carried out and, in many cases, when played by human players, games have outcomes very different from the Nash equilibrium points. An interesting case is the *ultimatum game* [1–6]. A simplified version is the following:

Let the game have two players, the *proposer* (P) and the *responder* (R). The proposer is given an amount of money which he is told he can either divide into two equal parts ($b+b$) or into one large part for himself (a) and a small amount (c) for the responder ($a+c=2b, a \gg c$). The proposer strategies are denoted P_1 and P_0.

If the responder accepts the split (R_0), it is implemented. If the responder refuses (R_1), nothing is given to the players. The payoff matrix is

	R_0	R_1
P_0	a, c	$0, 0$
P_1	b, b	$0, 0$

(1)

The Nash equilibrium is (P_0, R_0), corresponding to the payoffs (a, c). However, when the game is played with human players, greedy proposals are most often refused, even in one-shot games where the responder has no material or strategic advantage in refusing the offer. Based on this and similar results in other situations (public goods games, etc.), Bowles and Gintis [7–9] developed the notion of strong reciprocity (*Homo Reciprocans* [10]) as a better model for human behavior. *Homo Reciprocans would come to social situations with a propensity to cooperate and share but would respond to selfish behavior on the part of others by retaliating, even at a cost to himself and even when he could not expect any future personal gains from such actions.* This should be distinguished from cooperation in a repeated game or reciprocal altruism or other forms of mutually beneficial cooperation that can be accounted for in terms of self-interest.

The same authors, in collaboration with a group of anthropologists, conducted a very interesting "ultimatum game experiment" in many small-scale societies around the world [11], [12]. Homo Economicus is rejected in all cases and consistently different results are obtained in different societies, the players' behavior being strongly correlated with existing social norms and the market structure in their societies. This and other experiments [13], [14] strongly suggest that human decision problems involve a mixture of self-interest and a background of (internalized) social norms [15], [16].

Strong reciprocity is a form of altruism [17] in that it benefits others at the expense of the individual that exhibits this trait. Monitoring and punishing selfish agents or norm violators is a costly (and dangerous) activity without immediate direct benefit to the agent that performs it. It would be much better to let others do it and to reap the social benefits without the costs.

Strong reciprocator agents contribute more to the group than selfish ones and they sustain the cost of monitoring and punishing free-riders. For this reason it was thought that the strong reciprocity trait could not invade a population of self-interested agents, nor could it be maintained in a stable population equilibrium. To counter this belief, Bowles and Gintis [8] developed a simple (mean-field type) model that might apply to the structure of the small hunter-gatherer bands of the late Pleistocene. Taking the view that the *strong reciprocity* trait has a genetic basis, this would be a period long enough to account for a significant development in the modern human gene distribution. The model would give an evolutionary explanation of the phenomenon. Of course, if instead of gene-based, strong reciprocity is culturally inherited, emergence and (or) modification of this trait could be much faster.

Because we intend to explore the influence of the social (network) structure on the evolution of strong reciprocity, we will start by discussing a simplified version of the Bowles–Gintis model. The main simplification is that migration in and out of the evolving group to an outside pool of agents is not considered. The consideration of these migrations may be of interest for a realistic picture of the hunter-gatherer bands of the Pleistocene, but not for the general picture of strong reciprocity in a wider society. By simplifying and somewhat enlarging the punishment scenario (beyond ostracism) of the Bowles–Gintis model and framing it as a replicator one-dimensional map, a clear view is obtained of its dynamical aspects.

2. Emergence of Strong Reciprocity. The Bowles–Gintis Model

One considers a population of size N with two types of agents, one denoted *reciprocators* (R-agents) and the other *self-interested* (S-agents). In a *public goods* activity each agent can produce a maximum amount of goods q at cost b (with goods and costs in fitness units). The benefit that an S-agent takes from shirking public goods work is the cost of effort $b(\sigma)$, σ being the fraction of time the agent shirks. The following conditions hold:

$$b(0) = b, \quad b(1) = 0, \quad b'(\sigma) < 0, \quad b''(\sigma) > 0. \tag{2}$$

Furthermore $q(1-\sigma) > b(\sigma)$ so that, at every level of effort, working helps the group more than it hurts the worker.

For $b(\sigma)$ one chooses [8]

$$b(\sigma) = \frac{2}{2\sigma - 1 + \sqrt{1+4/b}} - \frac{2}{1+\sqrt{1+4/b}}, \tag{3}$$

which satisfies the constraints (2).

R-agents never shirk and punish each free-rider at cost $c\sigma$, the cost being shared by all R-agents. For an S-agent the estimated cost of being punished is $s\sigma$, punishment being ostracism or some other fitness decreasing measure. Punishment and cost of punishment are proportional to the shirking time σ. c is the reciprocator unit of punishment cost. s is the weight given by an S-agent to the punishment probability. It may or may not be the same as the actual fitness cost of punishment. Each S-agent chooses σ (the shirking time fraction) to minimize the function

$$B(\sigma) = b(\sigma) + sf\sigma - q(1-\sigma)\frac{1}{N}, \tag{4}$$

f being the fraction of R-agents in the population. $f\sigma$ is the probability of being monitored and punished. The last term is the agent's share of his own production. The value σ_S that minimizes $B(\sigma)$ is

$$\sigma_S = \max\left(\min\left(\frac{1}{2} - \sqrt{\frac{1}{4}+\frac{1}{b}} + \frac{1}{\sqrt{sf+\frac{q}{N}}}, 1\right), 0\right). \tag{5}$$

The contribution of each species to the population in the next time period is proportional to its fitness given by

$$\begin{aligned}\pi'_S(f) &= q(1-(1-f)\sigma_S) - b(\sigma_S) - \gamma f \sigma_S,\\ \pi'_R(f) &= q(1-(1-f)\sigma_S) - b - c(1-f)\frac{N\sigma_S}{Nf},\end{aligned} \tag{6}$$

for S- and R-agents. The baseline fitness is zero, that is, $\Pi_{S,R} = \max(\pi'_{S,R}, 0)$.

The first term in both π'_S and π'_R is the benefit arising from the produced public goods and the second term the work effort. The last terms represent the fitness cost of punishment for S-agents and the cost incurred by R-agents.

$\gamma = 1$ corresponds to ostracism from the group, other values to general coercive measures affecting the fitness of S-agents. The last term in π'_R emphasizes the collective nature of the punishment. Notice, however, the improbable heavy punishing burden put on reciprocators when in small number.

Finally one obtains[a] a one-dimensional map for the evolution of the fraction of R-agents:

$$f_{\text{new}} = f\frac{\Pi_R(f)}{(1-f)\Pi_S(f) + f\Pi_R(f)}. \tag{7}$$

Figures 1 and 2 display this map, as well as $\sigma_S(f)$, $\Pi_R(f)$ and $\Pi_S(f) - \Pi_R(f)$ for two different values of γ, the other parameters being the same. They show the general behavior of the map in Eq. (7). If γ (the fitness impact of punishment) is large enough, the map has an unstable fixed point A at f_A and a left-stable one B at f_B. Between f_B and 1 there is a continuum of marginally stable fixed points. For smaller γ the region between f_A and f_B (where $\Pi_S - \Pi_R$ is negative) disappears and only the marginally stable fixed points remain. In both cases the asymptotic behavior corresponds either to $f = 0$ (and $\sigma_S = 1$) or to f between 0 and 1 but $\sigma_S = 0$. That is, in this second case, both reciprocators and shirkers remain in the population but shirkers choose not to shirk because the minimum of $B(\sigma)$ is at $\sigma_S = 0$.

For an initial f smaller than f_A the fraction of reciprocators falls very rapidly to zero. This reflects the (may be unrealistic) fact that in this case a very small number of reciprocators has to carry the burden of punishing very many shirkers.

Hence, from the point of view of intragroup dynamics, either reciprocators are completely eliminated from the population or they remain in equilibrium with a probably large number of shirkers, which do not shirk for fear of being punished. Therefore, intragroup dynamics, by itself, cannot explain how the reciprocator attitude might have become a dominant trait. However, when very many groups are considered, for example assembled at random from a pool containing both reciprocators and shirkers [18], [19], then only the groups that contain at the start a fraction

[a]Here replicator dynamics is used for the population evolution. Notice that Bowles and Gintis [8] use a different (incremental) dynamics.

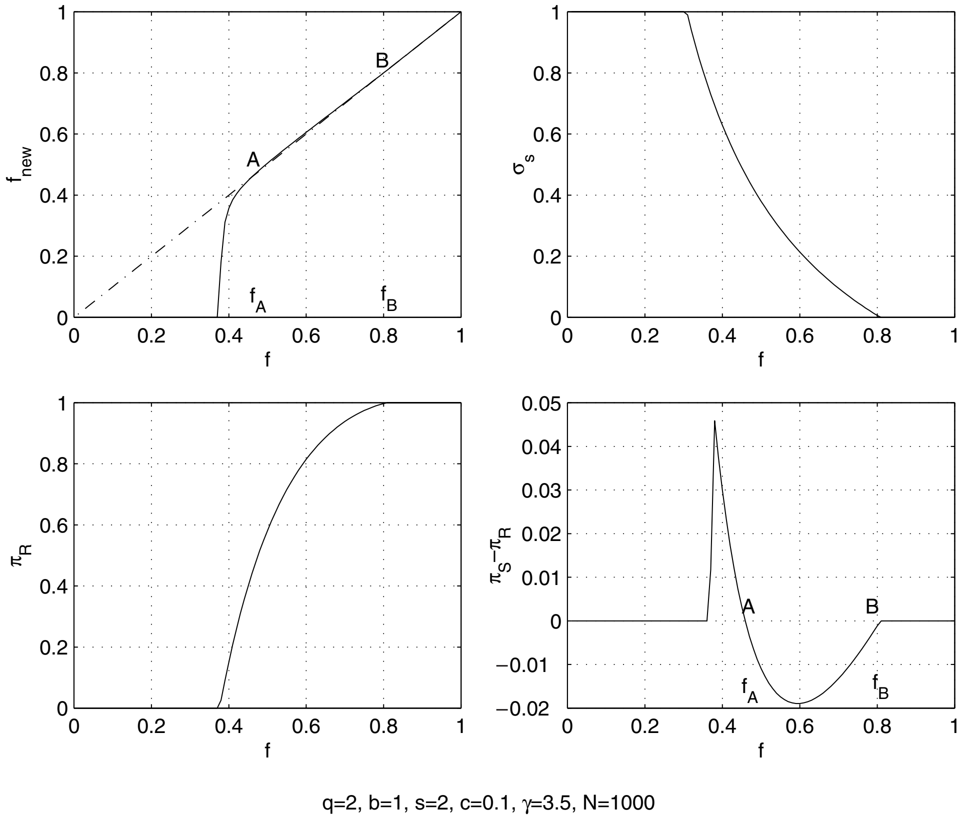

Fig. 1. One-dimensional map for the evolution of R-agents, shirking times and fitnesses.

f greater than f_A will have in the end a nonzero fitness. In all others, S-agents invade the population and suffer a "tragedy of the commons" situation with final zero fitness. Therefore, from an intergroup dynamics perspective the groups with reciprocators tend to dominate and impose an above average predominance of the reciprocator trait.

Although the model, together with intergroup dynamics, explains why strong reciprocity is an adaptive trait [20], the marginally stable nature of the (above f_B) fixed points also suggest that the shirker trait is never eliminated and will remain in the population.

Small independent groups assembling and disassembling is a likely scenario for the development of the reciprocator trait. In this sense the hunter-gatherer bands of the Pleistocene might have indeed provided the appropriate environment for the evolution of the trait, whether gene-coded or culturally-inherited.

It is well known that group size affects monitoring in public goods provision [21]. Therefore, a natural question is what happens when, later on, the Pleistocene reciprocators and their fellow shirkers become imbedded into a larger society. Monitoring

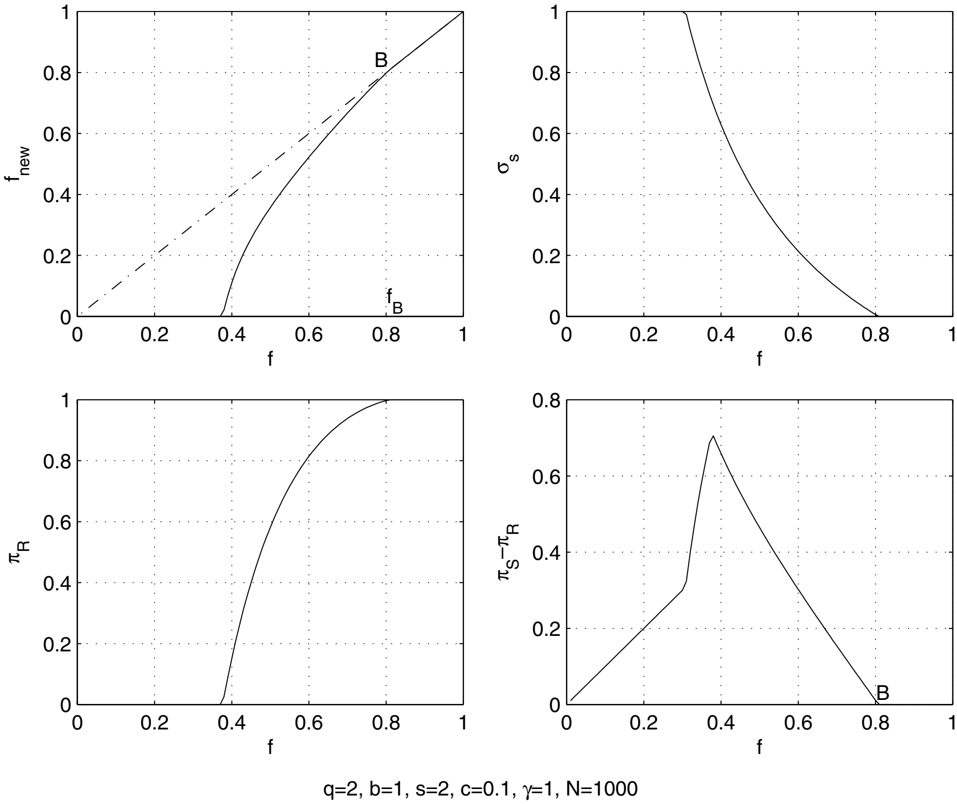

Fig. 2. Same as Fig. 1 with a different fitness cost of punishment.

and punishment of shirkers by reciprocators necessarily loses its global collective nature. Once monitoring loses its global nature, it becomes the business of the neighbors of the shirker. In addition to the individual cost of monitoring and (or) punishing free-riders, such punishing requires an amount of force that, in particular, ensures the effectiveness of the punishment and on the other hand puts the punisher safe from direct retaliation from the violator. This is one of the reasons for the creation of central authorities for this purpose. However if central authorities have enough force to implement punishment without retaliation, they are at times quite ineffective at monitoring. Also, laws and central authorities, in the role of reciprocators, play a role in the control of serious offences, but not so much in the day-to-day monitoring of public goods work. Therefore, in a large society the nature of the control performed by the neighbors is certainly going to play a role in the evolution of the reciprocator trait.

If the trait is genetically encoded, maybe the wider societies developed by modern man had no time to make significant changes to its structure. However, if it is (at least in part) culturally inherited, then a much shorter time scale may be involved.

What about the big city tales of a guy being mugged in full daylight while a crowd of passersby moves along quite indifferent to the event? Is it the $(1 - f)$ remnants of non-reciprocators in the population or are we watching the emergence of Homo Economicus in his full glory? Or is it something else?

3. Network Dependence of Strong Reciprocity

To explore the possible effect of the social network structure on the evolution of strong reciprocity we will consider an agent-based model, which will later be interpreted in a mean field sense similar to the model in Sec. 2.

As before, one considers R-agents and S-agents and the monitoring function performed by R-agents is kept at the neighbors level. However, punishment is only implemented if at least two neighbors are willing to do so. It is the same as saying that punishing a norm-violator cannot be an individual action, but requires a minimal social power and consensus. The need to be close to monitor and the need for agreement of at least two neighboring reciprocators to implement punishment, suggests that the structure of the network is going to play a role in the evolution of the group. The following is the mathematical coding of this idea.

As before, one has two agent types (S-agents and R-agents), the fraction of R-agents being f. The agents are placed in a network where, on average, each agent is connected to k other agents. k is called the *degree* of the network. To the whole population of dimension N one associates 3 N-dimensional vectors, Wk, Pu, Cpu. Wk is called the *work vector*, Pu the *punishment vector* and Cpu the *cost of punishment vector*.

The link structure of the network is chosen as in the β-model of Watts and Strogatz [22], [23]. Starting from a regular ring structure where each node is symmetrically connected to its k closest neighbors, each link is examined in turn and, with probability β, replaced by a random link to some other node in the network.

At time zero, fN R-agents and $(1 - f)N$ S-agents are placed at random in the network. The local neighborhood of agent i, that is the set of other agents connected to i, is denoted Γ_i. The entries of the vectors Wk, Pu, Cpu are then computed as follows:

For the Wk vector
R-agents; $Wk(i) = 1$
S-agents; $Wk(i) = \frac{n_R(i)}{k}$, where $n_R(i)$ is the number of R-agents connected to this S-agent, $n_R(i) = \#\{j : j \in R; j \in \Gamma_i\}$
For the Pu vector
R-agents; $Pu(i) = 0$
S-agents; $Pu(i) = n_P(i)(1 - Wk(i))$, where $n_P(i)$ is the number of pairs of R-agents in Γ_i which are also neighbors among themselves, $n_P(i) = \#\{(j, k) : (j, k) \in R; j, k \in \Gamma_i; j \in \Gamma_k\}$ and $(1 - Wk(i))$ is the shirking fraction.

For the Cpu vector

R-agents; $Cpu(i) = \sum_{k\in S} n_C(i,k)(1 - Wk(k))$ where $n_C(i,k)$ is the number of times that the agent i is in a R-pair punishing an S-agent k, $n_C(i,k) = \#\{(i,j) : k \in S; (i,j) \in R; (i,j) \in \Gamma_k; j \in \Gamma_i\}$

S-agents; $Cpu(i) = 0$

Summarizing; each reciprocator, on detecting an S-agent k, looks for another reciprocator in his own neighborhood also connected to k. If he finds one, he punishes k by an amount proportional to the fraction of shirking. An S-agent may be punished several times by all different pairs of reciprocators in his neighborhood.

The amount of work that an S-agent does is inversely proportional to the number of reciprocators in his neighborhood. However, lack of communication between neighboring reciprocators may make the probability of punishment much smaller.

The (average) fitness of R-agents and S-agents is

$$\pi'_R = \frac{q}{N}\sum_{\text{all}} Wk(i) - \frac{b}{fN}\sum_{i\in R} Wk(i) - \frac{c}{fN}\sum_{i\in R} Cpu(i), \tag{8}$$

$$\pi'_S = \frac{q}{N}\sum_{\text{all}} Wk(i) - \frac{b}{(1-f)N}\sum_{i\in S} Wk(i) - \frac{\gamma}{(1-f)N}\sum_{i\in S} Pu(i). \tag{9}$$

The baseline fitness is zero, that is

$$\pi_{R,S} = \max(\pi'_{R,S}, 0). \tag{10}$$

The constants q, b, c and γ have the same meaning as in the model of Sec. 2. Namely, q is the maximum amount of goods that each agent can produce at cost b, c is the cost of punishment and γ the fitness cost of being punished. Notice, however, that c is now the cost of punishing to one punisher, not the cost for each pair of punishers ($2c$). The total social cost might even be larger if the S-agent has more than one pair of R-agents in his neighborhood.

Once the fitness is computed the replicator equation

$$f_{\text{new}} = f\frac{\pi_R}{f\pi_R + (1-f)\pi_S} \tag{11}$$

is applied and a new cycle starts with a new random distribution, on the network, of Nf_{new} R-agents and $N(1 - f_{\text{new}})$ S-agents.

Running this agent model for several values of β and, in each case, for random initial f_0s one finds two separate regions in the (f_0, β) plane (Fig. 3). In region 1 the evolution drives f towards zero as well as the overall fitness π (example in Fig. 4(a)):

$$\pi = f\pi_R + (1-f)\pi_S. \tag{12}$$

In region 2 there is an asymptotic nonzero value for f and for the fitness (example in Fig. 4(b)).

As β increases it becomes less likely to have a stable nonzero f. The origin of this effect is clear. Although β-rewiring maintains the average degree of the network,

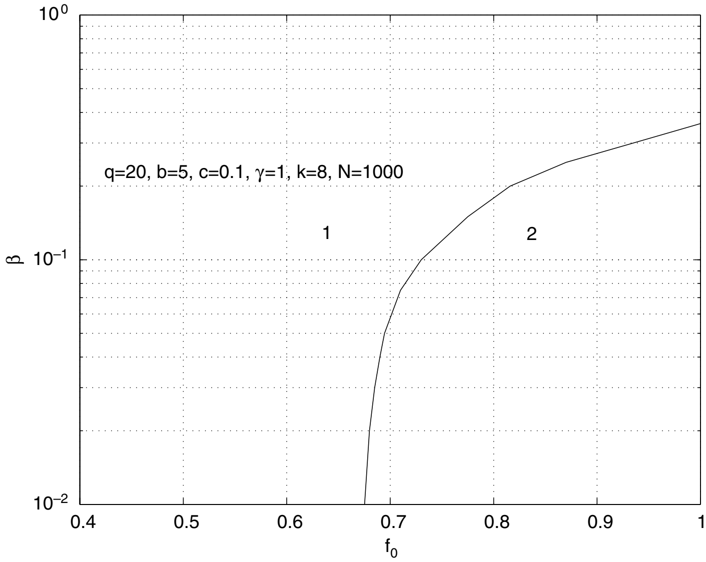

Fig. 3. The two phase regions in the (f_0, β) plane.

the probability of two neighbors of an agent to be themselves neighbors decreases. Therefore, it becomes increasingly difficult for reciprocators to find local consensus for the punishment of S-agents.

The average probability of two R-neighbors of a network node in S to be themselves neighbors, is called the (relative) *clustering coefficient*,

$$C_R = \frac{\overline{n_P(i)}}{\binom{\#\left\{\Gamma_i \cap R\right\}}{2}}, \tag{13}$$

$\binom{\#\{\Gamma_i \cap R\}}{2}$ being the maximum possible number of links between the R-neighbors of S-agent i. The network clustering coefficient is related to the notion of transitivity used in the sociological literature.

For the β-rewiring model, the clustering may be estimated from the number Φ of shortcuts which in this case is proportional to β [23].

$$C_\beta(\Phi, k) = \frac{\frac{3}{4}(1-\Phi)^2\left(k - \frac{2}{3}\right) - (1-\Phi)}{k-1}. \tag{14}$$

Therefore, a mean field version of the agent model may be written as follows

$$\Pi'_S = q(1-(1-f)\sigma_S(f)) - b(\sigma_S(f)) - \gamma f C_\beta(\Phi, fk)\sigma_S(f), \tag{15}$$

$$\Pi'_R = q(1-(1-f)\sigma_S(f)) - b - c(1-f)\frac{fk}{2}C_\beta(\Phi, fk)\sigma_S(f). \tag{16}$$

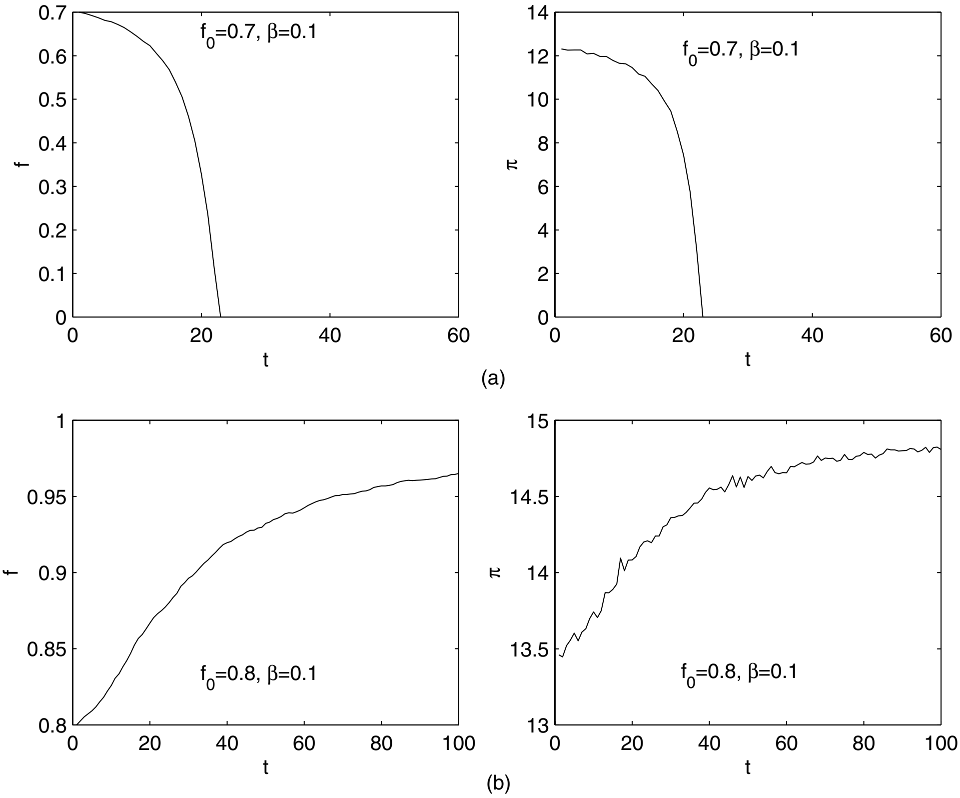

Fig. 4. Evolution of the fraction f of R-agents and global fitness in (a) region 1 and (b) region 2.

Notice the term fk in $C_\beta(\Phi, fk)$ and in the cost of punishment term in Π'_R. It reflects the fact that neighborhood relations for reciprocators are to be computed on their subnetwork of size fN.

$b(\sigma)$ is as in Eq. (3) with σ_S being computed to minimize

$$B(\sigma) = b(\sigma) + sfC_\beta(\Phi, fk)\sigma - q(1-\sigma)\frac{1}{N}. \tag{17}$$

This mean-field version gives results identical to the agent-based model. Clustering appears, therefore, as the determining network parameter driving the evolution of the reciprocator trait.

4. Conclusions

(i) With a structure of small groups with collective monitoring of the agents' activities, the fitness difference between groups with a sizable number of reciprocators and those where they have disappeared, makes the emergence of the strong reciprocity trait a likely event.

However, rather than being completely invaded by reciprocators, maintenance of a certain number of self-interested types is also likely, which only cooperate for fear of being punished. If, at a later stage, the social structure changes, they may be a source of instability and invade the population.

(ii) In a large population, monitoring of the public goods behavior of the agents cannot be a fully collective activity, rather being the chore of those in close contact with the free-riders. Punishment of free-riders also requires a certain amount of local consensus among reciprocators. Therefore, the clustering nature of the society may play an important role in the maintenance and evolution of the reciprocator trait.

Maybe the indifferent passersby that let the poor guy be mugged are not yet Homo Economicus. Maybe they are just reciprocators in the middle of strangers with whom they do not communicate nor trust. A small clustering coefficient might be the problem.

(iii) Culturally-inherited traits may have a much faster dynamics than gene-based ones. Modern societies are "small worlds" in the sense of short path lengths but not necessarily in the sense of also maintaining a high degree of clustering [24], [25]. Therefore, if the reciprocator trait has a high cultural component, it may very well happen that, eventually, we will see Homo Economicus leaving the benches of the economy classes for a life on the streets.

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