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Co-evolutionary Dynamics of Culture, Parochial Cooperation, and Networks

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Sociology

by

Jae-Woo Kim

June 2010

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Dedication

In memories of my late mother
who had dedicated her entire life to her family members
without ever making eye contact with them for six years
after one day in the Spring of 2003.

ABSTRACT OF THE DISSERTATION

Co-evolutionary Dynamics of Culture, Parochial Cooperation, and Networks

by

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Doctor of Philosophy, Graduate Program in Sociology
University of California, Riverside, June 2010
Dr. Robert Hanneman, Chairperson

Theoretically informed by recent computational and mathematical studies highlighting the importance of signals and networks in the evolution of cooperation, the present research undertakes simulation experiments to investigate socio-psychological bases and structural foundations of cooperation as institutional order. Simulated societies consist of three groups of agents with markers and tolerance: altruists, defectors, and parochial egoists. They simultaneously play a one-shot Prisoner's Dilemma game with neighbors by helping tolerably similar ones and by declining to help otherwise. They either imitate markers and tolerance of more successful neighbors or switch partners by breaking the old ones to out-group neighbors after creating new ties to others if both sides accept each other as in-group.

Our study furthers understanding of the dynamics of cooperation in human societies facing the Prisoner's Dilemma: altruists alone are less likely to defeat defectors regardless of network topology as cooperation becomes costly and the average number of interaction partners increases; under these conditions, parochialism is necessary for the institutionalization of cooperation; agents adapt themselves to increasingly homogenized environments by learning intolerance; emergent cooperative societies in the presence of imitation errors are vulnerable to free-riders with tolerably similar markers; either persistent cultural diversity or highly clustered networks with long paths stabilize cooperation; and even if markers are completely mutable, society-wide and robust cooperation is achievable with increased diversity as hierarchical networks of cultural groups self-organize where less tolerant agents in the periphery shield more tolerant ones in the core from emerging free-riders.

The current study provides sociologists with theoretical and methodological resources for a game-theoretical approach to institutional analysis. Socio-psychological research maintains that group identity enhances cooperation either because human subjects in pre-assigned groups maximize group-level rewards or when they expect continuing benefits from in-group favoritism. We rather demonstrate the evolution of cooperation without expectations of in-group reciprocity. Cultural groups emerge as arbitrary markers become salient together with stratification driven by parochial interactions. Our study also contributes to understanding of how stable markets can evolve out of repeated plays of a social dilemma game among parochial agents locally embedded in on-going exchange networks with limited knowledge about costs and opportunities.

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Chapter 1: Introduction

How the society holds together – the problem of social order – is the key question from the outset of the discipline of sociology. A society that is not able to maintain relatively high levels of cooperation among most of its members may confront considerable disintegrative pressures. Cooperation, however, faces a social dilemma which refers to a situation where the rational behavior of an individual aggregates to Pareto-inefficient outcomes. For instance, 'the tragedy of the commons' represents a dilemma in which the outcome may end up with the overutilization of a common resource when people pursue their own self-interests. Producing public goods through voluntary contribution (e.g. building bridges to other communities in a village) is another example of showing difficulties in improving the collective outcome when there are costs of helping others and incentives for opportunistic behavior.

A set of norms in societies render stable patterns of cooperative interactions possible. Direct reciprocity ('if you scratch my back, I will do yours') is one of the simplest yet most powerful explanations of where norms of cooperativeness come from (Axelrod, 1984). However, reciprocal cooperation by dyadic sanctions is not effective in sizeable groups consisting of those who rarely interact with the same partners because actors have to play with unknown others at each round.

Helping players with good reputation and otherwise declining to do so (Nowak and Sigmund, 1998) enhances cooperation even when there is a high risk of non-reciprocity. But, this principle of 'indirect reciprocity' (Alexander, 1987) has its own weakness: since those who punish players who do not help others lose their image scores, they are less likely to be rewarded by third parties (Nowak and Sigmund, 2005). Cooperative systems based on indirect reciprocity have to condone unconditional defectors who take advantages of others in one-shot interactions. Otherwise, such systems may be trapped in cascades of punishment.

It is a theoretical and empirical puzzle to explain the emergence of cooperation (e.g. first-mover cooperation) and its maintenance in the setting of one-shot social interactions and economic exchanges without reciprocity. Cooperating with strangers in spite of incurred costs requires trust as "the precontractual base of social solidarity" (Durkheim, [1893] 1933) from the beginning. However, unconditional cooperation based on the highest level of trust is a rare phenomenon. Rather, parochialism (Bowles and Gintis, 2004) and ethnocentrism (Hammond and Axelrod, 2006) are universal predispositions in human societies. People may read observable markers ("cues") to categorize others into "us" and "them" on the basis of perceived similarities, that is, social distances.

The present study raises the following four questions. First, how can global cooperation emerge from local interactions of actors who may have limited tolerance for cooperating with others who they see as different from themselves? Such parochial cooperation stops at group boundaries. Within-group cooperation and between-group non-cooperation do not result in globalized cooperation. Let us consider two ideal-type societies in Figure 1.1, where different colors represent different cultural markers. If emergent societies maintain high levels of cooperation, is it because their members look very alike in spite of low levels of tolerance (Right), or because more tolerant agents constitute a vast majority of the population who accept a broader range of diverse neighbors as in-group members (Left)?

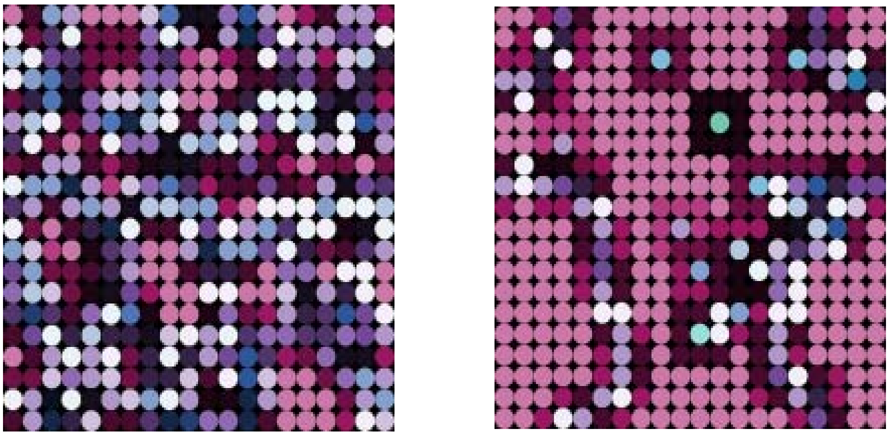


Figure 1.1. Two Ideal-type Cooperative Societies
Note: Different colors represent different cultural markers. It is not shown here, but the society on the left are almost double as tolerant as the society on the right.

However, it is less likely that emergent cooperative societies retain cultural diversity under social influence. For example, if people learn cultural traits from each other, local convergence tends to result in global homogenization in connected societies. We need to ask whether or not the diversity of both cultural markers and tolerance can be maintained given the tendency of human agents to change cultural traits toward those of influential others. Under what conditions would emergent cooperative societies preserve the global divergence of culture in spite of its local convergence?

Societies in which less parochial residents trust heterogeneous others are desirable with regard to the diversity of tolerance and cultural markers. But, they are more easily vulnerable to deviants displaying tolerably similar markers without providing any help (e.g. those who access to the p2p community with cracked passwords and just download files without any contribution). Generally, parochial cooperators recognize each other by “secret handshaking” (Robson, 1990) to share disproportionate benefits of in-group favoritism. However, emergent cooperative societies may be no longer stable in the presence of defectors who learn signals among conditional cooperators. The failure of secret handshaking may lead to serious downward spirals of cooperation. The next question, then, is how cooperation on the basis of similarity can be stable in spite of invasion by mutant defectors with tolerably similar markers.

People not only consider how to interact with partners, but usually have the option of whether to interact with others. Such partner selection can maintain global cooperation since cooperators can benefit from interactions with their own kind while avoiding contacts with defectors. But, again, this occurs at a cost. As with Schelling’s model (1971), if people select interaction partners based on homophily preferences (‘birds of a “cue” flock together’), a moderate degree of preference at the micro level can produce a high level of spatial segregation with very homogeneous factions at the macro level. The final question is, therefore, how it can be possible that emergent cooperative societies are still non-segregated or connected even if human agents parochially socialize with each other.

The current study is interested in the evolution of cooperation in the setting of a one-shot Prisoner’s Dilemma as a paradigmatic example where there is a temptation to free-ride, unlike the Stag Hunt game. The theory of kin altruism (Hamilton, 1964) is not suitable to explain cooperation among genetically unrelated people. Extant mathematical and computational research verifies that as long as agents randomly interacting with each other leave offspring in proportion to fitness, globalized cooperation is impossible in a one-shot Prisoner’s Dilemma game without reciprocity. Even if altruists establish a cooperative society, it can be easily destroyed by mutant defectors because they increasingly adopt the higher-scoring-strategy (i.e. defection) provided that the payoff from defection (i.e. exploiting cooperators) is higher than the payoff from mutual cooperation. The contemporary research across the disciplines has thus strived to identify the conditions for society-wide and stable cooperation in sizeable groups of non-kin.

We seek to find cultural bases and structural foundations of cooperation in human societies by using computer simulation experiments. In Chapter 2, we examine two competing but complementary mechanisms through which cooperators interact with each other preferentially so that they can continue to receive disproportionate shares of the benefit of cooperation. First, partner identification matters. Heuristic cues help agents distinguish those who are trustworthy from those who not. In the example of direct reciprocity (Axelrod, 1984), the behavior of an opponent on the previous round serves as a cue for the Tit-for-Tat strategy. Instead of always cooperating with others or always refusing to do, human agents may want to read tags as cultural markers to decide whether to cooperate or not depending on the trustworthiness of partners in one-shot interactions. As the number of discriminators in the population increases, the likelihood of assortative interactions among cooperative agents increases.

Second, network embeddedness is another important factor in the evolution of cooperative interaction and exchange. Agents interact with randomly selected others in the classical research, but this global random matching is not realistic. If agents locally interacting with a fixed set of partners leave offspring in the neighborhood in proportion to fitness, cooperation can be institutionalized (Nowak and May, 1992). If preferential partner selection (e.g. breaking ties with untrustworthy partners) is allowed to those agents, cooperative societies become more robust. Emergent clusters of cooperators on either static or dynamic networks can benefit from interactions with their own kind while avoiding interactions with defectors.

In Chapter 3, we discuss strengths and weaknesses of computational research followed by a full description of models and their assumptions. Agents in the present study have two inheritable traits: tags and tolerance. Tags as arbitrary markers are not innately related to the behavioral propensity to cooperate or not. Tolerance is an exact predictor of strategy (i.e. the higher tolerance, the more likely to cooperate with partners), but it is not observable in so-called tag-based societies. Agents simultaneously interact with partners in the neighborhood in a one-shot Prisoner's Dilemma game without either direct or indirect reciprocity[1].

The population consists of three types of agents. Altruists ('the good guys') always help others since they have the highest level of tolerance. Defectors ('the bad guys') with the lowest level of tolerance always decline to help others. Besides altruists and defectors who indiscriminately interact with partners, there is another group of agents who have intermediate levels of tolerance. These egoists ('the ethnocentric guys') cooperate toward tolerably similar neighbors ('us') on the basis of the shared belief in in-group favoritism. But, they refuse to cooperate toward dissimilar neighbors ('them') with a fear of being exploited by strangers. Agents in the population tend to break old ties unilaterally with out-group neighbors. Tie dissolution is allowed only when they can build new ones to in-group partners by mutual consent – who are randomly drawn from either neighbors-of-neighbors or players at greater distances.

In Chapter 4, we begin with the question of how it is possible that society-wide cooperation emerges from local interactions among parochial agents. It turns out that as agents with higher levels of fitness leave more offspring with their traits in the next generation, the population increasingly consists of egoists who take more discriminating actions against out-group in increasingly homogenized societies. Meanwhile, not only defectors but also altruists are weeded out under the force of natural selection. In spite of huge erosions of tolerance, high levels of global cooperation are maintained in highly homogeneous populations (cf. mechanical solidarity in a Durkheimian sense).

However, the stability of tag-based parochial cooperation rests on whether or not a shared belief continues that tags can predict the trustworthiness of interaction partners since tolerance is not an observable trait in tag-based societies. In other words, tag-based cooperative societies are not robust against mutant (or immigrant) free-riders with tolerably similar tags because they are predisposed to defect, but existing cooperators recognize them as in-group to cooperate toward them. Once such a shared belief is broken, there occur cascades of non-cooperation (i.e. deinstitutionalization) that result in societies of mutual betrayal. This result is consistent with the vulnerability of cue-based conditional cooperation to defectors who learn to fake signals of trustworthiness.

In Chapter 5, we search for alternative societies in which parochial cooperation is stable in the face of exploiters. We point out that existing models of tag-based cooperation are based on the idea of genetic inheritance. From the perspective of cultural evolution of cooperation, the same set of individuals (cf. parents and offspring) imitate (cf. copy) tags and tolerance from successful others with a small amount of error (cf. mutation) after playing the Prisoner's Dilemma game at every round (cf. generation).

In existing models of tag-based societies, tags are completely mutable in both processes of genetic copying and mutation. It leads to high levels of global cooperation because more agents become exactly alike, however long the tag strings they have. Also, it is one major reason for the susceptibility of tag-based parochial cooperation to invasion by mutant defectors with tolerably similar tags. We can reconceptulaize tags as cultural markers (i.e. simple forms of identities) with different levels of mutability. Tags are no longer completely mutable – some markers are more changeable (e.g. linguistic codes), whereas some others are less (e.g. skin colors). We propose alternative models of cultural evolution of tag-based cooperation, where each agent has one core identity which is not subject to both payoff-based imitation and its error.

Next, we aim to investigating structural foundations of cooperation, with special attention to two faces of social capital: network closure (i.e. making new ties to neighbors' neighbors to form closed triads) and bridging (i.e. making cross-cutting ties to agents at greater distances). Existing studies are more concerned with the evolution of reciprocity norms in highly clustered networks in the setting of repeated interactions, but they do not consider the effects of clustering on cooperation in one-shot interactions. Also, little attention is paid to the roles of short paths (‘small-world-ness’) through which locally emerging cooperation spreads while defectors invade the population.

In Chapter 6, we thus explore the dynamics of tag-based cooperation in static networks with different topologies such as regular networks, small-world networks, and random networks. The question is which network topology is more likely to preserve tolerance and cultural diversity, and render tag-based cooperative societies more stable against free-riders with tolerably similar tags even though tags are completely mutable.

In Chapter 7, parochial agents with a preference for homophily tend to socialize with the members of one’s group in terms of partner selection. Given a certain level of social mobility, they not only take discriminating actions toward neighboring partners, but also they either adopt cultural traits from successful neighbors or switch partners by breaking ties with perceived out-group unilaterally in favor of in-group by mutual consent. New partners are randomly chosen among neighbors’ neighbors (Colemanian social capital) or from agents at greater distances (Burtian social capital), given another exogenous parameter called the degree of closure.

Is it possible that parochial cooperation can be society-wide without network disintegration despite the fact that even moderate levels of homophily may lead to high degrees of segregation as with Schelling’s model? The research question under investigation is whether there is a parameter space of network plasticity and closure for alternative tag-based cooperative societies in which parochialism is not strong, cultural diversity is not wiped out, and cooperation is stable in spite of the relentless attack by defectors displaying tolerably similar markers. We also intend to discover what emerging norm-generating and sustaining networks look like in those societies.

In Chapter 8, we summarize the major findings of the present study and then discuss its contributions to understanding of the evolution of cooperation in human societies. We will draw some implications of the current study for research on group processes with a critical review of socio-psychological experiments on identity and cooperation since the so-called ‘minimal group’ study in the 1980s. The significance of our study to economic sociology of market dynamics will be also provided with reference to research on trust, parochial transaction, and exchange networks.

Chapter 2: Literature Review and Theory

Toward a Game Theoretical Approach to Institutional Analysis

The (Hobbesian) problem of social order is one of the key questions in sociology. Institutions can be defined as a set of norms and values (e.g. prosocial norms in our study) to organize relatively stable patterns of human activities related to fundamental problems in societies (e.g. cooperation). Sociologists have theorized institutions in two different ways. One approach defines institutions as regulatory systems or sectors such as economy, polity, kinship, education, religion, and law from a top-down perspective (Turner, 1997; Turner, 2003). Spencerian[1] or Parsonian[2] structural functionalism is one example in which people are (over-)socialized to follow norms. However, "much sociological theory takes social norm as given and proceeds to examine individual behavior or the behavior of social systems when norms exist. Yet to do this without raising at some point the question of why and how norms come into existence is to forsake the more important sociological problem in order to address the less important (Coleman, 1990a: 241)."

The other approach endogenizes institutions to conceptualize them as the collective outcomes of human behaviors rather than as entities that are purposefully designed. There are rival views within this bottom-up perspective: the rational choice approach and the interactionist approach. First, rational choice theorists in sociology such as Hechter (1987) and Coleman (1986) criticize that structural-functional arguments do not specify how human agents create social orders. They stress micro-foundations of macro patterns to locate the mechanism for the evolution of institutions as social orders in the decision making of rational actors. Given that the society is not equal to the sum of individuals, Coleman's Boat[3] of the macro-micro-macro linkage (Coleman, 1990a: 8) translates the direct relationships among macro variables into the multi-level causal processes.

Next, interactionists in sociology such as Berger and Luckmann (1966: 54-58) argue that "institutionalization occurs whenever there is a reciprocal typification of habitualized actions by types of actors. Put differently, any such typification is an institution… The institutions are now experienced as possessing a reality of their own, a reality that confronts the individuals as an external and coercive fact." Durkheim's view on institutions is a prototype of this phenomenological approach: "It may be said that nearly all the great social institutions have been born in religion" (Durkheim, [1912] 1965: 127). His sociology of emergence (Sawyer, 2002; 2005) conceptualizes institutional orders as emergent patterns from the interactionist framework. For another example, practitioners of the new institutionalism in sociology consider institutions as routinized patterns of human actions and culture as scripts providing templates for them (DiMaggio and Powell, 1991).

In this dissertation, we take a game theoretical approach to institutional analysis[4] for several reasons. First, game theory pays due attention to the discrepancy between individual interest and collective outcomes which is the critical issue in the dynamics of institutional orders in human societies (e.g. cooperation, coordination, resource allocation, intergroup conflicts, and so forth). In other words, game theory offers a powerful set of verbal and mathematical nuts and bolts for formulating theories of 'social dilemmas' (Dawes, 1980; Glance and Huberman, 1994; Kollock, 1998). Second, the concept of interaction in a strategic context as its starting point is very consistent with Weber's concept of social action – the action taking into account the behavior of others. Furthermore, game theory provides possibilities that the rational choice perspective and the interactionist perspective complement each other. Culture is a set of shared beliefs – legitimized protocols in the new institutionalism in sociology – and available (and appropriate) strategies for Weberian social action. Third, game theory has a strong affinity with the evolutionary perspective, which we will discuss in detail later. Institutions as social orders emerge, evolve, and dissolve out of repeated plays of games: "a social institution – which is none other than a shared course-of-action-type Schűtz[5] called – is a regularity in the behavior of members of a group upon confronting a recurrent situation" (Foss, 1996: 80).

The Evolution of Cooperation in the Prisoner's Dilemma Game

The Prisoner's Dilemma game is the most commonly used type of social dilemma game to tackle the evolution of cooperation in not only human societies but also primate groups. Each thief is offered a reduced jail term if she testifies against her partner. Because the jail term is lower regardless of whatever the other player chooses, both rationally betray each other. This is a dilemma because mutual cooperation is

Pareto optimal, but rationality leads to a collectively suboptimal set of actions. Mutual betrayal is the unique Nash equilibrium since the defection strategy is (strictly) dominant over the cooperation strategy.

Table 2.1. Payoffs in Prisoner's Dilemma Game

	Cooperate	Defect
Cooperate	3 (*R*)	0 (*S*)
Defect	5 (*T*)	1 (*P*)

Table 2.2. Payoffs in Helping Game

	Help (C)	Refuse to help (D)
Help (C)	$b–c$	$–c$
Refuse to help (D)	b	0

In the payoff matrix of the Prisoner's Dilemma game (Table 2.1), R, T, S, and P stands for Reward for Mutual Cooperation, Temptation to Defect, Sucker's payoff, and Punishment for Defection, respectively. $T > R > P > S$ and $2R > T + S$ are satisfied in the Prisoner's Dilemma game. It should be noted here that the Prisoner's Dilemma game is the same with the helping game, where if Person 1 (donor) helps Person 2 (recipient) at a cost c, Person 2 receives a benefit b; if Person 1 does not help, both individuals receive zero payoff; and $b > c > 0$. Table 2.2 is the payoff matrix of this helping game. Because the payoff of cooperation, $b – c$, is smaller than the payoff of defection, b, if both individuals are self-interested, then they are worse off.

Evolutionary game theory has developed since Maynard Smith (1982) with concerns about weaknesses in the classical game theory. The current study draws on evolutionary game theory since it is more adequate to explaining the evolution of institutional orders than the classical game theory for a couple of significant reasons (Hargreaves Heap and Varoufakis, 1995). First, evolutionary game theory is motivated by milder assumptions of rationality than the classical game theory. Strategies in evolutionary games are conceptualized as genetically coded behavioral propensities rather than as rationally calculated ones. Second, the classical game theory has been criticized for failing to explain the origins of conventions. The concept of the subgame perfect Nash equilibrium (Selten, 1975) does not tell what would happen if there were multiple Nash equilibria in indefinitely repeated games. Third, it is also difficult to account for why institutions change with the idea of the Nash equilibrium. In other words, the classical game theory does not offer a robust theory of dynamic equilibria. An evolutionary stable configuration of the population can be called an equilibrium of evolutionary games. This concept of Evolutionarily Stable Strategy (ESS) is an evolutionary version of the Nash Equilibrium Strategy (NES). It should be noted here that ESS is always NES, but not vice versa.

Unfortunately, evolutionary game theory is never introduced in the literature by even evolutionary sociologists including sociobiologists (van der Berghe, 1990; Dietz, Burns, and Buttel, 1990; Maryanski, 1994, 1998; Lopreato, 2001; Sanderson, 2001; Lenski, 2005), with the exception of Machalek and Martin (2004). As Maynard Smith (1982: vii) prefaces his work, “paradoxically, it has turned out that game theory is more readily applied to biology than to the field of economic behavior for which it was originally designed.” The theory of evolutionary games in complex (adaptive) systems is indeed powerful to model the dynamics of institutional order[6] in a Darwinian sense (Dixit and Skeath, 2004: 430).

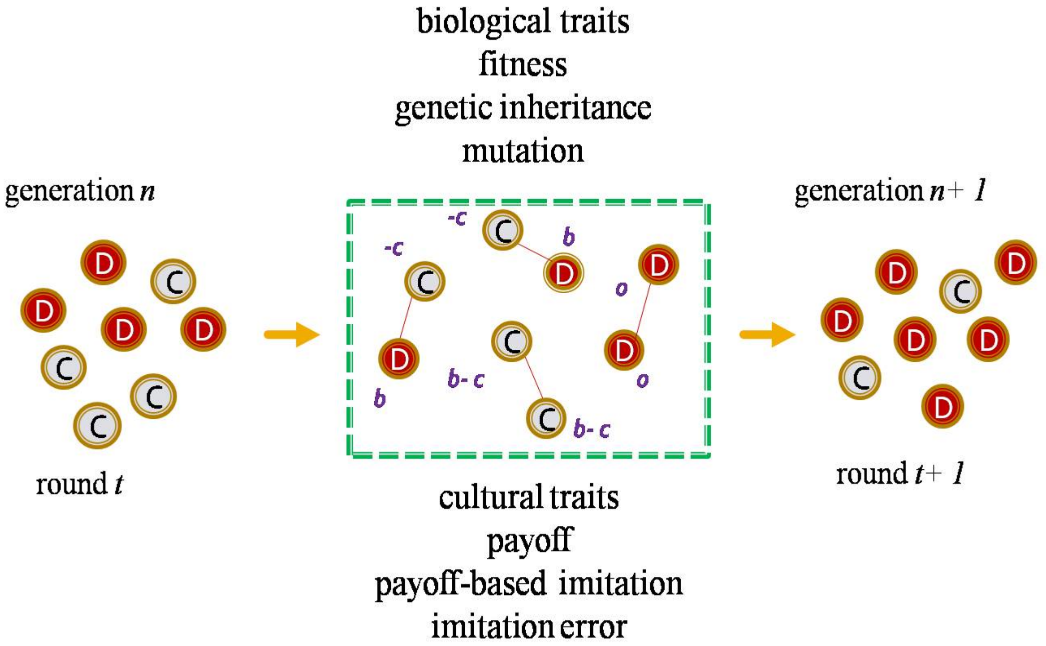


Figure 2.1. Evolutionary Game and Population Dynamics

The basic idea (Figure 2.1) is that a game takes place in a population of multi-agents who have biologically inheritable traits that govern certain patterns of behaviors, say whether or not to cooperate toward others (cooperate C and defect D in Figure 2.1). Agents at one generation play a game with partners randomly drawn from the population (cf. "playing the field" in biology). They leave offspring in proportion to fitness (benefit b and cost c in the dashed box of Figure 2.1. See the payoff matrix in the Table 2.1 and Table 2.2) at the next generation with some copying errors as mutation. Selection pressure suggests that the payoff for a particular strategy *s* at a generation t affects its frequency at the next generation $t + 1$. If the frequency of a particular strategy, f_s increases if its fitness π_s exceeds the average fitness of the population π, and otherwise it decreases: $df_s / dt = f_s (\pi_s - \pi)$. In this way, population dynamics is density-dependent (so-called the replicator dynamics). This evolutionary game is equivalent to the process that the same set of agents, after playing a game, imitate culturally transmissible traits of higher-scoring others (i.e. payoff-based imitation) with some learning errors. There are no direct or indirect reciprocity elements because it is assumed that agents are minimally cognitive so that they cannot choose strategies on the basis of whether or not their partners cooperate in the past.

Darwin's theory of natural selection states that the evolutionary force will weed out organisms which do not maximize fitness ("the survival of the fittest"). First, a cooperative society is impossible if parents leave offspring in proportion to their fitness because the defector's payoff (Temptation to Defect) is higher than the cooperator's payoff (Reward for Mutual Cooperation). Second, even if there is a population purely composed of altruists who always help others, such a cooperative society is not evolutionarily stable since a mutant defector successfully invades the population. For this reason, how to explain society-wide and stable cooperation in human societies has been not only an interesting theoretical puzzle but also a substantively important question for biologists and social scientists. Under which conditions does natural selection favor cooperation in the evolutionary Prisoner's Dilemma game as a one-shot multi-agent game?

Mechanisms of Cooperation

Several mechanisms have been proposed to explain the evolution of cooperation in human societies: kin selection, direct reciprocity, indirect reciprocity, network reciprocity, and group selection (Nowak, 2006). We focus only on the classical models of the first four mechanisms since our models are not based on the theory of group selection. Another reason is that an intense debate is still going on in spite of its recent resurgence under the idea of ‘multi-level selection.’

Kin selection theory (Hamilton, 1964) maintains that kinship is the ultimate basis of cooperation in primate groups including human societies. Mathematically, altruism can be preferred if its benefit-to-cost ratio in Table 2.2 is higher than the probability of sharing a gene (Nowak, 2006). The theory of kin selection from the viewpoint of sociobiology contributes to our understanding of nepotistic phenomena prevalent even in human societies today, not only altruism but also ethnic conflicts and kin-based business networks (e.g. Quanxi-based Chinese business). However, humans tend to cooperate with non-kin more than other primates. How to explain altruistic behavior directed at genetically unrelated others, then?

‘As long as you help me, I will help you’ can be another route of cooperation between two players even if they are not necessarily genetically related. A player using Rapaport’s tit-for-tat strategy cooperates at the first round (‘niceness’). And then, her next move depends on her partner’s previous move: she chooses the same strategy her partner used at the previous round (‘forgiveness’ and ‘retaliation’). Axelrod (1984) advances the idea of reciprocal altruism (Trivers, 1971) by demonstrating that a tit-for-tat player defeats not only defectors, but also any other players employing sophisticated strategies. Mathematically, direct reciprocity leads to cooperation if the benefit-to-cost ratio in Table 2.2 is higher than the possibility of another encounter between the same two individuals (Nowak, 2006). However, the tit-for-tat strategy is not applicable to large-sized populations[7] in which people so rarely interact with the same partners that there can be very high risks of non-reciprocity.

Next, the idea of indirect reciprocation, 'if I will help you, someone else will help me,' explains the evolution of cooperation in such a one-shot Prisoner's Dilemma game in large-sized populations of multiple non-relatives. According to Boyd and Richerson (1989), cooperation can emerge and continue if people use the 'downward Tit-for-Tat' strategy. This conditional strategy is just an extension of the Tit-for-Tat strategy: 'if you cooperate, a third party will cooperate toward you; if you refuse to cooperate, a third party will punish you.' In this sense, indirect reciprocity is a consequence of direct reciprocity occurring in the presence of others (Alexander, 1987).

Nowak and Sigmund (1998) demonstrate that cooperation can prosper even in a one-shot Prisoner's Dilemma game where agents interact with randomly selected partners if the population consists of not only those who always help partners and those who always refuse to help partners, but also those who have limited tolerance for helping partners with bad reputation. These discriminating egoists are concerned with image score building to receive help from others. They conditionally cooperate only with partners who have good image scores.

We note here that the aforementioned three mechanisms commonly consider the role of 'cues' in the evolution of cooperation (McElreath, Boyd, and Richerson, 2003). The kinship hypothesis is that the propensity to cooperate between two individuals is determined by the genetic relatedness between them: the more genetically related, the more reliable, and the more likely it is that they cooperate toward each other. Kinship is a cue in this kin-based reciprocity. Direct reciprocity is predicated on repeated interactions between the same two individuals. Therefore, the behavior of an opponent on the previous round can serve as a cue in the Tit-for-Tat strategy as a discriminating strategy. In Nowak and Sigmund (1998), an individual's image score is a heuristic cue in an indirect form of reciprocity, that is, 'your cooperative behavior will be rewarded by third parties (not necessarily the recipient of your help) reading your increased reputation.'

The last mechanism pays due attention to the role of territoriality in the evolution of cooperation. As Nowak (2006) points it out, the argument for natural selection of defection is predicated on a well-mixed population, where everybody interacts equally likely and also randomly with everybody else. This approximation is used by all standard approaches to evolutionary game dynamics. But, real populations are not well mixed. Instead, some individuals interact more often than others, which indicates that people embedded in social networks interact with a subset of population.

Nowak and May (1992) validate that if agents interact with local neighbors to leave offspring in the neighborhood in proportion to fitness, there can exist dynamic equilibria in which altruists co-exist with defectors as long as altruists group together to form cooperative network clusters, consistent with 'kaleidoscopes' predicted by Axelrod (1984: 162-3). Natural selection favors defection over cooperation in unstructured populations, but global cooperation can be enhanced under the very simple condition that the benefit-to-cost ratio in Table 2.2 exceeds the average number of neighbors regardless of network topology, degree-homogeneous (e.g. torus, ring lattice) or degree-heterogeneous (e.g. small-world network, random network), according to Ohtsuki, Hauert, Lieberman, and Nowak (2006). Altruists (unconditional cooperators) are less likely to survive in the presence of defectors as cooperation is more costly and the density of social network becomes high. Suffice to say here that the term, network 'reciprocity,' may cause confusion or misunderstanding when applied to one-shot games, but we keep it throughout the dissertation.

Table 2.3. Two Routes to Cooperation

	Cue-based Cooperation	Network Reciprocity
What actions to choose	Discriminators (Conditional strategies)	Indiscriminators (Unconditional strategies)
How partners are selected	Random Matching (Unstructured populations)	Spatiality (Structured populations)

We conclude that both cue-based partner identification and network reciprocity highlight the importance of preferential interactions among those who (are more likely to) cooperate toward others. Both approaches have complementary strengths and shortcomings (Table 2.3). Existing models of cue-based cooperation in the evolutionary Prisoner's Dilemma game assume unstructured populations in which agents randomly interact with one another (i.e. global mating or playing). However, they aptly underline the role of discriminators in the dynamics of cooperation (Nowak and Sigmund, 2005). The population in models of cue-based cooperation is composed of not only the 'good' guys (indiscriminating altruists) and the 'bad' guys (indiscriminating defectors) but also the discriminators who use conditional strategies depending on the trustworthiness of interaction partners. This approach is more realistic in the sense that cooperation in human societies more often hinges on our biological and cognitive capacity to use various symbols and signals than other animals. These heuristic cues, albeit inherently fallible, help human agents distinguish those who are more trustworthy and also more likely to cooperate from those who are not.

In the existing classical models of network reciprocity, the population consists of the 'good' guys who unconditionally help all neighbors and the 'bad' guys who unconditionally refuse to help all neighbors, without the discriminators with intermediate levels of tolerance. In other words, it is unrealistically assumed that human agents have either the highest or lowest level of tolerance. However, research on evolutionary games in networks is aptly concerned with structural mechanisms of cooperation by emphasizing 'assortative meeting' (Eshel and Cavalli-Sforza, 1982) through which cooperators benefit from more interactions with their own kind and less interactions with defectors. This approach implies that 'viscosity' (Hamilton, 1964) in animal societies – limited dispersal of offspring in the neighborhood instead of their random dispersal – renders network reciprocity workable (Grim, Wardach, Beltrani, 2006), while clustering in human societies characterizes norm-generating and sustaining networks.

Tag-based Parochial Cooperation

One challenge to the theory of kin selection is that it assumes psychological mechanisms through which individuals can identify how much genes they share. "Of course, the trick is to distinguish between 'us' and 'them.' In the ancestral society, it was hardly a problem. Clan members were related by blood or ties of marriage, and lived their lives in close proximity" (Lopreato, 2002: 423). In this aspect, proximity must be a critical heuristic cue for reciprocity on the basis of kin-recognition in earlier societies. However, how to explain cooperation in increasingly differentiated and highly mobile societies today consisting of genetically unrelated people?

People strain to detect 'ethnic markers' such as genetically transmitted phenotypes (e.g. skin color) and behavioral characteristics (e.g. speech, manner), as is addressed by van der Berghe (1981: 28-29) who theorizes the dynamics of extended nepotism and conflict in ethnic groups (as extended forms of the family). Stating that the theory of kin selection is silent on a route to altruism toward nonrelatives, Krebs (1987) regards 'phenotype matching' as vital for humans to identify who is who[8]. In general, "people often related to each other in ways that are influenced by observable features such as sex, age, skin color, and style of dress. These cues allow a player to begin an interaction with a stranger with an expectation that the stranger will behave like others who share these same observable characteristics… This happens because the observed characteristics allow an individual to be labeled by others as a member of a group with similar characteristics" (Axelrod, 1984: 146-7).

Holland (1993; 1995) suggests that 'tags' as observable markers are engaged in group processes of complex adaptive systems. Human agents have tags as the phenotype of "memes" (Dawkins, 1976) to form "memetic kin" (Heylighten and

Campbell, 1995). Reading tags enables humans to make distinctions between in-group members and ‘others.’ Recent research on tag-based systems reports that tag-based discriminating actions among randomly selected agents significantly enhance the level of global cooperation in a one-shot multi-agent Prisoner’s Dilemma game (Riolo, Cohen, and Axelord, 2001).

Agents may display “in-group favoritism” (Hammond and Axelrod, 2006), “parochialism” (Bowles and Gintis, 2004) in choosing how to interact, based on their tolerance of differences with others. For instance, what action an ego chooses is contingent on whether or not her perceived social distance to an opponent is less than or equal to her tolerance level (Riolo et al., 2001). In Hammond and Axelrod’s model, one of four colors is assigned to agents with tags (ethnic markers) whereby their group membership is determined. An ethnocentric agent helps a partner of her own color, and otherwise does not help. In these examples, the predisposition of individuals to behave cooperatively depends on the identities of their interaction partners: ‘insiders’ are favored over ‘outsiders,’ but not necessarily with out-group hostility.

Weaknesses of Tag-based Parochial Cooperative Societies

Riolo et al. (2001) demonstrate that if agents cooperate only with others with tolerably similar tags and they leave offspring in proportion to fitness measured by the payoffs at the previous generation, then societies reach high levels of cooperation. But, tolerance decreases drastically as the average level of cooperation (measured by the donate rate in a helping game) increases rapidly during the first few generations

(Figure 2.2). After this transient period, “the agents in the resulting ‘dominant tag cluster’ have an advantage as there are more of them to help each other” (Riolo et al., 2001: 442). Riolo et al. (2001: 442) report that “about 75-80% of the agents have tags that are so similar that they are within each other’s tolerance range.”

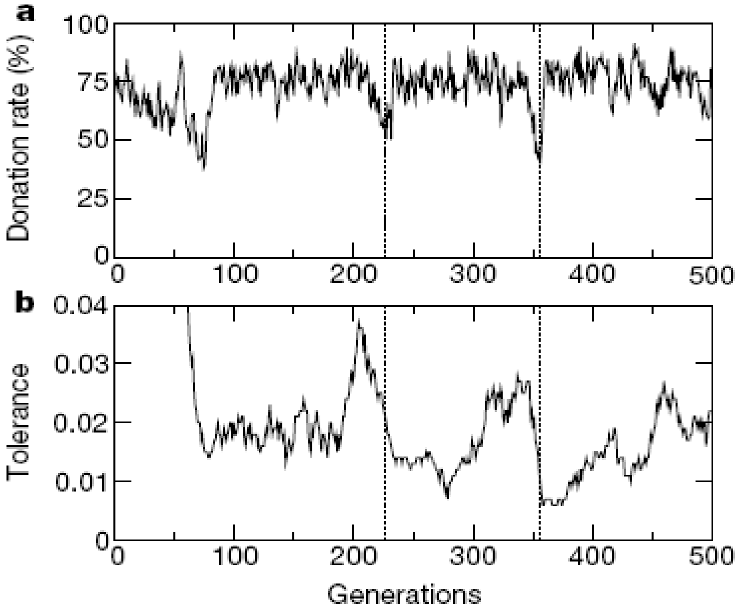


Figure 2.2. Dynamics of Tag-based Cooperation and Tolerance Change.
Note: Riolo et al. (2001: 441).

Cooperators in the dominant tag cluster are, however, vulnerable to invasion by relatively intolerant mutants with tags within the range of tolerance of the typical members of the dominant cluster. Once these mutants have higher payoffs, a transition to a new tag cluster occurs. The average tolerance drops significantly once again, but the average donation rate returns to its previous level as with Figure 2.2 (Riolo et al., 2001: 441). A significant erosion of tolerance is a major trend, but if more tolerant agents benefit from each other to spread across the population, the average tolerance can increase temporarily. They conclude: “in our model, the cycle of increasing and decreasing tolerance could reflect, for example, a loss of sensory discrimination in a population when there is little selection pressure to retain it, followed by a recovery when a more discriminating individual succeeds” (Riolo et al., 2001: 442).

With respect to the four questions of the present study, Riolo et al.’s research answers the first two issues in tag-based cooperative societies. The ethnocentric tendency in the population becomes increasingly reinforced over generations since parochial agents displaying stronger discrimination against out-group are more likely to survive. Nonetheless, they continue to cooperate with each other because the degree of tag diversity in the population decreases over generations. In other words, agents adopt intolerance from more successful others as societies become more homogenized, but high levels of cooperation are still possible in spite of a huge erosion of tolerance because it is more likely that cooperation occurs among more homogeneous agents.

However, Riolo et al. do not explore theoretical possibilities of alternative cooperative societies where culture is globally divergent in spite of its local convergence, which is the second question of the current study. They find that tag-based in-group favoritism significantly facilitates cooperation, but according to the replication by Edmonds and Hales (2003: 9.4), “the simulation quickly becomes dominated by a single group of individuals, all of whom have exactly the same tag.” This indicates that emergent societies in Riolo et al.’s model almost always reach universal cooperation in completely homogenized populations consisting of agents who have the minimum tolerance and the identical markers. However, “tags can also present major obstacles in overcoming segregation,” as is aptly addressed by Sigmund and Nowak (2001: 405). “Although the simulations by Riolo et al. do not produce dominant clusters that split into rival tribes, any territorial distribution would favor such ‘speciation.’ Tags would then act as self-reinforcing stereotypes, making it hard for tolerance to cross the divide.”

Recall that agents in their model basically play a one-shot Prisoner’s Dilemma game with randomly selected partners in unstructured populations. This is why it is difficult for Riolo et al. to examine the spatial configuration of parochialism and tag clusters. Regarding the fourth question, we intend to investigate the dynamics of tag-based cooperation in structured populations where agents play the game with immediate neighbors: how boundaries of cultural groups evolve over time?; and what they look like either at deterministic equilibrium or at dynamic equilibrium? Riolo et al. do not consider that tags influence with whom individuals interact, but we will furthermore probe into the network topologies of evolving cultural groups that have different markers when agents with similar tags tend to socialize with each other (i.e. tag-based cooperation on dynamic networks).

Another fundamental limitation of Riolo et al.’s model is related to the third question of the current research. Riolo et al. discover that if a mutant with a lower level of tolerance has similar tags tolerable to existing cooperators, such an immigrant earns a higher payoff (fitness) so that she can easily invade the population. The number of offspring with her tolerance and tags increases over generations. Since less parochial agents perceive a broader range of interaction partners as in-group, they are more likely to be vulnerable to more parochial mutants displaying similar tags. However, there are no unconditional defectors in their model since agents with the minimum tolerance are those who still cooperate with partners displaying the identical tags (See Section 4.1 and also Endnote 4 in Chapter 3). We want to investigate the third question – the evolutionary stability of tag-based parochial cooperative strategies in the presence of mutant defectors[9].

Chapter 3: Method and Model

3.1. Method

There are three ways of constructing theories for formal sociology: statistical analysis; mathematical modeling; and computer simulation. Statistical analysis is the most commonly used approach in sociology to find patterns in data and test hypotheses. Mathematical sociologists prefer proving theorems based on axioms. Beginning with proved propositions (lemmas), they intend to draw another set of propositions to verify them. Semi-mathematical computational language can capture both the material and cultural aspects of social dynamics for building formal sociology, which is hard to do with either everyday languages or mathematical languages (Hanneman, 1989), but it seems that computer simulation as ‘thought experiment’ is not widely acknowledged as an alternative method among sociologists (Collins, 1988; Macy and Willer, 2002).

Statistical analysis of empirical data comes in very handy, but most statistical techniques are designed for the analysis of realizations of systems at equilibrium, and hence are appropriate to theories of comparative statics (Collins, 1988: 513). They are not adequate to identify social mechanisms as multi-level processes (except hierarchical models, for example) and to distinguish causation from correlation (except structural equation models, for example). Mathematical modeling is most powerful for building formal sociology by proving theorems based on a set of axioms. Nonetheless, deductive reasoning in mathematical models very often requires simplified assumptions about the reality in order to make equations solvable. Also, mathematics is 'acausal.' For example, the formula $y = \mathrm{f}(x)$ itself does not tell anything what makes y or x, only that quantitative variation in y is formally (not substantially) related in some way to quantitative variation in x (Sayer, 1992: 179). In the similar vein, a mathematical formula itself is devoid of explanatory power despite its descriptive accuracy (Epstein, 1999: 51). Particularly when there are many elements in the system interacting with each other in complicated ways, either the statistical approach or the deductive approach is not suitable.

Computer simulation necessarily must specify what affects what at various points in time, and it directs attention to how that process operates over time. The resulting dynamic theories are much closer to a full approximation of reality as it actually happens (Hanneman, 1995; Collins, 1988: 510-511). It is also acknowledged as a third scientific discipline, neither induction nor deduction (Axelrod, 1997), to natural and social scientists who increasingly recognize difficulties in analyzing complex systems mathematically (Hanneman and Patrick, 1997). Computer simulation, like mathematical modeling, begins with a set of explicit assumptions, but it generates data to analyze them inductively, instead of proving theorems deductively. Unlike typical induction, however, the simulated data comes from a rigorously specified set of rules rather than direct measurement of the real world.

Deduction is much more powerful for theory construction than computer simulation. Any lemma (proved propositions) is definitely true under any combination of parameters. But, computational models provide only a set of simulated data that cannot cover all possible combination of parameters. This problem becomes more serious when the number of parameters increases. Generally, it is highly demanding to do an exhaustive search of the whole parameter space and to undertake all possible sensitivity tests to confirm the robustness of conclusions from main experiments that cover a part of the whole parameter space. Sensitivity test is highly recommended to be done for model assumptions as well.

Verification is another problem in communities of computer simulation practitioners (Gilbert and Troitzsch, 1999). Verification refers to the process of evaluating whether or not a model is built in the way researchers want to do (internal validity). Since researchers very frequently make mistakes in making programs, debugging is required at all stages of model building. Furthermore, making programming codes open to the public for replication is not firmly established as a legitimized practice (Wilensky and Rand, 2007).

Nevertheless, computer simulation has complementary advantages over either statistical analysis or mathematical modeling. Computational research, even empirically calibrated simulation model, cannot replace empirical analysis in terms of validation (external validity), but researchers rarely have the empirical data (from field studies, lab experiments, or surveys) with varying conditions. On the contrary, simulation experiment produces different sets of data enough to clarify initial and scope conditions of theoretical arguments. In other words, the very fact that computer models handle the data in simulated societies, not the real-world data, gives simulation studies advantages over statistical analysis of the empirical data. Besides, computational modeling is particularly useful to handle nonlinear behaviors of the system under study because linearity is assumed in most statistical techniques.

Mathematical models are more parsimonious than computational models. The analytical intractability of the dynamics on networks and the dynamics of network renders analytical methods less attractive, but dynamic processes in complex systems (e.g. emergence, non-linearity, self-organization, etc.) may lead to the simulation outcomes with highly complicated patterns. This weakness of computational modeling can be its strength from another angle, but it is the only solution when analytic methods are not available due to the degree of the complexity under study.

Agent-based modeling has several advantages compared to equation-based system dynamics modeling. First, agent-based modeling satisfies both the structure-agency duality and the group-person duality. System dynamics modeling tends to attribute forces to social structure separately from agent's action ("structuralist determinism"), but agent-based modeling is closer to "structuralist constructionism" (Emirbayer and Goodwin, 1994) and the structuration theory Giddens (1984). System dynamics modeling remains at the aggregated level, while agent-based modeling bridges the macro-micro gap focusing on the interplayed relationship between the attributes and behavior of individuals and the global properties of groups.

Second, agent-based modeling does not assume the particular tendency at the global level. System dynamics modeling begins with *ex ante* assumptions about the causal relationships among macro variables (e.g. differentiation and integration as the master trend of socio-cultural evolution). On the contrary, agent-based modeling "decouples" (Epstein, 1999) individual rationality from macroscopic equilibrium. For example, individual tendencies do not necessarily extrapolate to group behavior as with Schelling's model (1971) that pronounced segregation does not necessarily imply a high degree of intolerance (Ball, 2004: 315).

Third, agent-based modeling can handle population of heterogeneous agents embedded in spatial environments, unlike system dynamics modeling (Epstein and Axtell, 1996). For instance, random interactions among homogenous agents are implicitly assumed in the system dynamics model of interaction rituals by Collins and Hanneman (1998). The key question is how the decentralized local interactions of heterogeneous and autonomous agents could generate the given regularity over time at the global level from the bottom-up perspective (Schelling, 1978; Epstein, 1999; Sawyer, 2003). This is why agent-based modeling is particularly useful to understanding how emergence comes into play in evolutionary dynamics of self-organizing complex adaptive systems in which boundedly rational agents play social dilemma games.

3.2. Model

Agents in all models in the present study are selected in a random order without any particular schedules, and they are updated synchronously[1]. The simulated longitudinal data are collected in Excel files through NetLogo Behavior-Space (Wilensky, 1999). All models in the present study consist of the steps in Table 3.1, either initialization followed by 1, 2, 3, and 4-1 (cooperation in static societies in Chapter 4, 5, and 6) or initialization followed by 1, 2, 3, and 4-2 (the co-evolutionary dynamics of cooperation and networks in Chapter 7).

Table 3.1. Stages of Simulation

```
Initialization
For each generation (or round),
    1)  For each agent,
            Similarity perception
        End
    2)  For each agent,
            Interactions
        End
    3)  For each agent,
            Fitness (payoff) calculation
        End
    4-1)  For each agent,
              Reproduction or
              (Imitating cultural traits from more successful neighbors)
          End
    4-2)  For each agent,
              Cultural evolution or Network evolution
          End
End
```

‘Reproduction’ in the baseline model of genetic evolution of cooperation in Chapter 4 is equivalent to ‘imitating cultural traits, tags and tolerance, from more successful neighbors’ in two alternative models in Chapter 5 where each agent has one core identity and the models in Chapter 6 and 7 where agents adjust their tolerance levels toward those of more successful neighbors by one unit, either on static networks with different topologies or on evolving networks, respectively.

Table 3.2. Full List of Models in Main Experiments

Chapter	Model (M)	Traits are always changeable in copying and mutation?	A step-wise change in tolerance?
4	Baseline (M1) on torus: *Genetic Inheritance*	Yes (Genetic)	No (Genetic)
5	Caste Society (M2) on torus: *Cultural Transmission* Modern Society (M3) on torus: *Cultural Transmission*	No (Cultural)	No
6	Baseline (M4) on static networks (torus/ regular/ small-world/ random) *Cultural Transmission*	Yes	Yes (Cultural)
7	Baseline (M5) on dynamic networks: *Cultural Transmission*	Yes	Yes (Cultural)

Tolerance changes from one level to any other level in the models in Chapter 4. In other words, agents can take whichever level of tolerance they adopt from more successful neighbors, regardless of their previous levels of tolerance. This rule is not an issue in genetic inheritance given the selection rule that recessive agents are replaced by dominant agents in terms of fitness. However, it is problematic from the viewpoint of learning cultural traits. First, the reality is rather that people are very likely to adjust their tolerance levels in a step-wise manner. Second, agents can precisely predict behaviors of their partners with information about tolerance, but it is assumed to be unobservable in tag-based societies. Agents instead rely on tag-based distinction between 'us' and 'them' while believing that in-group members are more likely to cooperate given that tolerance is not discernable. Tolerance change between any two levels implicitly assumes that agents are able to read exactly the tolerance levels of their neighbors. For these reasons, a step-wise change in tolerance is applied to the models of cultural evolution of cooperation in Chapter 6 and 7. However, tags are completely mutable in Chapter 6 and 7, as is the same with the baseline model of genetic evolution of cooperation in Chapter 4 because our focus is on how network properties affect the dynamics of tag-based parochial cooperation, not on how persistently heterogeneous identities come into play (M2 and M3 in Chapter 5).

Initialization. Each agent i has a tag list with its length L in which arbitrary cultural traits are binary,[2] assuming that agents perceive dissimilarity in a dichotomized way: $t_i \in \{0, 1\}^L$. $t_{i(l)}$ denotes agent i's trait value on the lth position of her tag list. Each agent also has tolerance $T_i \in \{0, 1, \ldots, L+1\}$. Therefore, $\min(T) = 0$ and $\max(T) = L + 1$. We define the neighborhood set N_i as agents who are directly connected with agent i. $G(N, E)$ represents a social network, where the set of vertices N denotes agents and the set of edges E denotes their relations. The adjacency matrix $A(G)$ in our study is symmetric and the entry is binary, that is, $a_{\text{ij}} = a_{\text{ji}} = 1$ if there is a link between agent *i* and *j* ($i \neq j$), and $a_{\text{ij}} = 0$ otherwise.

100 agents with randomly assigned tags and tolerance are located on the torus (TO hereafter) in Chapter 4 and 5, on fixed networks with different topologies in Chapter 6, or on a random network in Chapter 7. In Chapter 4 and 5, the number of adjacent neighbors on the torus is 8 (i.e. Moore neighborhood). In Chapter 6, the average degree of the regular network (RN hereafter) (i.e. each agent is connected to her three neighbors on either side) is exactly 6, and it is 6 on small-world networks (SW hereafter) and random networks (RN hereafter). A random network in Chapter 6 and 7 has a Poisson degree distribution in which every possible edge is created independently, given *n* vertices, with a fixed probability, called Erdös-Rényi probability is .06. A small-world network is a graph with *n* vertices and average degree *k* that exhibits the average path length $APL \approx APL_{\text{random}}(n, k)$, but the average clustering coefficient $ACC >> ACC_{\text{random}} \approx k/n$ (Watts, 1999). A small-world network can be generated from its equivalent regular network when the following two tests are satisfied at a significant level ($\alpha = 0.05$) in both: the average clustering coefficient of a graph after a certain number of rewiring should be significantly bigger than that of the initial regular graph (one-tailed test); and there should be no significant difference in the average path lengths between the two graphs (two-tailed test).

Similarity perception. If $L \geq 1$, agent *i* has perception of dissimilarity to neighbor *j* based on Hamming Distance defined by $HD_{ij} = \sum_{l=1}^{L} \left| t_{i(l)} - t_{j(l)} \right|$. If $HD_{ij} < T_i$, agent *i* accepts agent *j* as in-group; otherwise, out-group[3]. Suffice to say here that HD_{ij}

always equals to HD_{ji}.

Interactions. Agents play a one-shot Prisoner's Dilemma game with all their neighbors at each round. Agent i cooperates with j ($s_{ij} = 1$) if neighbor j is perceived as in-group; otherwise, agent i defects ($s_{ij} = 0$)[4]. It should be noticed here that: if $L = 0$, there is no dissimilarity perception since all agents are identical ($HD = 0$). Since $\min(T) = 0$ and $\max(T) = 1$ at $L = 0$, one group of agents with $T = 1$ always cooperate, but the other group with $T = 0$ always defect. In this way, our model at $L = 0$ represents a population composed only of unconditional cooperators and defectors (i.e. no parochial agents); and generally at $L \geq 1$, agents with the minimum tolerance ($T = 0$) are unconditional defectors, while agents with the maximum tolerance ($T = L + 1$) are unconditional cooperators, but agents of in-between values ($T \in \{1, 2, \ldots, L\}$) are ready for discriminatory actions[5].

Payoff calculation. If an ego cooperates, it pays cost c and produces benefit b. If it defects but alter cooperates, it gets the benefit b produced by its partner, without paying c. If $b > c > 0$, the payoff matrix[6] in Table 2.2 satisfies the Prisoner's Dilemma game in which mutual cooperation is Pareto optimal. The total payoff of agent i at each round can be defined by $\pi_i = \sum_{j \in Ni} -s_{ij}c + s_{ji}b$.

Reproduction (Payoff-based imitation). One player i is randomly chosen, and then another agent $j \in N_i$ is randomly selected. Only if $\pi_j > \pi_i$ (i.e. the no-bias method[7]), agent i dies without producing her offspring, and agent j can leave her offspring not only at her own site but also at the empty site once occupied by agent *i* (asexual reproduction with 'viscosity'). This rule applied to the baseline model in Chapter 4 is equivalent to payoff-based imitation in Chapter 5 – each individual's payoff is compared to the payoff of a role model drawn from the agent's neighbors. If the role model, agent *j* here, turns out to be more successful than the ego, agent *i*, agent *i* adopts tags and tolerance from agent *j*[8]. Imitation is local and payoff-based in the models of Chapter 6 and 7, but since tolerance is not observable in both societies, agent *i* copies agent *j*'s tags and adjusts her tolerance level by one unit toward agent *j*'s. Imitating tags and tolerance from successful neighbors may be disrupted by 'learning error,' which is equivalent to the concept of mutation in genetic inheritance. Either way this stochastic error is implemented into all models with probability μ_1, in which an ego's tags and tolerance is replaced by a new set of traits that are randomly generated.

In Chapter 7, there are a number of related and contingent processes in the co-evolution of agent's tags, tolerance, and network ties. After each round of interactions with all neighbors and a payoff calculation, an agent either updates its cultural traits toward those of a randomly chosen neighbor, if that neighbor is more successful ('payoff-based imitation'); or, it breaks a tie and makes a new one ('homophily-based partner selection'), if a new partner is available. Each of these processes is subject to stochastic errors in learning and partner change ('cultural perturbation' and 'network perturbation'). The likelihood of learning versus tie rewiring depends on network plasticity ('cultural evolution or network evolution'). The whole process (4-2 in Table 3.2) is summarized in Table 3.3.

Table 3.3. Pseudo-codes of Evolution of Culture and of Networks

```
For each agent,
    Given a random integer $r \in \{0, 1, \ldots, 99\}$ and a random real number $m \in [0, 1)$,
    If $r >$ network plasticity $p$ then
        If $\mu_1 > m$ then
            If $N_i \neq \varnothing$ then
                Error in imitation
            End
        Else
            If $N_i \neq \varnothing$ then
                Payoff-based imitation
            End
        End
    Else
        If $\mu_2 > m$ then
            If $N_i \neq \varnothing$ then
                Error in tie-rewiring (Random tie breaking and random tie making)
            Else
                Error in tie-rewiring ((Random tie making)
            End
        Else
            If $N_i \neq \varnothing$ then
                Homophily-based Partner Selection (Making new ties to in-group)
            Else
                Homophily-based Partner Selection
                (Breaking ties with out-group and making new ties to in-group)
            End
        End
    End
End
```

Note: $\mu_2 = 0$ in static networks where 1% of agents err in learning at $\mu_1 = .01$. The conditional probability of cultural perturbation, however, decreases as network plasticity increases. A single $\mu = .01$ in the main experiments thus implies that one agent is exposed to cultural perturbation while another agent errs in partner change. For example, $\mu_1 = 1/10$ and $\mu_2 = 1/90$ at network plasticity $p = 10(\%)$, but $\mu_1 = 1/50$ and $\mu_2 = 1/50$ at $p = 50(\%)$. In this way, the strengths of two types of randomness are equal regardless of the level of network plasticity in the main experiments.

Homophily-based Partner Selection. Given a randomly selected agent $j \in N_\mathrm{i}$, if $HD_{ij} \geq T_i$, an ego i can break ties with j unilaterally only if ego finds a new partner[9]. New partners are selected with a closure bias q(%)[10]. If closure is selected, an agent r is randomly chosen given that $r \in N_\mathrm{j}$ and $j \in N_\mathrm{i}$ $(r \neq i)$. If and only if $HD_{ir} < T_i$ and $HD_{ir} < T_r$, ego i makes a new tie to r. If a partner is selected without the closure bias – with $(100 - q)$(%), agent h $(h \neq i)$ is randomly selected from those not in the two-step neighborhood. A new tie can be made only if $HD_{ih} < T_i$ and $HD_{ih} < T_h$. A special rule is needed for agents that become isolated. Isolate i is assumed to make a new link to agent $z \in N$ $(z \neq i)$ as long as $HD_{iz} < T_i$ and $HD_{iz} < T_z$.

With probability μ_2, errors may occur in homophily-based partner selection, which is called 'network perturbation.' Ego breaks one tie to a randomly selected neighbor. Ego then makes a new tie to a player $y \in N$ $(y \neq i)$ without mutual consent. Isolates subject to perturbed partner selection create a new tie to a partner randomly drawn from the entire population. The probability of network perturbation is 0 in all models of cooperation on fixed networks in Chapter 4, 5, and 6.

Cultural Evolution or Network Evolution. A parameter of network plasticity p is introduced to reflect the ratio of a time scale of agent's switching interaction partners (τ_a) to another time scale of agent learning from neighbors (τ_e)[11].

$p = \dfrac{\tau_a}{\tau_a + \tau_e} \times 100(\%)$. Plasticity ($p$) controls the relative likelihood of homophily-based partner selection versus payoff-based learning. For examples, the network topology is static (i.e. frozen networks) at $p = 0$ like all models in Chapter 4, 5, and 6.

At $p = 100$, network is updated after playing the game without learning from neighbors. At $p = 50$, culture and network evolve at the same rate (on the average across many trials).

Chapter 4: Characteristics of Tag-based Parochial Cooperation

4.1. Problem Statement

The findings in tag-based cooperative societies (Riolo et al., 2001) are discouraging – global cooperation can be maintained only with the loss of diversity and with the growth of intolerance. However, agents in Riolo et al.'s model interact with others randomly chosen from the entire population (i.e. global mating or playing) and parents leave offspring globally (i.e. no 'viscosity'). The first question in this chapter is whether those disturbing results still hold true in our structured population where agents play the Prisoner's Dilemma game with local partners (i.e. local mating or playing) and they leave offspring in the neighborhood (i.e. 'viscosity'): what are the characteristic levels of tag diversity and tolerance in emergent cooperative societies at equilibrium?; whether or not emergent cooperative societies consist of multiple parochial clusters with different markers as tags increasingly act as self-enforcing stereotypes?; and what their spatial configuration looks like at equilibrium?

What Riolo et al. (2001) can explore are small-scale fluctuations between cooperative societies, as is shown in Figure 2.2. This is due to the fact that agents with the minimum tolerance in their model still cooperate with identical partners – there are no unconditional defectors (who indiscriminately refuse to help others) in the population. Even in structured populations, altruists alone cannot defeat unconditional defectors when the cost of helping and the average number of ties are relatively high, as is verified by Ohtsuki et al. (2006). The second question is thus whether the cognitive ability to distinguish between in-group members and 'others' promotes cooperation in competition with defectors in our structured populations under those unfavorable conditions for cooperation.

There is no possibility in Riolo et al.'s model that mutant unconditional defectors may cause a great transformation of cooperative societies into betrayal ones. It is expected that even the strongest parochial cooperators in their model would have been vulnerable to mutant defectors with exactly the same tags because they want to help partners with the identical tag list. Generally speaking, tag-based cooperative societies may disintegrate in the presence of mutants who are predisposed to defect while displaying tolerably similar tags.

This is consistent with the conclusions from some other studies on the long-term dynamics of cue-based cooperation – its high susceptibility to free-riders displaying similar cues: cooperators can share the disproportionate benefits of cooperation through signaling among them; however, it fails to continue immediately after the emergence of defectors who mimic the communication tokens or the linguistic markers shared by (conditional) cooperators (Miller, Butts, and Rode, 2002; Nettle and Dunbar, 1997). In other words, discriminating cooperators identify each other by 'secret handshaking' (Robson, 1990), but once mutant defectors (or immigrant exploiters) uncover cues among those cooperators, cue-based cooperation dissolves as ‘secret handshaking’ loses its values. The last question in this chapter is, therefore, how evolutionarily stable tag-based parochial cooperation can be under mutation in our structured populations.

4.2. Experimental Design

Main Experiments

We examine the likelihood that cooperation survives, and the average tolerance and the average of social distances agents perceive toward neighbors at cooperative equilibrium (not necessarily at the state of universal cooperation), under varying conditions of the benefit-to-cost ratio (b/c) and the tag length (L) in the absence of mutation (Table 4.1). For the baseline model (M1) in which tags are completely mutable, each experiment is run until societies reach either universal cooperation or universal defection. Otherwise, it is run for 1,000 time steps. 100 replications are done for each condition.

Table 4.1. Parameter Setting of Main Experiments on Model 1 ($\mu = .00$).

Parameters	Values or Ranges
Number of agents	100
Interaction space	Torus
Number of adjacent neighbors	8 (Moore)
Benefit-to-cost ratio	2, 4, 6, 8, 10
Tag length	0, 2, 4, 6, 8, 10
Mutation rate	0
Condition for cooperation	$\lvert t_A - t_B \rvert < T_A$
Reproduction rules	Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies both her tags and tolerance

Supplementary Experiments: Sensitivity Tests of Model 1

One might ask whether the initial proportion of unconditional defectors ($T = 0$) influences the likelihood of the survival of cooperation and universal cooperation. For example, the initial proportion of agents with $T = 0$ is $1/(L + 2) = 1/2$ given $L = 0$, whereas 1/12 at $L = 10$. Recall that agents with $T \geq 1$ cooperate toward identical partners in our model. It is, therefore, reasonable to suspect that the longer the tag length L and the higher proportion of agents with $T \geq 1$ from the beginning, it is more likely that cooperation can survive and societies can achieve universal cooperation.

Table 4.2. Parameter Setting for Sensitivity Test 1 of Model 1

Parameters	Values or Ranges
Number of agents	100
Interaction space	Torus
Number of adjacent neighbors	8 (Moore)
Benefit-to-cost ratio	4
Tag length	4
Initial number of unconditional defectors	17 to 33 in increments of 1
Mutation rate	0
Condition for cooperation	$\mid t_A - t_B \mid < T_A$
Reproduction rules	Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies both her tags and tolerance

There are two ways of testing the sensitivity of the results about the likelihood of the survival of cooperation and universal cooperation. For the first supplementary experiment (SE 1) in Table 4.2, we begin with the condition of $b/c = 4$ and $L = 4$ since intermediate values of the b/c ratio and the tag length are used for the main experiments in Chapter 6 and Chapter 7. Under this condition, the number of unconditional defectors at the beginning is approximately 16.7 = (1/6)(100). We examine whether there are significant differences in the average likelihood across varying numbers of defectors at the initial stage from 17 to 33 in increments of 1. Once the number of unconditional defectors is set, agents with $T = 1$ through $T = 5$ are uniformly distributed. 50 independent replications are done for each condition. Each experiment is run until societies reach either universal cooperation or universal defection. Otherwise, it continues until 1,000 time steps.

Table 4.3. Parameter Setting for Sensitivity Test 2 of Model 1

Parameters	Values or Ranges
Number of agents	100
Interaction space	Torus
Number of adjacent neighbors	8 (Moore)
Benefit-to-cost ratio	4
Tag length	2, 6, 10
Initial number of unconditional defectors	25 (on average)
Initial number of Tolerance = 1, 2, 3	25 for each (on average)
Mutation rate	0
Condition for cooperation	$\mid t_A - t_B \mid < T_A$
Reproduction rules	Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies both her tags and tolerance

Another sensitivity test (*SE 2*) should be done in order to check whether or not it is the tag length that affects the likelihoods of the survival of cooperation and universal cooperation (Table 4.3). It should be noticed that the numbers of unconditional defectors and the rest ($T = 1$ from $T = L + 1$) at the beginning vary according to the tag length. Since we want to identify the pure effect of the tag length, the initial distribution of the experimental population should be controlled. In this sensitivity test, we begin with $b/c = 4$ and $L = 2$ instead of $L = 4$ because cooperation always survives and emergent societies almost always arrive at universal cooperation when $L \geq 4$ as in Table 4.4. Given $L = 2$, the maximum tolerance is 3 (= $L + 1$). Therefore, there are four different groups ($T = 0$ through $T =3$) in the population at the beginning. Each group is always composed of 25 (= 100/4) agents on average with the same level of tolerance. Of course, the number of indiscriminate defectors at the initial stage is controlled. The population distribution at the initial stage is determined by a single condition ($L = 2$). But, we manipulate the experiment by allowing agents to have different lengths of tag ($L = 2$, 6, and 10 in increments of 4) before playing the game in order to examine the effect of fine-grained partner identification (with longer tag strings) on both likelihoods. 100 independent replications are executed at each of three conditions, and we employ the same stop conditions used in *SE 1*.

4.3. Results

Main Experiments

Our model at $L = 0$ is equivalent to the classical model of the evolutionary Prisoner's Dilemma game with network reciprocity. Since agents do not have tags, they cannot distinguish 'us' from 'them.' As a result, the population is purely composed of those who always help neighbors and those who always decline to help neighbors. Under this condition, there exist only three possible states in the long run. The equilibrium population consists of defectors (the 'bad' guys), altruists (the 'good' guys), or both. Either altruists alone or both altruists and defectors constitute emergent cooperative societies. Also, emergent societies are always culturally homogeneous, either cooperative or betrayal.

Table 4.4. Likelihood of Survival of Cooperation and Universal Cooperation in Model 1

	b/c				
L	2	4	6	8	10
0	0	0	0	0	43 (0)
2	23 (22)	56 (50)	73 (63)	62 (50)	88 (46)
4	100 (89)	100 (81)	98 (85)	96 (81)	98 (70)
6	100 (81)	100 (80)	100 (91)	98 (82)	100 (87)
8	100 (87)	100 (84)	100 (87)	100 (90)	100 (79)
10	100 (87)	100 (95)	100 (89)	100 (84)	100 (86)

Note: The number at each cell represents the possibility that societies reach the cooperative equilibrium, that is, how many times out of 100 trials cooperators ($T \geq 1$) survive. For example, when $b/c = 2$ and $L = 2$, the chance that cooperation survives is 23%. The number in parentheses at each cell indicates the probability of universal cooperation. It is 22% at $b/c = 2$ and $L = 2$.

Table 4.4 shows that network reciprocity alone without 'tagging' is not sufficient for the institutionalization of cooperation when $b/c < 8$. Recall that we use the Moore neighborhood. The results at $L = 0$ indicate that unconditional cooperators can survive in the presence of defectors – in structured populations where agents interact with neighbors and then leave offspring in proportion to fitness in the neighborhood – only when the benefit-to-cost ratio in the Prisoner's Dilemma game is higher than the average number of interaction partners. This is similar to the finding by Ohtsuki et al. (2006)**[1]**.

Tag-based local interaction and the local dispersion of offspring ('viscosity') significantly increase the likelihood of the survival of cooperation. When agents use only a few dimensions ($L = 2$) to distinguish 'us' from 'them,' cooperation is more likely to evolve even at the benefit-to-cost ratios lower than the average number of neighbors. The likelihood that cooperators ($T \geq 1$) survive also increases as the relative benefit of cooperation increases. If agents make more fine-grained distinctions with four or more dimensions of tags, the likelihood increases up to about 90% within the whole range of the *b/c* ratios under experiment.

When conditional strategies on the basis of similarity are available to agents, societies in the long run reach either of the two absorbing states. One is that the population purely consists of defectors. The level of global cooperation is, therefore, 0. The degree of homogeneity in the population at this state ranges from 0 (completely heterogeneous) to 1 (completely homogeneous). The cooperative equilibrium is the other, either universal cooperation or not.

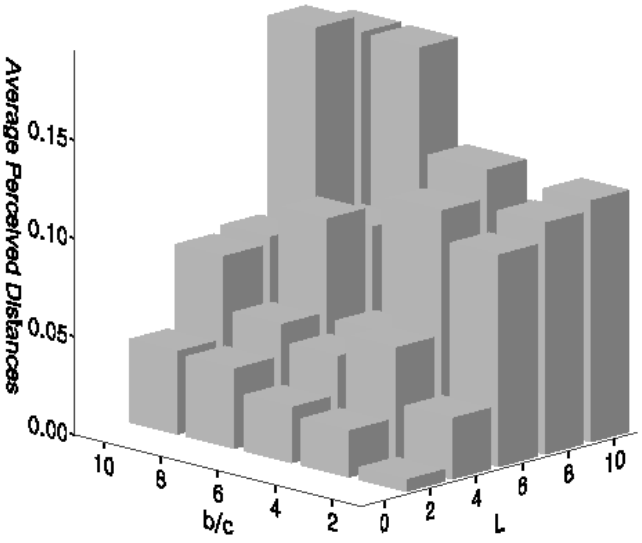


Figure 4.1. Average Perceived Distance at Cooperative Equilibrium in Model 1.
Note: $\mu = .00$.

We measure the average of the mean of social distances each agent perceive toward all her neighbors across population defined by $\frac{1}{N}(\sum_{i}^{N}(\frac{1}{k}\sum_{j}^{k}HD_{ij}))$ at the cooperative equilibrium. Here, N denotes the population size, and k is the number of neighbors agent i has. At $L = 0$, the population is always homogeneous: agents do not feel social distances toward neighbors. The overall trend at $L \neq 0$ is that tag diversity is seriously eroded in emergent cooperative societies as more successful agents asexually leave more offspring with their cultural traits. Nonetheless, Figure 4.1 also indicates that emergent societies are more (less) likely to become dominated by a single group of agents with exactly the same markers as the tag length become shorter (longer), the benefit-to-cost ratio becomes lower (higher), or both.

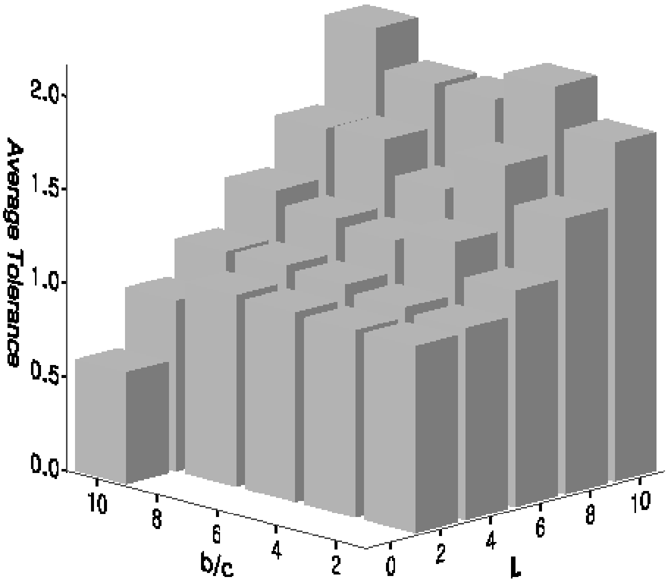


Figure 4.2. Average Tolerance at Cooperative Equilibrium in Model 1.
Note: $\mu = .00$.

In the absence of markers ($L = 0$), the population can consist of altruists with the maximum tolerance ($T = 1$), defectors with the minimum tolerance ($T = 0$), or both. The average tolerance around 0.5 at $L = 0$ in Figure 4.2 points to the polymorphic state in which altruists co-exist with defectors at equilibrium when $b/c = 10$. In the presence of conditional strategies ($L \neq 0$), less tolerant agents have advantages over not only more tolerant agents but also defectors. When agents have relatively short lengths of tags ($L = 2$), the most parochial cooperators ($T = 1$) increasingly dominate the population. Meanwhile, not only defectors but also more tolerant agents ($T = 2$) and altruists ($T = 3$) weed out under the force of selection. The significant erosion of tolerance in emergent cooperative societies is still the case when agents have longer tags. Nevertheless, we notice that as agents have longer lengths of markers and cooperation is less costly, the more likely it is that more tolerant agents ($T \geq 2$)

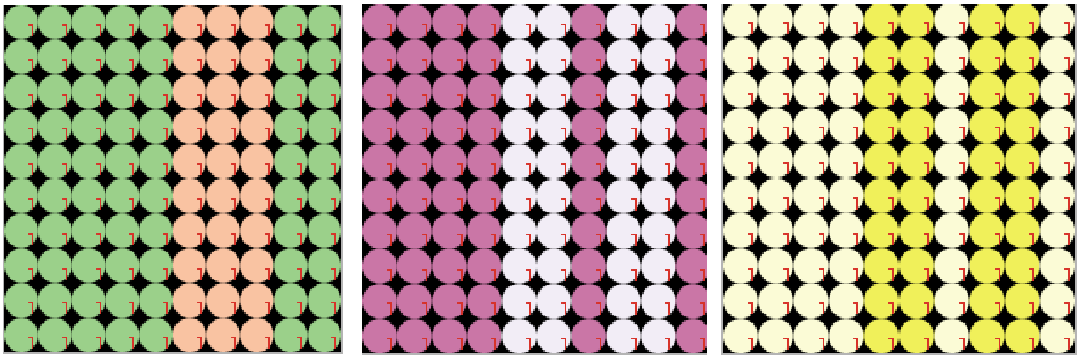
maintain emergent cooperative regimes together with the most parochial cooperators. Accordingly, it is less likely that tag diversity completely disappears as is observed from Figure 4.1.

The spatial distribution of tags and tolerance in emergent cooperative societies at equilibrium is another question related to their characteristic levels we have examined so far. We are particularly concerned with how it sometimes happens that emergent societies still reach high levels of global cooperation without the complete loss of tolerance or tag diversity, or without both. In other words, what kind of spatial topology makes it possible that tagging serves as self-enforcing stereotyping to sustain the co-existence of within-group parochial cooperation and between-group non-cooperation at the global level in spite of assimilative influence at the local level?

The archetypal case of the cooperative equilibrium is that the most discriminating cooperators ($T = 1$) dominate the population. Either defectors or more tolerant agents including altruists cannot survive. Recall that $T = 1$ is the minimum level for cooperation because agents with $T = 1$ cooperate only toward neighbors with identical phenotypes, and otherwise refuse to do. Most of time, societies based on the strongest parochialism reach universal cooperation in completely homogeneous populations. But, it occasionally happens that tag diversity persists in cooperative societies purely composed of agents who cooperate only toward identical neighbors. Some other times, less parochial agents (either with or without the most discriminating cooperators) govern emergent societies attaining universal cooperation.

Figure 4.3. Aligned Tribes under a Single Level of Tolerance in Model 1

(a) Distribution of Markers (b) Perceived Distances (c) Distribution of Strategies

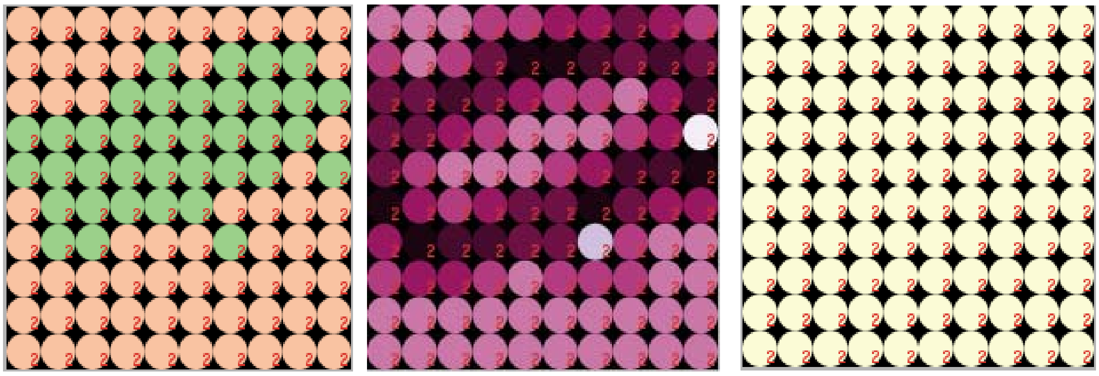


Note: The number colored red in each agent indicates her tolerance level. $T = 1$ for all. $b/c = 4$, $L = 4$, and $\mu = .00$.

Figure 4.3 is one of the examples. Given an L-dimensional binary tag space ($L = 4$), the number of all possible sets of markers is $16 = 2^4$. We observe the emergence of two communities (tribes) with different sets of markers salient. All members have [0 0 0 1] in one community (green), whereas [1 0 0 0] in the other (pink) in the panel (a). The spatial distribution of social distances agents feel toward immediate neighbors is shown in the panel (b). As in the panel (c), all members in the population are those who cooperate only with identical neighbors. However, agents in group boundaries help their group members while refusing to cooperate toward neighbors in the other community. In sum, Figure 4.3 indicates the case that emerging cooperative clusters are structured in segregated enclaves with persistent cultural diversity.

Figure 4.4. Nonaligned Tribes under a Single Level of Tolerance in Model 1

(a) Distribution of Markers (b) Perceived Distances (c) Distribution of Strategies

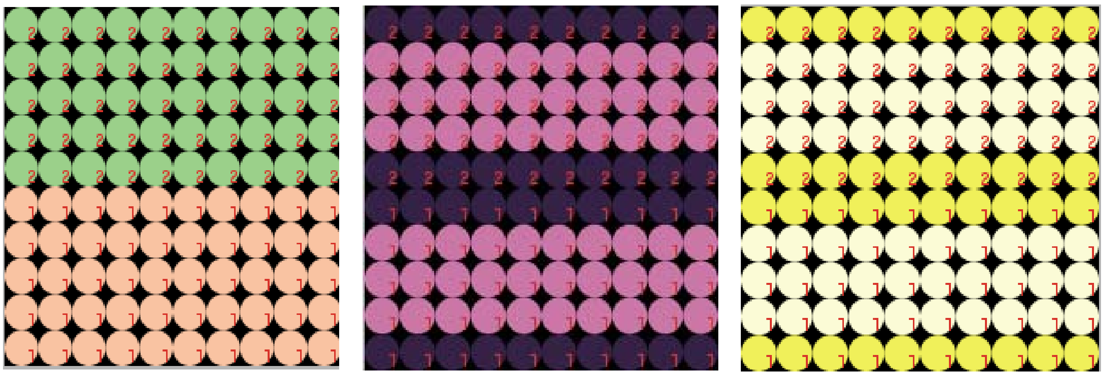


Note: The number colored red in each agent indicates her tolerance level. *T* = 2. *b/c* = 4, *L* = 4, and μ = .00.

Another outcome is shown in Figure 4.4 when controlling for the b/c ratio and the tag length. It is less likely to happen, but the population is sometimes occupied by a single group with a higher level of tolerance ($T \geq 2$). Recall that more tolerant agents perceive a broader range of neighbors as in-group. In other words, it is more likely that emergent societies consisting of less parochial guys maintain tag diversity. In Figure 4.4, we observe that tag diversity remains in spite of universal cooperation in an emergent cooperative society purely consisting of agents with $T = 2$. Generally speaking, if tolerance becomes homogenized at $T \geq 2$, then cultural groups with different markers can emerge which are not necessarily parallel to each other.

Figure 4.5. Aligned Tribes under Two Levels of Tolerance in Model 1

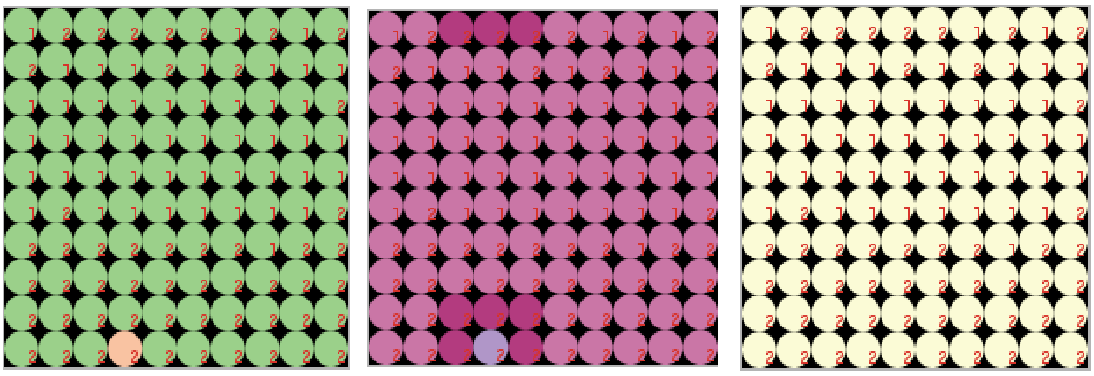
(a) Distribution of Markers (b) Perceived Distances (c) Distribution of Strategies



Note: The number colored red in each agent indicates her tolerance level. $T = 1$ and $T = 2$. $b/c = 4$, $L = 4$, and $\mu = .00$.

Figure 4.6. Nonaligned Tribes under Two Levels of Tolerance in Model 1

(a) Distribution of Markers (b) Perceived Distances (c) Distribution of Strategies



Note: The number colored red in each agent indicates her tolerance level. $T = 1$ and $T = 2$. $b/c = 4$, $L = 4$, and $\mu = .00$.

We notice from Figure 4.3 that high levels of global cooperation can be sometimes maintained in populations structured by tribes with different markers facing each other in parallel. Figure 4.4 indicates that universal cooperation does not necessitate the complete loss of diversity if agents in populations are less parochial. However, both emergent societies are composed of a single cooperative phenotype. Yet another pattern is the emergence of cooperative societies in which agents with different levels of tolerance co-exist (cf. ‘polymorphism’ in evolutionary biology).

Figure 4.5 shows a typical case that there can be two or more groups of agents with different strengths of parochialism in emergent cooperative societies: within-group cooperation and between-group non-cooperation co-exists (as in the society in Figure 4.3), but more tolerant agents and less tolerance ones together establish universal cooperation even though the population is not completely homogeneous. The society in Figure 4.6 represents another example of polymorphism: only one agent has a different list of tags, but tag diversity does not completely disappear even in the population reaching universal cooperation because she is protected by more tolerant members. However, this pattern of enclave formation is very rarely found.

In sum, societies consisting of altruists, defectors, and parochial agents at the beginning become eventually either cooperative or betrayal in the absence of mutation. We do not find any case of the dynamic (polymorphic) equilibrium in which defectors co-exist with cooperative agents at $L > 0$. This case occurs only at $L = 0$. In contrast to Riolo et al. (2001), we discover the possibilities, albeit small, of the evolution of multiple tribes displaying different tags with sustainable boundaries, either two or more cooperative clusters with different levels of tolerance or a single cooperative cluster. They are realized only if there is no further stratification in fitness measured by material payoff. Not surprisingly, parochial cooperation stops at group boundaries, but the level of global cooperation can sometimes be highest (Figure 4.4 and 4.6) or still relatively high (Figure 4.3 and 4.5). Either way emergent cooperative societies retain some degrees of tag diversity unless the most discriminating agents dominate the population to build universal cooperation without rivals.

Supplementary Experiments

As is discussed in Section 4.2, the effects of tagging on the likelihoods of the survival of cooperation and universal cooperation in Table 4.4 might be spurious. Both likelihoods might be rather affected by the initial proportion of defectors contingent on the tag length. However, we confirm that cooperation is more likely to survive and also societies are more likely to reach universal cooperation as agents make distinctions with more tags, given the results from the following two supplementary experiments.

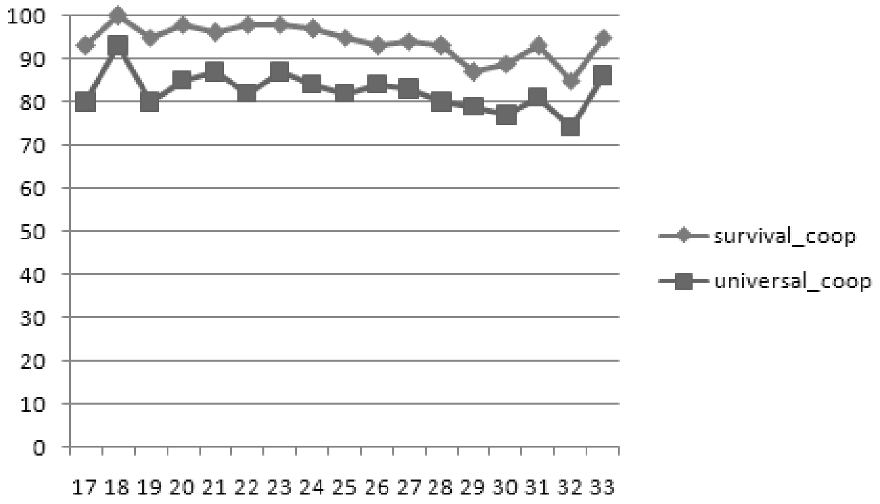


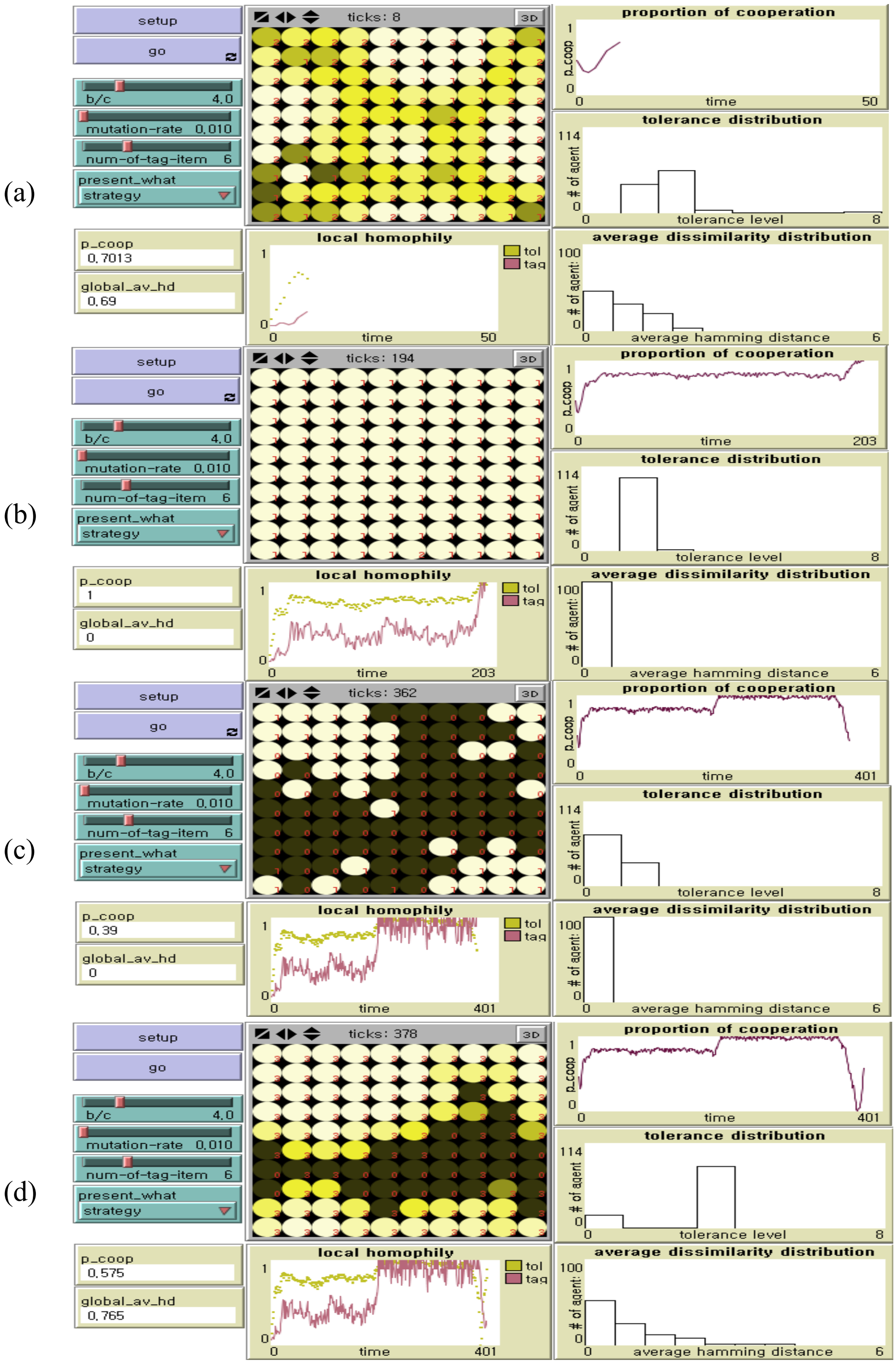
Figure 4.7. Summary of Sensitivity Test 1 Results of Model 1.

Note: *b/c* = 4, *L* = 4, and μ = .00. The numbers of defectors at the initial stage are displayed at the X-axis.

We first test the sensitivity of the likelihoods of cooperation survival and universal cooperation to the initial proportion of defectors at *b/c* = 4 and *L* = 4 as is described in Table 4.2. Figure 4.7 shows the results. It turns out that both likelihoods (100 and 81, respectively, from Table 4.4) are sufficiently robust even when the initial percentage of defectors is almost double (33%) the average percentage of defectors in the main experiment (16.67%).

Another sensitivity test discussed in Table 4.3 is undertaken at the same level of *b/c* = 4 and *L* = 2. But, agents are allowed to have *L* = 2, 6, and 10 before playing the game in order to investigate the effects of making fine-grained distinction on both likelihoods. Notice that the initial percentage of unconditional defectors is constant at all three experimental conditions of this test (i.e. 25(=100/4), on average, determined by *L* = 2), but it is 12.5(=100/8) at *L* = 6 and 8.3(=~100/12) at *L* = 10 in Table 4.4. Out of 100 independent runs, the likelihoods of the survival of cooperation are 100% at *L* = 6 and *L* = 10. These are significantly higher than 56, the likelihood obtained at *L* = 2 in Table 4.4. We also have the significantly higher likelihoods of universal cooperation, 91% (*L* = 6) and 87% (*L* = 10) than 50% (*L* = 2).

Finally, we present here the dynamics of tag-based cooperation and its evolutionary stability in the presence of 1% mutation with a series of snapshots from (a) to (d) in Figure 4.8. At the beginning (a), an almost equal number of agents (100 / 8) have each level of tolerance, from 0 through 7, given the tag length *L* = 6. For the first few generations, there is a transient state in which within-group cooperation co-exists with between-group discrimination with a significant amount of tag diversity.



(a)
b/c 4.0
mutation-rate 0.010
num-of-tag-item 6
present_what strategy
p_coop 0.7013
global_av_hd 0.69

(b)
b/c 4.0
mutation-rate 0.010
num-of-tag-item 6
present_what strategy
p_coop 1
global_av_hd 0

(c)
b/c 4.0
mutation-rate 0.010
num-of-tag-item 6
present_what strategy
p_coop 0.39
global_av_hd 0

(d)
b/c 4.0
mutation-rate 0.010
num-of-tag-item 6
present_what strategy
p_coop 0.575
global_av_hd 0.765

Figure 4.8. Dynamics of Tag-based Cooperation in Model 1.

Note: $b/c = 4$, $L = 6$, and $\mu = .01$. The number colored red in each agent indicates her tolerance level. The brightness of each node is proportional to how many neighbors with whom she cooperates out of the total number of neighbors.

However, agents become less tolerant in increasingly homogeneous environments. In other words, dominant tribes displaying stronger parochialism emerge as the number of clusters with different tags decreases over time. The level of global cooperation goes up in spite of a continuous loss of the average tolerance because cooperation occurs among more homogeneous agents. Agents with $T = 2$ are dominant in the population in the panel (a) who cooperate toward not only identical neighbors but also very similar neighbors with the same tags except one dimension as their own. This is why although the emerging society reaches a high level of cooperation with a significant degree of tag diversity.

Existing cooperators are, however, vulnerable to agents with $T < 2$, either more discriminating guys or defectors. As mutants displaying stronger parochialism ($T = 1$) win against existing leaders ($T = 2$), a new tag cluster begins to replace the old one. Meanwhile, the society becomes much more homogenized. This is why the level of global cooperation can be restored to its previous one. Finally, the society based on the strongest parochialism arrives at the state of universal cooperation without any degree of tag diversity in the panel (b). In this way, our model shows small-scaled perturbations between cooperative regimes in Riolo et al. (2001).

Recall the major difference between our model and Riolo et al.'s: unconditional defectors ("the bad guys") are constantly generated through mutation. Even the new leaders with the strongest degree of parochialism fail to maintain their cooperative society in the face of mutant defectors who display exactly the same tags as their own in the panel (c). This invasion by indistinguishable mutant defectors followed by a downward spiral of cooperation is what Riolo et al. (2001) do not consider. In our model, there are not only minor shifts between cooperative regimes but also qualitative transitions from cooperative societies to betrayal societies.

Because defectors do not benefit from each other, cooperation can re-emerge locally once parochial agents happen to cluster together (‘network reciprocity’) in the panel (d). The emerging cooperative community now consists of moderate discriminators with $T = 3$. We can predict that although they temporarily cooperate with heterogeneous neighbors they will be disturbed by more parochial agents in the near future with a serious loss of cultural diversity. Otherwise, since they regard a broader range of neighbors as in-group, the society will be more quickly destroyed by identical mutant defectors or defectors with the same tags except either one or two dimensions.

Generally, parochial cooperators recognize each other by sending and receiving signals of trustworthiness. In our study, tags as observable markers play the same role in partner identification for discriminators. Once immigrant defectors mimic signaling among those discriminators, making distinctions between “us” and “them” no longer work. “Secret handshaking” loses its advantages: a self-enforcing belief is broken that helping similar partners produces a differential share of the benefits of cooperation. Parochial cooperators must establish new signals (Skyrms, 2004). In the long run, this competition leads to endless spirals of global cooperation and global betrayal without absorbing states in the presence of mutation (equivalent to agent’s error in imitating tags and tolerance of more successful neighbors).

4.4. Concluding Remarks

In this chapter, we first confirm that ‘network reciprocity’ can promote global cooperation when the benefit-to-cost ratio in the Prisoner’s Dilemma game is higher than the average number of local interaction partners. It is otherwise impossible for altruists (indiscriminate cooperators) to survive in the face of defectors even in structured populations.

The population at the beginning in tag-based societies consists of altruists (‘the good guys’ with the highest tolerance) who always help others, defectors (‘the bad guys’ with the lowest tolerance) who always refuse to help others, and egoists (‘the ethnocentric guys’ with intermediate tolerance) who can read observable tags to make a distinction between ‘us’ and ‘them.’ These discriminating guys help perceived similar others on the basis of the shared belief in in-group favoritism, but otherwise they refuse to help with a fear of being exploited by dissimilar others.

If agents cooperate only with in-group members, such parochial cooperation will stop at group boundaries. How is society-wide cooperation possible in a mixed population of altruists and ethnocentric egoists, then? Consistent with Riolo et al. (2001), we find that if agents leave offspring in their neighborhood in proportion to fitness, then the population becomes increasingly characterized by stronger ethnocentrism under selection pressure. In other words, agents in emergent societies become more parochial to adapt themselves to increasingly homogenized environments. Meanwhile, both “the bad guys” and “the good guys” are weeded out. Since less tolerant agents become more successful than more tolerant ones as tag diversity disappears, agents who cooperate only with identical others finally become dominant in emergent cooperative societies (cf. Macy and Skvoretz, 1998). In spite of a continuous erosion of tolerance, high levels of global cooperation can be maintained in highly homogeneous populations (e.g. ‘mechanical solidarity’ in a Durkheimian sense). We also observe emergent societies sometimes arrive at the equilibrium where within-group parochial cooperation evolves with between-group non-cooperation. In this case, tags act as self-enforcing stereotypes to make it difficult for tolerance to cross structurally segregated enclaves with different markers.

We find that even the strongest parochial cooperators are vulnerable to mutant defectors as long as they display exactly the same tags. Since conditional cooperators with lower degrees of parochialism perceive a broader range of neighbors as in-group, they are more likely to be disrupted by more heterogeneous mutant defectors (not necessarily with the identical tags). In this way, the stability of parochial cooperation depends on “labeling” (or “stereotyping”) under uncertainty – whether or not a shared belief continues that markers predict each other’s behavior, given that tolerance is not observable in tag-based societies. Once the shared belief is broken, there occurs a downward spiral of cooperation that leads to societies of mutual betrayal. While there are no mutual benefits for agents in betrayal societies, once mutant discriminators are clustered with each other to receive a differential share of the benefits of cooperation, they can establish new cooperative societies with new salient markers.

Our model discovers that the conditional cooperative strategy based on the strongest parochialism is ‘weakly Nash dominant’ since it wins against defectors and also it is always as good as any other cooperative strategies based on higher levels of tolerance. However, it cannot be an evolutionarily stable strategy in the presence of mutation. We show not only quantitative changes between one cooperative regime and another but also qualitative shifts back and forth between cooperative societies and betrayal societies in the face of indiscriminating free-riders. These endless cycles proceed along with ‘the tide of tolerance” (Sigmund and Nowak, 2001) and the formation and dissolution of tag clusters as tribes. The baseline model in this chapter demonstrates how tribes emerge as arbitrary markers at the beginning become salient over time through the reinforcement of the disproportionate benefits of parochialism, and also how they dissolve in the face of deviants displaying tolerably similar markers.

Chapter 5: Roles of Persistent Heterogeneity in Parochial Cooperation

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5.1. Problem Statement

We identified from the previous chapter the loss of diversity, the growth of intolerance, and the instability of cooperation on the basis of similarity against mutant defectors in societies, where agents have genetically inheritable tags and tolerance. Are there mechanisms that may enable tag-based societies to establish robust parochial cooperation without a great amount of erosion of tag diversity and tolerance in structured populations? There seem to be a couple of solutions.

First, very high rates of mutation in both tags and tolerance could supply enough tag heterogeneity to enable agents to continue to draw distinctions between 'us' and 'them.' Also, mutant discriminators would be more frequently generated to form cooperative clusters before cooperation is completely wiped out. As the amount of mutation increases, tag-based cooperation becomes more robust against the invasion by mutant defectors in terms of stability, but the level of global cooperation becomes low in terms of efficiency. High levels of mutation in genetic inheritance are equivalent to large amounts of mistakes in payoff-based imitation. Too high and arbitrary mutation rates (or learning errors) are not acceptable in genetic transmission (or cultural transmission).

Second, the population size is definitely a critical factor in the dynamics of tag-based parochial cooperation. In larger societies, either universal cooperation driven by the strongest parochial cooperators or universal defection by unconditional defectors is less likely to happen because local homogenization through limited dispersal of offspring in the neighborhood ('viscosity') could hardly overcome an increased amount of heterogeneity in tags and tolerance. There would remain a greater number of less parochial agents who accept a broader range of heterogeneous partners as in-group members. It is expected that increased path lengths in large-sized societies render tag-based cooperation more robust in terms of stability, but with a decrease in the level of global cooperation in terms of efficiency. This is why the present study does not intend to examine the dynamics of tag-based parochial cooperation in very large-sized populations.

In this chapter, we first consider recent studies suggesting another solution to stable tag-based cooperation: "tags should mutate faster than strategies" (Hales, 2004; Edmonds and Hales, 2005). In other words, cooperative tag groups need to spread by mutation of tags before free-riders (by mutation on strategies) invade the group. The intuition behind the idea of differential mutation rates of tags and tolerance is consonant with Labov's sociolinguistic study addressed by Nettle and Dunbar (1997). Labov (1972) demonstrates "not only that the adoption of linguistic variables correlates with membership of a social group but that when a group feels itself threatened by outsiders, it will increase its usage of the linguistic markers that make it distinctive, thus producing divergence over time" (Nettle and Dunbar, 1997: 94). We apply the idea in Hales (2004) and Edmonds and Hales (2005) to our model. The characteristics of emergent cooperative societies where tags mutate faster than tolerance will be discussed.

The current study stresses that existing models are basically concerned with genetic evolution of cooperation and assume tags are completely mutable so that indistinguishable mutant defector can be born through mutation. From the viewpoint of cultural transmission, the instability of tag-based cooperative societies is due to the fact that mistakes in learning cultural traits often produce agents who have a predisposition to defection and the similar (or exact) tag strings of existing cooperators. In other words, exploiters can mimic signals shared among existing cooperators without difficulty.

In one study on the co-evolution of cooperation and linguistic codes associated with group membership, Nettle and Dunbar (1997: 98) bring up more sociological concepts of cultural markers as simple identities: "the free-rider… could not possibly survive in populations where each local group had its own language or dialect. Each group would be able to tell by his speech that he was an outsider and where he came from. This is not to imply, of course, that social identity is an unchanging, clear-cut matter. In real life, it is always being renegotiated and redefined and loses or gains significance according to the situation at hand." In other words, some markers are less changeable (e.g. skin color), while others are more changeable (e.g. linguistic codes, attitudes, and opinions).

In this chapter, following Nettle and Dunbar's suggestion, we propose alternative models of cultural evolution of cooperation in which tags as cultural markers and simple identities have different levels of mutability (M2 and M3 in Table 3.2). Unlike the baseline model in which agents have genetically inheritable traits in the previous chapter (M1 in Table 3.2), each agent in alternative societies is assumed to have one core identity which is not subject to both learning and its error.

We compare the evolutionary dynamics of tag-based parochial cooperation across three models: the baseline model of genetic evolution of cooperation in the previous chapter (M1); a "caste" society where each agent has such a core identity at the same dimension, and therefore the society as a whole has one unchangeable dimension of culture (M2); and a "modern" society where each agent has such a core identity at different dimensions. The society as a whole does not have such an intransmissible cultural dimension (M3).

It is expected that complete homogenization of markers does not occur in both caste and modern societies due to those immicable markers. We first need to ask whether or not societies can evolve to retain more tolerance, and thereby achieve high levels of global cooperation. In addition to the efficiency of cooperation, we also seek to understand the roles of persistent tag heterogeneity in the resilience of emergent cooperative societies against the invasion by exploiters who fake signals of trustworthiness.

5.2. Experimental Design

Main Experiments

We undertake the same set of experiments done in the previous chapter (See Table 4.1) on Model 2 ("Caste Societies" in which each agent has one core identity at the same dimension) and Model 3 ("Modern Societies" in which each agent has one core identity at different dimensions). We intend to examine the possibility of the survival of cooperation, and the average tolerance and the averaged social distances each agent from her neighbors at cooperative equilibrium, under varying conditions of the benefit-to-cost ratio (*b/c*) and the tag length (*L*) in the absence of mutation (Table 5.1).

Table 5.1. Parameter Setting of Main Experiments on Model 2 and 3 (μ = .00).

Parameters	Values or Ranges
Number of agents	100
Interaction space	Torus
Number of adjacent neighbors	8 (Moore)
Benefit-to-cost ratio	2, 4, 6, 8, 10
Tag length	0, 2, 4, 6, 8, 10
Imitation error	0
Condition for cooperation	$\| t_A - t_B \| < T_A$
Payoff-based imitation rules	Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies both her tags and tolerance

The number of runs each experimental condition is 100. We allow each replication 1,000 time-steps, but terminate only if either universal cooperation or universal defection is reached. Note that we use the terms, “imitation error” and “payoff-based imitation rules” for Model 2 and Model 3 (Table 5.1) – where agents have tags and tolerance as culturally transmittable traits – instead of “mutation rate” and “reproduction rules” for Model 1 (Table 4.1) – where agents have them as genetically inheritable ones.

Table 5.2. Parameter Setting of Main Experiments on Model 2 and 3 ($\mu = .01$).

Parameters	Values or Ranges
Number of agents	100
Interaction space	Torus
Number of adjacent neighbors	8 (Moore)
Benefit-to-cost ratio	2, 4, 6
Tag length	5
Imitation error	.01
Condition for cooperation	
Payoff-based imitation rules	$\mid t_A - t_B \mid < T_A$ Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies both her tags and tolerance

We explored the dynamics of tag-based cooperation in the presence of mutation ($\mu = .01$) under a single experimental condition in the previous chapter (See Figure 4.8) when tags as genetic traits are completely mutable (Model 1). Now that we are concerned with cultural evolution of cooperation when tags as cultural markers are not necessarily mimicable, with special attention to possible differences between Model 2 and Model 3, we intend to investigate its dynamics under varying conditions of *b*/*c* ratios (2, 4, and 6) at the same rate of mutation as imitation error (μ = .01). An intermediate tag length $L = 5$ is chosen. Each replication has 5,000 steps, and 100 replications are executed for each experimental condition.

We basically measure the average tolerance and the average social distance at the global level, as in the previous chapter. In order to examine the spatial configuration of parochialism and tribes as tag clusters in our structured populations, we introduce two new measures at the local level: the degree of link homophily in tags and the degree of link homophily in tolerance. The minimum is 0 and the maximum is 1 for both measures. In Chapter 3, the neighborhood set N_i is defined as immediate partners who are directly connected with agent *i*. For agent i, a function $f_j = 1$ only if $\overline{HD}_{ij} = \overline{HD}_{jr}$, and otherwise $f_j = 0$, given that $j \in N_i$ and $r \in N_j$.

$\overline{HD}_{ij}$ denotes $\frac{1}{k}\sum_{j}^{k} HD_{ij}$. In the same way, $\overline{HD}_{jr}$ indicates $\frac{1}{k}\sum_{r}^{k} HD_{jr}$. *k* is the number of neighbors each agent *i* and *j* has. We can define the degree of link homophily in tags as $\frac{1}{N}(\sum_{i}^{N}(\frac{1}{k}\sum_{j}^{k} f_j))$. Here, *N* is the population size. Given another function $g_j = 1$ only when $T_i = T_j$, and otherwise $g_j = 0$, the degree of link homophily in tolerance can be measured by $\frac{1}{N}(\sum_{i}^{N}(\frac{1}{k}\sum_{j}^{k} g_j))$. Since unconditional defectors (T = 0) never cooperate toward neighbors, we exclude them from the population when calculating the degree of link homophily in tolerance.

Table 5.3. Parameter Setting of Model where 'Tags Mutate Faster than Tolerance'

Parameters	Values or Ranges
Number of agents	100
Interaction space	Torus
Number of adjacent neighbors	8 (Moore)
Benefit-to-cost ratio	2, 4, 6
Tag length	5
Mutation rate	.01
Mutation factor	5, 10, 15, 20, 25, 30
Condition for cooperation	$\mid t_A - t_B \mid < T_A$
Reproduction rules	Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies both her tags and tolerance

We test the proposition in Hales (2004) and Edmonds and Hales (2005) that "tag should mutate faster than tolerance" in terms of both efficiency and stability of parochial cooperation. There are two major parameters in their studies: the rate of tag mutation (mf); and the rate of strategy mutation (m). f denotes the mutation factor. For example, if f is 10, tags mutate 10 times faster than strategy (equivalent to tolerance in our study). We measure not only the average cooperation, the average tolerance, and the average perceived dissimilarity at the global level, but also the average link homophily in tolerance and the average link homophily in tags at the local level. 100 independent replications for each experimental group are done under varying conditions of the benefit-to-cost ratios and the mutation factor, given the same tag length ($L = 5$). Each replication has 5,000 steps.

5.3. Results

Main Experiments

In the absence of imitation errors, both caste and modern societies with one core marker per agent eventually arrive at either the equilibrium of defection or the equilibrium of cooperation. There are no cases where cooperators co-exist with defectors. Tag-based local interaction and local imitation significantly enhance the likelihood of the survival of cooperation and universal cooperation. All these results are congruent with those from the baseline model in the previous chapter.

Table 5.4. Likelihood of Survival of Cooperation and Universal Cooperation in Model 1, 2, and 3

	b/c				
L	2	4	6	8	10
0	0	0	0	0	43 (0)
2	23/0/0 (22/0/0)	56/18/39 (50/0/0)	73/62/92 (63/0/0)	62/83/98 (50/0/0)	88/96/98 (46/2/0)
4	100/94/99 (89/3/0)	100/89/100 (81/16/0)	98/93/100 (85/26/0)	96/97/100 (81/27/0)	98/100/100 (70/30/0)
6	100/95/100 (81/54/0)	100/100/100 (80/70/0)	100/100/100 (91/66/0)	98/100/100 (82/80/1)	100/100/100 (87/73/0)
8	100/98/100 (87/82/2)	100/100/100 (84/82/2)	100/100/100 (87/83/0)	100/100/100 (90/80/2)	100/100/100 (79/82/5)
10	100/100/100 (87/85/6)	100/100/100 (95/89/8)	100/100/100 (89/89/16)	100/100/100 (84/87/8)	100/100/100 (86/85/13)

Note: The numbers at each cell represent how many times out of 100 trials societies reach the cooperation equilibrium in the absence of mutation. For example, when $b/c = 4$ and $L = 4$, it is 100% in Model 1, 89% in Model 2, and 100% in Model 3. The numbers in parentheses at each cell indicate the likelihood of universal cooperation. At $b/c = 4$ and $L = 4$, it is 81% in Model 1, 16% in Model 2, and 0% in Model 3.

In all three societies, cooperation can survive even at the benefit-to-cost ratios lower than the average number of neighbors ($k = 8$) as long as agents use the very short tag strings ($L = 2$) for partner identification. At $L = 2$, there are, however, significant differences in the likelihood of its survival across three societies particularly when cooperation is more costly ($b/c = 2$ and $b/c = 4$). Note that the likelihood differences become smaller as cooperation is less costly and the complexity of culture increases. If the tag length is sufficiently long ($L \geq 4$) that agents can make more fine-grained distinctions between 'us' and 'them,' cooperative agents almost always win against defectors regardless of the typology of society.

We observe quite different patterns in the possibility of universal cooperation across three societies. Universal cooperation is less likely to happen in both caste and modern societies in which each agent has one immutable marker because they are resistant to cultural homogenization. This tendency is more remarkable when cooperation is relatively costly and the dimension of the tag space is comparatively small. However, as the number of available cultural markers increases, there are no significant differences in the likelihood of universal cooperation between societies with completely mutable tags (Model 1) and caste societies where each agent has one non-negotiable identity at the same dimension (Model 2). Universal cooperation is much less likely to happen in modern societies where such core identities are distributed across different dimensions than in caste societies with the same number of cultural markers. The disparities between both societies do not decrease even if the tag space size increases.

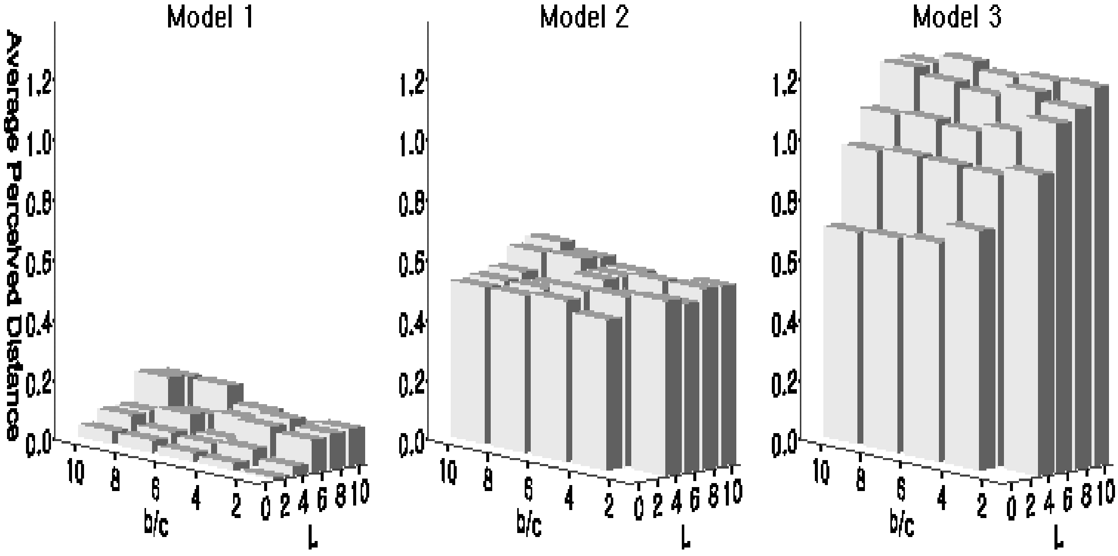


Figure 5.1 Average Perceived Distance at Cooperative Equilibrium in Model 1, 2 and 3

Table 5.5. ANOVA Test on Average Perceived Distance across Model 1, 2, and 3

L	Model 1	Model 2	Model 3	Post-hoc Test (Scheffé)
4	.06 (.134)	.55 (.122)	.98 (.118)	All pairs **
6	.10 (.192)	.56 (.145)	1.10 (.177)	All pairs **
8	.13 (.249)	.60 (.232)	1.21 (.256)	All pairs **
10	.14 (.299)	.60 (.235)	1.25 (.314)	All pairs **

Note: * $p < .05$ ** $p < .01$ (Two-tailed tests). The number in each cell denotes the average. The number in each parenthesis indicates the standard deviation.

High levels of cooperation necessitate huge losses of tag diversity in societies where tags as genetic inheritable traits are completely mutable (Model 1). The degree of tag diversity, in spite of moderately high levels of cooperation, is much higher in both caste and modern societies because one marker per agent which is immutable in the process of cultural transmission increases heterogeneity (Figure 5.1). When holding the tag length constant, Model 3 ranks highest, Model 2 second highest, and Model 1 lowest in the average perceived dissimilarity. The differences between any two of them are statistically significant (Table 5.5).

We notice that the average perceived social distance at the equilibrium of cooperation remains almost constant across varying lengths of tag strings in Model 2 (and Model 1), whereas it increases as the tag space dimension becomes larger in Model 3. In other words, although payoff-based imitation results in assimilative influence, agents in modern societies continue to look at each other from some distances without losing the average degree of cultural heterogeneity at the beginning.

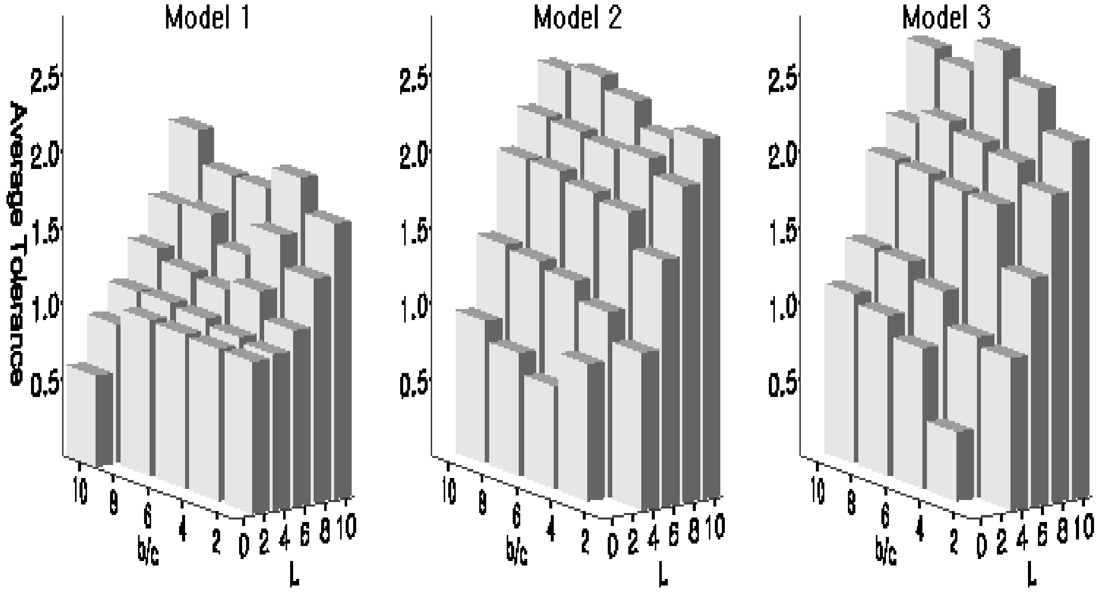


Figure 5.2. Average Tolerance at Cooperative Equilibrium in Model 1, 2, and 3.

Table 5.6. ANOVA Test on Average Tolerance across Model 1, 2, and 3

L	Baseline Model	Model 1	Model 2	Post-hoc Test (Scheffé)
4	1.08 (.226)	1.32 (.453)	1.22 (.381)	All pairs **
6	1.28 (.457)	1.87 (.411)	1.84 (.367)	Model 1 and Model 2 ** Model 1 and Model 3 **
8	1.58 (.694)	2.16 (.405)	2.16 (.419)	Model 1 and Model 2 ** Model 1 and Model 3 **
10	1.94 (.904)	2.42 (.604)	2.59 (.549)	All pairs **

Note: * $p < .05$ ** $p < .01$ (Two-tailed tests). The number in each cell denotes the average. The number in each parenthesis indicates the standard deviation.

Figure 5.2 shows no differences in the average tolerance at the equilibrium of cooperation across three societies when the tag space is not much differentiated ($L = 2$). First, the most discriminating cooperative strategy ($T = 1$) is weakly Nash dominant. Second, as long as the tag space size is very small, both caste and modern societies also rapidly lose tolerance despite the fact that they retain higher degrees of cultural heterogeneity than societies with completely mutable tags as in Figure 5.1: at $L = 2$, the average tolerance (and its standard deviation) is .54 (.078) in Model 2, .71 (.051) in Model 3, and .03 (.082) in Model 1.

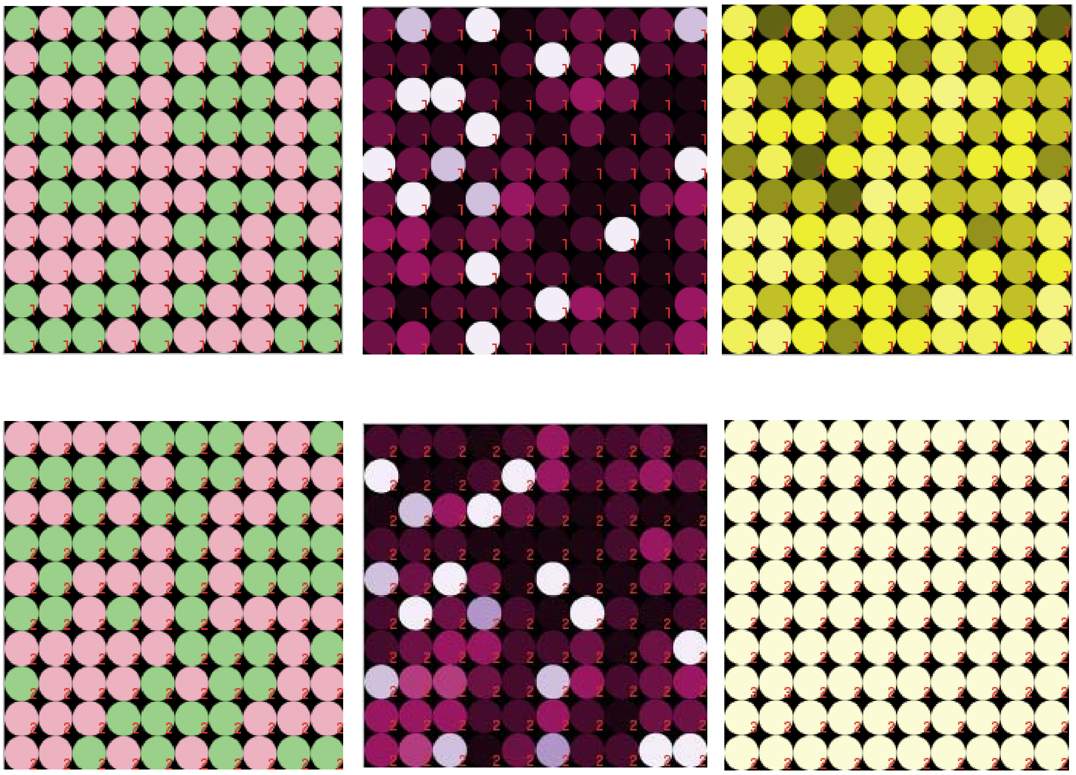
However, societies do not necessarily grow into a fully blown parochialism as long as there remain sufficient amounts of heterogeneity for partner identification. Figure 5.2 indicates that both caste and modern societies with one immutable marker tend to preserve more tolerance as they becomes less homogenized. At $L \geq 4$, the average tolerance in those societies at the cooperative equilibrium is significantly higher than the average in societies with genetically inheritable tags, according to the ANOVA test in Table 5.6. We also notice that as the tag space becomes larger, agents in modern societies tend to have higher levels of tolerance than those in caste societies.

In the previous chapter, we observed that emergent cooperative societies with completely mutable tags are extremely parochial and highly homogeneous. Under the strong force of homogenization, tags rarely act as self-enforcing markers enough to stabilize the segregation of emerging enclaves. Given increased cultural heterogeneity in caste and modern societies with one immutable marker per agent, how differently is parochialism spatially distributed? And, how are "social circles" (equivalent to tribes in Model 1) linked to each other in emergent societies?

The upper panel of Figure 5.3 represents a typical example of emerging social circles in caste societies. The society in this figure purely consists of agents displaying the strongest parochialism, but it reaches an intermediate equilibrium level of global cooperation (.485) due to increased cultural heterogeneity (the average perceived social distance is .515). All members have [1 0 0 0] in one cultural group colored green, while [0 0 0 0] in the other colored pink. In this way, universal cooperation with the complete loss of tag diversity (i.e. all agents have $T = 1$) rarely happen in caste societies when the tag length is relatively short (e.g. 25% of tags out of the total (1 or 0 in the first dimension) are immutable at $L = 4$ in Figure 5.3). The emergence of multiple groups much more frequently occurs in Model 2 than in Model 1. Also, two or three tribes with different tags are aligned along straight lines with their group boundaries preserved in Model 1 (See Figure 4.3), whereas the symmetric spatial alignments of tag clusters and strategies are not required in Model 2 in spite of synchronous updating.

Figure 5.3. Nonaligned Social Circles under a Single Level of Tolerance in Model 2

(a) Distribution of Markers (b) Perceived Distances (c) Distribution of Strategies



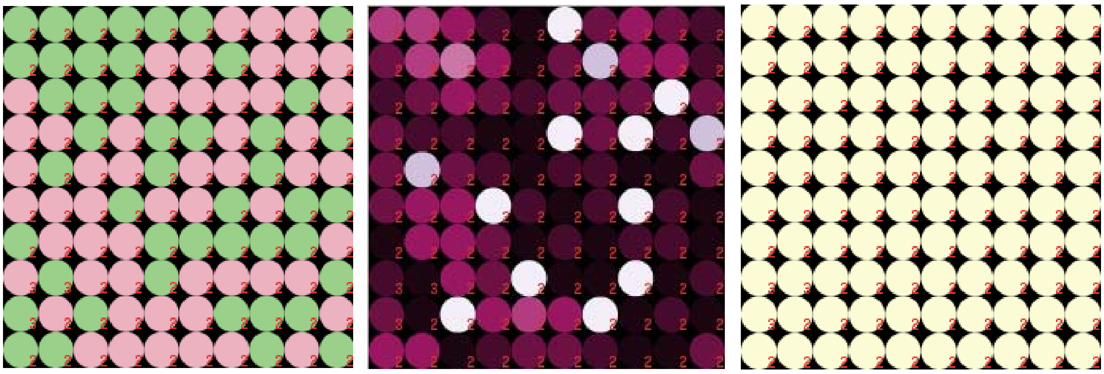
Note: The number colored red in each agent indicates her tolerance level. $b/c = 4$, $L = 4$, and $\mu = .00$. $T = 1$ for all agents (Upper) and $T = 2$ for all (Lower).

The lower panel of Figure 5.3 presents another case of cooperative caste societies divided into multiple social circles. The *b/c* ratio and the tag length are controlled. As is the same with the upper panel, the population is composed of two cultural groups: one with [0 0 1 1] (Green) and the other with [1 0 1 1] (Pink).

Cultural markers in all other dimensions are converged except those in the first dimension. However, the level of global cooperation at equilibrium is 1 because agents are more tolerant of diversity (*T* =2 for all agents). This pattern of the emergence of multiple groups is similar to the case in Figure 4.4, but it is more likely to happen in caste societies. More importantly, social circles in Model 2 are not necessarily highly segregated in contrast to tribes in Figure 4.4.

Figure 5.4. Nonaligned Social Circles under Two Levels of Tolerance in Model 2

(a) Distribution of Markers (b) Perceived Distances (c) Distribution of Strategies

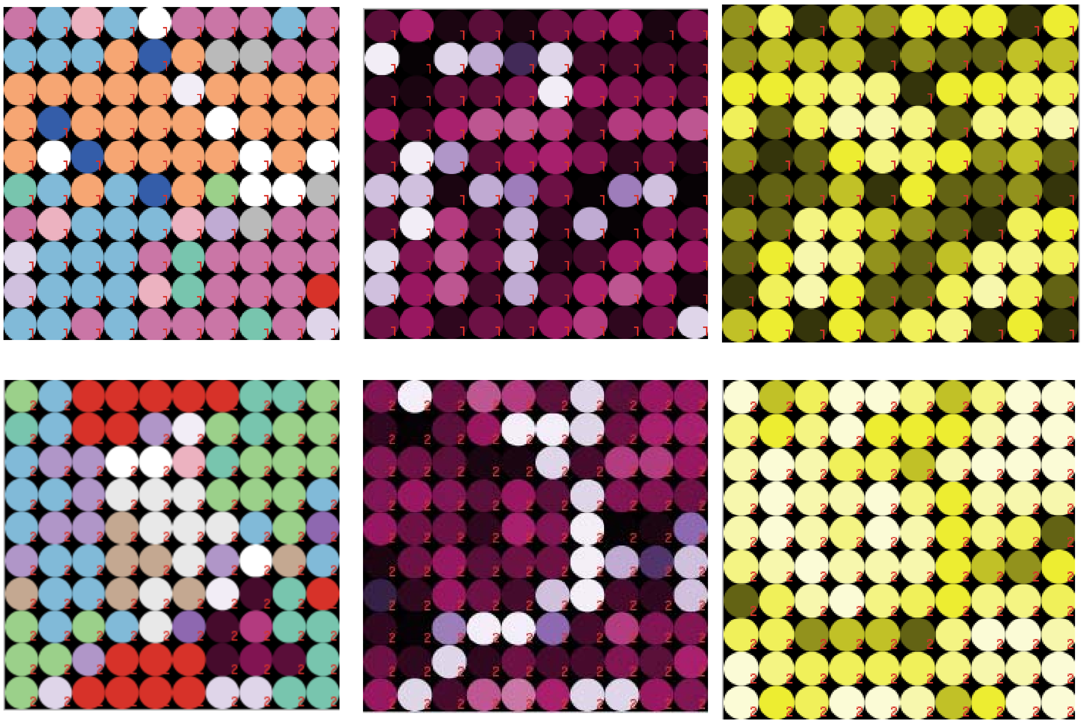


Note: The number colored red in each agent indicates her tolerance level.
$b/c = 4$, $L = 4$, and $\mu = .00$.

As with Model 1 (See Figure 4.5 and Figure 4.6), polymorphism (the co-existence of more than two cooperative phenotypes) is yet another case of cooperative equilibrium in Model 2 although it does not frequently occur in both societies. The population in Figure 5.4 consists of 97 agents with $T = 2$ and three agents with $T = 3$. Two distinguishable social circles stably remain: [0 1 0 1] (Pink) and [1 1 0 1] (Green). This society, albeit displaying much weaker parochialism, reaches universal cooperation in spite of a significant level of the average perceived social distance among agents (.48). Similar to the society in the lower panel of Figure 5.3, emergent cultural groups in Figure 5.4 are connected to one another without very high degrees of isolation and clustering. This spatial configuration is in stark contrast to that in Figure 4.6.

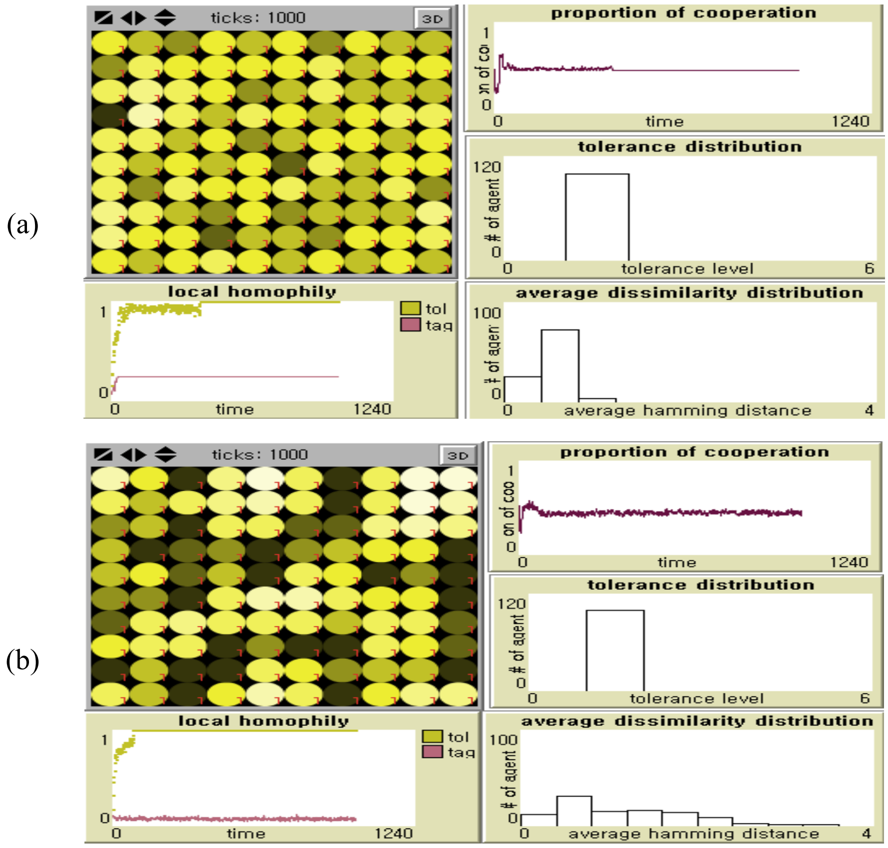
Figure 5.5. Nonaligned Social Circles under a Single Level of Tolerance in Model 3

(a) Distribution of Markers (b) Perceived Distances (c) Distribution of Strategies



Note: The number colored red in each agent indicates her tolerance level. $b/c = 4$, $L = 4$, and $\mu = .00$. The level of global cooperation is .398 (Upper) and .745 (Lower). $T = 1$ for all agents (Upper) and $T = 2$ for all (Lower).

Figure 5.6. Static Equilibrium versus Dynamic Equilibrium



Note: Model 2 (a); Model 3 (b). The number in each agent represents her tolerance level. The brightness of each node is proportional to how many neighbors with whom she cooperates out of the total number of neighbors. $b/c = 4$, $L = 4$, and $\mu = .00$ for both models.

The equilibrium co-existence of parochial cooperators with different levels of tolerance (‘polymorphism’) does not very often appear in modern societies. In both societies (Figure 5.5), all agents have the same level of tolerance (i.e. $T = 1$ in the upper and $T = 2$ in the lower). Most of time, a single group of cooperators evolve to dominate the population in caste societies and modern societies, but we find different patterns of the spatial configuration of tags and tolerance between the two societies. In three examples of caste societies above, markers in the first dimension of the tag space are immutable. At the equilibrium of cooperation, those in the last three dimensions converge to become identical: [1 0 0 0] and [0 0 0 0] in Figure 5.3 (Upper); [0 0 1 1] and [1 0 1 1] in Figure 5.3 (Lower); and [0 1 0 1] and [1 1 0 1] in Figure 5.4. On the contrary, agents in modern societies have one non-negotiable marker in different dimensions. Accordingly, cultural heterogeneity is not only high at the global level (.98 in the upper and 1.00 in the lower of Figure 5.5) but also more persistent at the local level. It is, therefore, more difficult for emergent cultural groups to expand their boundaries by assimilating other group members. The consequence is that small-sized homogeneous social circles emerge (10 in the upper and 9 in the lower of Figure 5.5). Meanwhile, agents with more heterogeneous markers are not firmly affiliated with any of adjacent groups. Members at the boundaries of social circles, although they hold the same level of tolerance, continue to modify their strategies toward those heterogeneous agents. Hence, the cooperation equilibrium is always dynamic, not static, in spite of the absence of imitation errors (Figure 5.6).

We discover that the strategy of conditional cooperation based on the strongest parochialism is still favored not only in societies with completely mutable tags but also in two societies where each agent has one immutable marker. However, even the most discriminating cooperators are inevitably gullible to mutant defectors with exactly the same markers in tag-based societies. We also know that a broader range of mutant defectors can easily disintegrate parochial cooperation based on higher levels of tolerance. Are there mechanisms that may enable tag-based societies to stably maintain parochial cooperation in spite of persistently emerging defectors in the presence of mutation (imitation errors)?

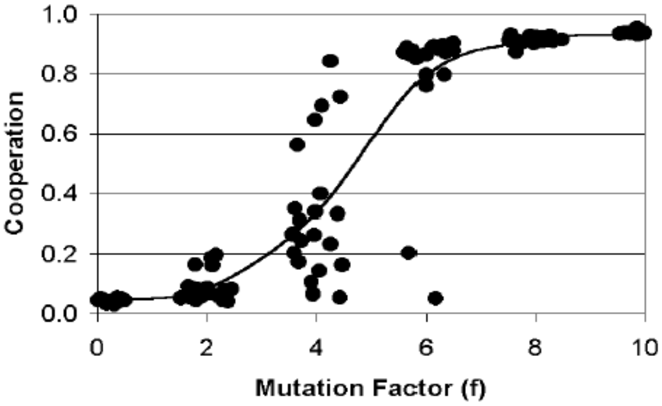
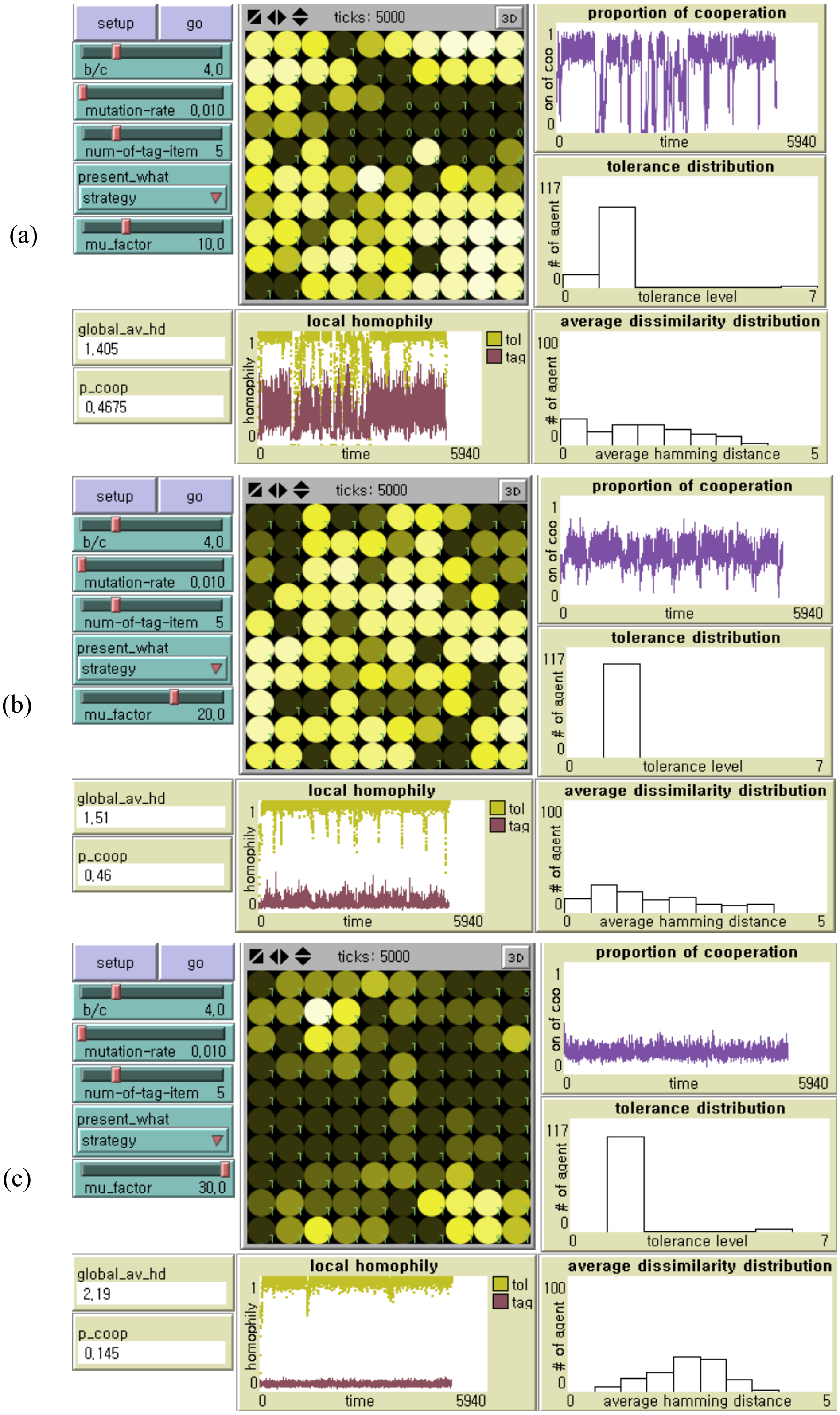


Figure 5.7. Level of Cooperation against Mutation Factor
Note: Hales (2004: 8)

We first consider the relationship between the speed of tag change and the speed of tolerance change. Hales (2004) and Edmonds and Hales (2005) provide two necessary conditions for tag-based systems to support high levels of cooperation: tags must mutate faster than strategies; and cooperative tag groups need to spread by mutation of tags before free-riders by mutation on strategies invade the group.

Applying different rates of mutation μf and μ to the tag change and the strategy change respectively, Hales (2004) demonstrates that high levels of cooperation continue when the mutation factor $f > 5$ (Figure 5.7). From the dispersion of the level of cooperation across multiple replications in each experimental condition, we notice that cooperation also becomes more stable as tags mutate faster than strategies.

How to select partners, not what actions to choose, is influenced by tagging in Hales (2004) and Edmonds and Hales (2005): strategies are not necessarily based on tag-based perception and tolerance in their models. Nonetheless, their idea can be applied to our models in which tolerance is a proxy strategy to explore the dynamics of tag-based cooperation across different levels of the mutation factor.


(a)

ticks: 5000

b/c 4,0

mutation-rate 0,010

num-of-tag-item 5

present_what strategy

mu_factor 10,0

global_av_hd 1,405

p_coop 0,4675

(b)

ticks: 5000

b/c 4,0

mutation-rate 0,010

num-of-tag-item 5

present_what strategy

mu_factor 20,0

global_av_hd 1,51

p_coop 0,46

(c)

ticks: 5000

b/c 4,0

mutation-rate 0,010

num-of-tag-item 5

present_what strategy

mu_factor 30,0

global_av_hd 2,19

p_coop 0,145

Figure 5.8. Dynamics of Tag-based Cooperation across Mutation Factors

Note: $b/c = 4$, $L = 5$, and $\mu = .01$. $f = 10$ (a); $f = 20$ (b); $f = 30$ (c).

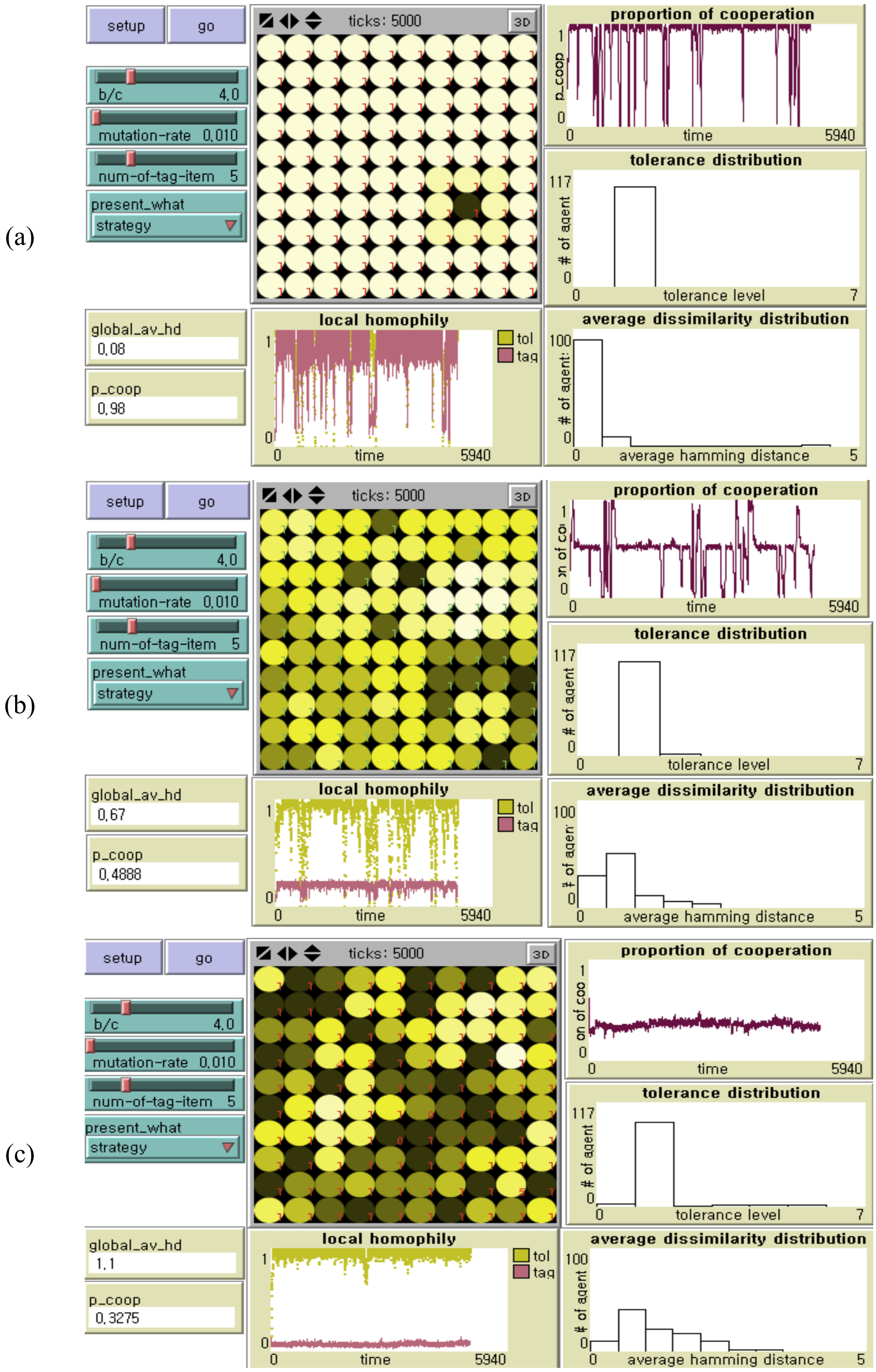
Table 5.7. Population Characteristics in Societies with Tags Mutating Faster than Tolerance

Variables	f	$b/c = 2$	$b/c = 4$	$b/c = 6$	Post-hoc Test
(a) Average cooperation	5	.727 (.291)	.721 (.278)	.742 (.261)	
	10	.673 (.201)	.675 (.194)	.676 (.189)	
	15	.573 (.148)	.575 (.146)	.581 (.136)	
	20	.459 (.112)	.466 (.103)	.469 (.100)	2-4*2-6**
	25	.302 (.074)	.310 (.074)	.312 (.073)	2-4* 2-6**
	30	.197 (.043)	.201 (.043)	.202 (.045)	2-4** 2-6**
(b) Average tolerance	5	.878 (.313)	.902 (.329)	.929 (.318)	2-6**
	10	.943 (.228)	.952 (.239)	.960 (.244)	
	15	.978 (.168)	.982 (.186)	1.001 (.191)	2-6** 4-6*
	20	1.004 (.125)	1.017 (.126)	1.022 (.134)	2-4** 2-6**
	25	1.022 (.090)	1.031 (.101)	1.039 (.109)	2-4** 2-6**
	30	1.023 (.086)	1.034 (.096)	1.045 (.115)	All pairs **
(c) Average link homophily in tolerance	5	.841 (.268)	.834 (.252)	.852 (.230)	
	10	.907 (.171)	.901 (.172)	.900 (.167)	
	15	.938 (.111)	.928 (.123)	.929 (.116)	
	20	.956 (.080)	.954 (.079)	.951 (.081)	2-6*
	25	.967 (.060)	.964 (.066)	.961 (.069)	2-6*
	30	.968 (.060)	.964 (.065)	.960 (.070)	All pairs **
(d) Average perceived distance	5	.562 (.541)	.541 (.502)	.495 (.449)	2-6**
	10	.783 (.416)	.767 (.395)	.755 (.379)	
	15	1.074 (.337)	1.056 (.325)	1.046 (.306)	2-6**
	20	1.396 (.285)	1.379 (.267)	1.369 (.262)	2-4** 2-6**
	25	1.815 (.209)	1.797 (.211)	1.797 (.210)	2-4** 2-6**
	30	2.088 (.130)	2.082 (.130)	2.083 (.130)	2-4** 2-6**
(e) Average link homophily in tags	5	.471 (.223)	.464 (.221)	.477 (.214)	
	10	.269 (.129)	.270 (.127)	.271 (.127)	
	15	.145 (.069)	.146 (.069)	.147 (.069)	
	20	.085 (.033)	.086 (.033)	.086 (.033)	2-6*
	25	.063 (.014)	.063 (.015)	.063 (.015)	2-6*
	30	.066 (.014)	.066 (.014)	.066 (.014)	2-4*

Note: $L = 5$ and $\mu = .01$. The number (in the parenthesis) at each cell indicates the average of each measure over time from 0 until 5,000 steps (and the averaged value of the standard deviation of each measure over time, not the standard deviation of the average of each measure). * $p < .05$; ** $p < .01$. For example, 2-4*** indicates the significant mean difference between $b/c = 2$ and $b/c = 4$ at $\alpha = .01$.

Figure 5.8 shows the dynamics of tag-based cooperation across different levels of the mutation factor *f* when the fixed mutation rate $\mu = 0.01$. At $f = 10$, an emergent society is not that robust in the presence of indistinguishable mutant defectors in the panel (a). We observe cooperation evolve more stably, but sometimes with cascades of non-cooperation at $f = 20$ in the panel (b). If tags mutate 30 times faster than tolerance, cooperation becomes highly robust in the panel (c). Notice that the level of global cooperation declines as tags mutate faster than tolerance. In other words, the trade-off relationship between the efficiency of tag-based cooperation and its stability depends on the ratio of how fast tags mutate to how fast tolerance.

In Table 5.7, we present the characteristic levels of the average cooperation, the average tolerance, the average social distance (global), the average link homophily in tolerance, and the average link homophily in tags (local) under varying conditions of the mutation factor *f* and the b/c ratios ($\mu = 0.01$). As tags mutate faster than tolerance when controlling for the b/c ratio, emerging societies are less likely to reach high levels of cooperation in terms of efficiency in the panel (a). This is because societies are still based on the strongest parochialism ($T = 1$) displayed in the panel (b) in spite of increased tag heterogeneity at the global and local level, as in both the panel (d) and (e). The measure of local homophily in tolerance in the panel (c) indicates that the degree of spatial homogeneity of parochialism increases as tags mutate faster than tolerance. In other words, parochial cooperators can develop new signals by changing tags rapidly although mutant defectors consistently invade existing cooperative clusters.


(a)

ticks: 5000

b/c 4,0

mutation-rate 0,010

num-of-tag-item 5

present_what strategy

global_av_hd 0,08

p_coop 0,98

(b)

ticks: 5000

b/c 4,0

mutation-rate 0,010

num-of-tag-item 5

present_what strategy

global_av_hd 0,67

p_coop 0,4888

(c)

ticks: 5000

b/c 4,0

mutation-rate 0,010

num-of-tag-item 5

present_what strategy

global_av_hd 1,1

p_coop 0,3275

Figure 5.9. Dynamics of Tag-based Cooperation in Model 1, 2, and 3.

Note: $b/c = 4$, $L = 5$, and $\mu = .01$. Model 1 (a); Model 2 (b); Model 3 (c). The brightness of each node is proportional to how many neighbors with whom she cooperates out of the total number of neighbors.

There are a couple of problems with the application of the idea that tags must mutate faster than tolerance. First, it is acceptable to assume that tags are completely mutable in genetic inheritance. From the perspective of cultural evolution of cooperation, tags as cultural markers are not necessarily completely imitable, as discussed at the beginning of this chapter. Second, the circumstances should be explained under which one genetic string of tags can mutate faster than another string of strategies. Relatedly, if tags are regarded as cultural markers, it should be justified why errors in imitating tags occur more frequently than errors in adopting tolerance.

We instead seek to find theoretical possibilities of alternative tag-based societies in which cooperation is not only more efficient but also stable from our existing models. There is no significant difference in the possibility of cooperation survival between Model 2 and Model 3 (See Table 5.4), but we find fundamental differences between caste societies and modern societies in the long-term dynamics of cooperation in the presence of 1% imitation errors (Figure 5.9). At *b/c* =4 and *L* = 5, caste societies in the panel (b) very frequently undergo downward spirals of cooperation followed by its re-institutionalization, which is similar to the pattern in societies with completely mutable tags in the panel (a). Under the same conditions, tag-based cooperation in modern societies, on the contrary, is highly stable as in the panel (c). It is not shown here, but parochial cooperation in modern societies is robust against defectors with tolerably similar markers within a broader range of the b/c ratios (from 2 through 6) and the tag lengths (from 2 through 10).

Table 5.8. Population Characteristics in Caste and Modern Societies

Variables	$b/c = 2$		$b/c = 4$		$b/c = 6$	
	Model 2	Model 3	Model 2	Model 3	Model 2	Model 3
(a) Average cooperation	.427 (.196)	.361 (.048)	.492 (.238)	.429 (.070)	.525 (.234)	.526 (.096)
(b) Average tolerance	.938 (.409)	1.022 (.125)	1.081 (.506)	1.186 (.216)	1.147 (.508)	1.478 (.273)
(c) Average link homophily in tolerance	.816 (.287)	.951 (.075)	.823 (.238)	.926 (.089)	.839 (.195)	.900 (.097)
(d) Average perceived distance	.688 (.255)	1.216 (.150)	.652 (.222)	1.172 (.139)	.637 (.209)	1.162 (.141)
(e) Average link homophily in tags	.180 (.046)	.069 (.015)	.189 (.040)	.072 (.015)	.190 (.037)	.076 (.015)

Note: $L = 5$ and $\mu = .01$. The number (in the parenthesis) at each cell indicates the average of each measure over time from 0 until 5,000 steps (and the averaged value of the standard deviation of each measure over time). At $b/c = 6$, no mean difference in the average cooperation between Model 2 and Model 3. In the rest of the case, the mean differences in all five measures between the two models are significant at $\alpha = .01$.

As with Table 5.7 about societies with tags mutating faster than tolerance, we present the demographic characteristics of both caste and modern societies. First, modern societies are less efficient in terms of the level of global cooperation than caste societies particularly when cooperation is relatively costly ($b/c = 2$ and $b/c = 4$) in the panel (a) of Table 5.8). Second, most of time, the strongest parochialism ($T = 1$)

is dominant in the population, but agents who are more tolerant of culturally different neighbors more frequently remain in modern societies than in caste societies, as in the panel (b). Third, polymorphism – the equilibrium co-existence of cooperators with different levels of tolerance – does not very often occur in both caste and modern societies. But, we note that the average degree of link homophily in tolerance tends to decrease as the benefit-to-cost ratio goes up in modern societies, which is not the case in caste societies, according to the panel (c). This pattern implies that when cooperation becomes less costly, it is more likely in modern societies that weak discriminators are adjacent to strong discriminators. Consistently high degrees of the average link homophily in tolerance in the panel (c) also indicate that modern societies are characterized by significantly stable cooperative clusters. Fourth, the average Hamming Distance in the population in the panel (d) shows that agents in modern societies feel more dissimilar to each other than agents in caste societies when holding the tag length *L* constant. Lastly, the panel (e) indicates that the average degree of local link homophily in tags is significantly lower in modern societies than that in caste societies.

Parochial cooperation on the basis of similarity is inherently vulnerable to mutant defectors with tolerably similar markers. Our experiments reveal that it is not stable against those defectors in societies with completely mutable tags (Model 1) and caste societies with one non-negotiable marker per agent in the same dimension (Model 2). However, it turns out that it is highly stable in the presence of them in societies with tags mutating faster than tolerance and modern societies with one non-negotiable marker per agent in different dimensions (Model 3).

We are now interested in scrutinizing similarities and differences in the dynamics of parochial cooperation between the last two societies (Table 5.9). The experimental conditions are the same for both societies: $b/c = 4$, $L = 5$, and $\mu = .01$. The results about societies with faster-mutating tags in Table 5.9 are excerpted from Table 5.7. The last two levels of the mutation factor ($f = 25$ and 30) are selected for the sake of comparison, where cooperation is significantly stable (See Figure 5.8). The results about modern societies are extracted from Table 4.8.

Table 5.9. Population Characteristics in Societies with Tags Mutating Faster than Tolerance and Modern Societies

Variables	Societies with tags mutating faster than tolerance	Modern societies
(a) Average cooperation	.310 (.074) $^{+}$ .201 (.043) $^{++}$	.429 (.070)
(b) Average tolerance	1.031 (.101) $^{+}$ 1.034 (.096) $^{++}$	1.186 (.216)
(c) Average link homophily in tolerance	.964 (.066) $^{+}$ .964 (.065) $^{++}$	.926 (.089)
(d) Average perceived distance	1.797 (.211) $^{+}$ 2.082 (.130) $^{++}$	1.172 (.139)
(e) Average link homophily in tags	.063 (.015) $^{+}$ .066 (.014) $^{++}$	.072 (.015)

Note: $b/c = 4$, $L = 5$ and $\mu = .01$. + at the mutation factor $f = 25$ and ++ at $f = 30$. The number (in the parenthesis) at each cell indicates the average of each measure over time from 0 until 5,000 steps (and the averaged value of the standard deviation of each measure over time).

Both societies are very similar for the following reasons. First, the dominant group in emerging societies consists of those who cooperate only with neighbors with exactly the same tags as theirs ($T = 1$), according to the panel (b). Second, there is no significant difference ($\alpha = .01$) in the averaged values of the standard deviation of the average cooperation across time from 0 to 5,000 steps: .074 at $f = 25$ in comparison to .070 in the panel (a). Third, the average degrees of link homophily in tolerance are very high: .964 at $f = 25$ and $f = 30$ in comparison to .926 in the panel (c). These last two aspects refer to the noticeable robustness of cooperation in both societies. Lastly, persistent tag heterogeneity common to both cases enables emergent cooperative societies to be more stable in the presence of mutant defectors. As in the panel (e), the average degrees of link homophily in tags are sufficiently low: .063 at $f = 25$ and .065 at $f = 30$ in comparison to .072.

However, different mechanisms contribute to the robustness of cooperation in both societies. In societies with tags mutating faster than tolerance, existing cooperative clusters are continuously reorganized into new ones before mutant defectors with tolerably similar markers attack them. Members in new groups have new signals whereby they recognize each other. In modern societies, one immutable element of cultural markers is distributed along different dimensions of the tag space. Parochial cooperators do not need to develop new signals in the presence of those defectors. Even if discriminating cooperators in some clusters accept mutant defectors displaying tolerably similar markers as in-group members, it is less likely to happen to their neighboring clusters.

These disparate routes to stable parochial cooperation in both societies result in different levels of global heterogeneity and thereby global cooperation. The average degree of tag heterogeneity at the global level in societies with faster mutating tags is much higher than that in modern societies: 1.797 at $f = 25$ and 2.082 at $f = 30$ in comparison to 1.172 from the panel (d). Consequently, modern societies reach significantly higher levels of cooperation (.429) than societies with faster mutating tags (.310 at $f = 25$ and .201), as is presented in the panel (a). Relatively high and also stable cooperation is achievable only in modern societies – where each agent has one non-negotiable marker in different dimensions of the cultural space, but the society as a whole does not have any unchangeable dimension.

5.4. Concluding Remarks

We recognize from the previous chapter that cooperation can evolve even in the setting of one-shot interaction when agents read tags and conditionally help reliable partners by reading tags as genetically inherited traits. Emergent cooperative societies are highly parochial and homogeneous. Emergent cooperative societies are inevitably vulnerable to mutant defectors displaying tolerably similar tags who are thereby identified as in-group members. In the long term, tag-based societies experience the endless cycles of global cooperation and global betrayal.

In search for alternative societies, we first apply the suggestion by Hales (2004) and Edmonds and Hales (2005) that tags should mutate faster than strategies (equivalent to tolerance in our study). And then, we consider tags (and tolerance) as culturally transmissible traits rather than as genetically inheritable ones in most of existing studies such as Riolo et al. (2001), Hales (2004), and Edmonds and Hales (2005). From the viewpoint of cultural evolution of cooperation, tags are no longer completely mutable – some markers are more mimicable (e.g. linguistic codes), whereas some others are less (e.g. skin colors). We construct two new societies, one where each agent has one non-negotiable identity at the same dimension (caste societies) and the other where such an identity in different dimensions (modern societies).

The first main finding is that the faster tags mutate than tolerance, the more stable tag-based cooperation. Recall the ideas of “secret handshaking” and “learning secret handshaking.” As parochial cooperators change their signals (e.g. passwords) more frequently, the chance of the invasion by defectors (e.g. hacking passwords) will decrease. We discover that if tags mutate fast, but it is not sufficient, emergent societies are yet frequently damaged by cascades of non-cooperation triggered by mutant defectors; and if tags mutate fast enough parochial cooperation shows high robustness despite the fact that all elements of tags are easily mimicable.

Next, we find that both caste and modern societies are highly parochial as in societies in the previous chapter: agents with the minimum tolerance for cooperation are still in the majority of the population although emergent societies tend to be more tolerant as cooperation becomes less costly. In the absence of imitation errors, there is no significant difference in the likelihood of the survival of cooperation in both caste and modern societies.

The societies are significantly different in some aspects. First, universal cooperation rarely happens in highly heterogeneous modern societies because agents have immicable markers in different dimensions. Besides, those who are more tolerant of culturally diverse others constitute modern societies. Nonetheless, parochial cooperation is very stable against mutant defectors displaying tolerably similar identities only in modern societies.

We identify the conditions for the stable institutionalization of relatively society-wide cooperation in tag-based societies. First, parochial cooperators should share a minimal number of markers that are difficult for defectors to imitate: the average dissimilarity at the global level should not be too low for the efficiency of cooperation. As the number of such core markers increases, the level of global cooperation declines. In societies with faster mutating tags, parochial cooperators are able to develop new signals by changing tags rapidly before mutant defectors invade existing cooperative clusters. However, if tags mutate faster than a threshold value of the ratio of tag mutation and tolerance mutation, emergent societies do not reach high levels of cooperation because too much tag heterogeneity is constantly introduced into the population. On the contrary, modern societies reach higher levels of global cooperation than societies where tags mutate faster than tolerance because they have the lower degrees of cultural heterogeneity at the global level.

Second, parochial cooperators should have those markers in different dimensions of the cultural space: the average homophily in tags at the local level should be low enough for the stability of cooperation. We observe that although both caste and modern societies retain a similar degree of cultural diversity, cooperation is seriously vulnerable to mutant defectors only in caste societies. Given that only a few cultural groups emerge, caste societies are destined to disintegrate as long as defectors concurrently appear who are identical except the core dimension to parochial cooperators. In modern societies, on the contrary, emerging cultural groups are manifold. Consequently, modern societies consisting of multiple small-sized groups loosely coupled with one another (cf. Perrow, 1984) can be highly robust against emerging free-riders. Even if discriminating cooperators in some clusters accept mutant defectors displaying tolerably similar markers as in-group members, it is less likely to happen to their neighboring clusters. In this way, multiple social circles in modern societies tend to self-organize their group boundaries through 'tagging' as self-enforcing labeling even in the presence of cultural perturbation.

Chapter 6: Parochial Cooperation on Static Networks with Different Topologies

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6.1. Problem Statement

Human agents interact with randomly selected others in the classical model of evolutionary games, but this global random matching is not realistic. For example, Riolo et al. (2001) implicitly consider the average number of interaction partners (i.e. "pairings" defined by the number of times per generation each agent has an opportunity to interact with a randomly encountered other), but agents in their model play the Prisoner's Dilemma game with randomly chosen partners in unstructured populations. Human agents may have stable sets of interaction partners relative to the rate of cultural evolution, as in our study. Furthermore, human agents may switch partners based on their preferences under a certain level of mobility, which will be explored in the next chapter.

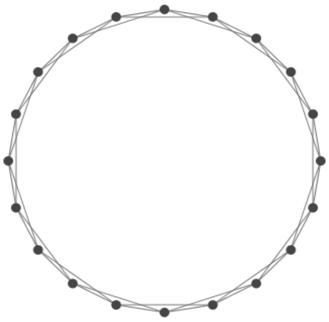
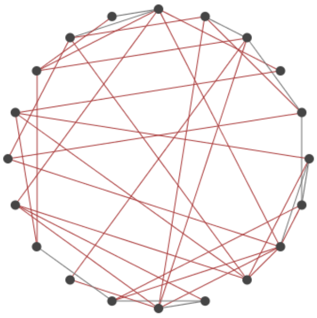
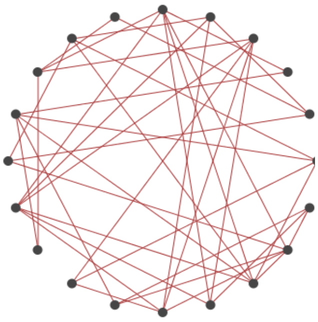
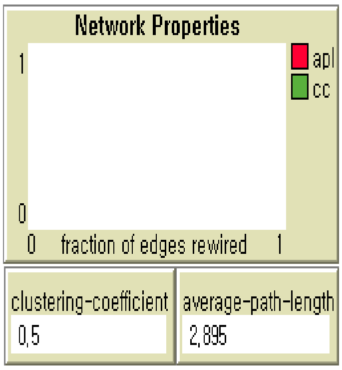
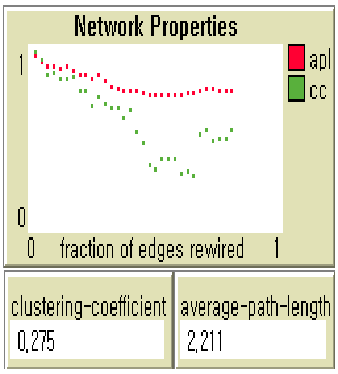
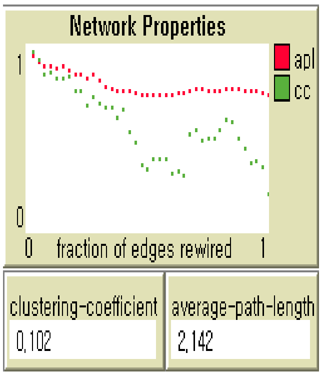
Researchers have paid due attention to 'spatialized' evolutionary games since the classical study of network reciprocity as another route of cooperation (Nowak and May, 1992), as is discussed in Chapter 2. In most spatial models agents, however, play a game with neighboring partners on the toroidal lattice. In this sense, extant spatial models are concerned exclusively with the effects of network degree (e.g. Von Neumann, hexagonal, Moore) on the evolution of cooperation.

This limitation is the case with existing models of tag-based cooperation. Only a few of them consider spatiality in the sense that agents play the Prisoner's Dilemma game with their neighbors, but on the torus: either they leave offspring in proportion to fitness (Hammond and Axelrod, 2006) or they imitate cultural traits from more successful neighbors (Choi, Yang, and Jo, 2006). The torus structure is degree-homogeneous, but agents may have different numbers of interaction partners.

None of the existing tag-based models scrutinizes how the dynamics of cooperation may vary across societies with different network topologies. Clustering is ubiquitous in networked world and provides different types of benefits (as network externalities). People tend to trust each other in cohesive small groups consisting of more homogeneous members (Granovetter, 1985). In a similar vein, Coleman (1986) raises two interesting questions: how cooperation toward strangers (foreigners) can spread across the population (or can be possible in large-sized societies); and how cooperating with others depends on the degree of social closure. We note here that he addresses these questions in the setting of repeated interactions, not one-shot interaction in our study. In other words, the effects of clustering on the evolution of cooperation in a one-shot game are not fully understood.

Second, small-world-ness matters in the evolution of cooperation. For example, asking how collective rationality is affected by community network structure, Granovetter (1973) points out that interpersonal relations based on cohesive ties may cause the overall fragmentation of social network at the community level. His hypothesis is that the community's capacity of acting in concert increases on small-world networks where cohesive groups are connected through a few bridges. In other words, it is expected that fully globalized cooperation rarely happen in large societies with long path lengths. Granovetter (1973) does not consider how fast deviants can disrupt cooperative relations in a small-world community, but we expect that more robust cooperation in the presence of free-riders, which is discussed in the beginning of the previous chapter.

Table 6.1. Network Topologies and Structural Features

Ring Lattice: RG	Watts-Strogatz (1998): SW	Random Network: RN
Large world Highly clustered	Small-world Well clustered	Small-world Poorly clustered
		
 clustering-coefficient 0,5 average-path-length 2,895	 clustering-coefficient 0,275 average-path-length 2,211	 clustering-coefficient 0,102 average-path-length 2,142
$p = 0$ (Order)	$0 < p < 1$	$p = 1$ (Disorder)

Agents in this chapter play the game on static networks in which local clustering (i.e. making new ties to neighbors' neighbors to form closed triads) and global reachability (i.e. making outward ties towards different clusters) vary. The ring lattice in the left panel of Table 6.1 is a high clustered network of overlapping local tribes of equal size with long path lengths. This regular network is homogeneous in terms of the degree distribution. The society on the other end of network topology is characterized by randomized connections of interaction partners with lower degrees of clustering in the right panel. A network of different-sized tribes between the world of order (the rewiring probability $p = 0$) and the world of disorder ($p = 1$) shows a small-world-ness, like a random network, despite the fact that it is more clustered than an equivalent random network, as is shown in the middle panel.

We intend to examine which network topology can preserve higher tolerance and more cultural diversity without imitation errors (i.e. mutation). We also investigate how much the dynamics of the local reinforcement of parochial cooperation, its global diffusion through cross-cutting ties, and the collapse of cooperative regime by mutant defectors can differ across static networks with different topologies in the presence of the same amount of imitation error.

We hypothesize that global cooperation is less likely to be wiped out through cascades of non-cooperation on large regular networks with higher degrees of clustering and longer path lengths than on small-world or random networks of the same size. Tag-based cooperation can be more stable on large regular networks, but with a decrease in its efficiency. When controlling for the population size, it will be on small-world networks rather than on random networks that mutant discriminators are expected to be more frequently generated and clustered before cooperation is completely destroyed by mutant defectors. There will be no significant differences in the likelihood of universal cooperation between small-world networks and random networks of the same size because their path lengths are almost the same.

6.2. Experimental Design

Main Experiments

The first experiments are on the dynamics of cooperation on fixed networks with different topologies in the absence of mutation: regular networks (RG); small-world networks (SW), and random networks (RN). We use the experimental design, where the benefit-to-cost-ratio and the tag length are manipulated, at the average degree $k = 8$ (Table 6.2). Each experiment is terminated if societies reach either universal cooperation or universal defection. Otherwise, each replication runs until 5,000 time steps (instead of 1,000 time steps in Chapter 4 and 5) since we consider long path lengths of regular networks. Each experimental group has 100 replications.

Table 6.2. Parameter Setting of Main Experiments on Model 4 ($\mu = .00$).

Parameters	Values or Ranges
Number of agents	100
Interaction space	Regular/ Small-world/ Random networks
Number of adjacent neighbors	8
Benefit-to-cost ratio	2, 4, 6, 8, 10
Tag length	0, 2, 4, 6, 8, 10
Imitation error	0
Condition for cooperation	$\| t_A - t_B \| < T_A$
Payoff-based imitation rules	Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies her tags and adjusts his tolerance toward her level by one unit.

As is discussed in the previous chapters, as the benefit-to-cost ratio and the tag length increases, there are higher possibilities that more tolerant agents and tag diversity are preserved. This is why the experiment continues at the intermediate conditions of $b/c = 4$ and $L = 5$ in the presence of the same amount of imitation errors (Table 6.3)[1].

Table 6.3. Parameter Setting of Main Experiments on Model 4 ($\mu = .01$).

Parameters	Values or Ranges
Number of agents	100
Interaction space	Regular/ Small-world/ Random networks
Number of adjacent neighbors	8
Benefit-to-cost ratio	2, 4, 6
Tag length	5
Imitation error	.01
Condition for cooperation	$\mid t_A - t_B \mid < T_A$
Payoff-based imitation rules	Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies her tags and adjusts his tolerance toward her level by one unit.

We compare the outcomes at $b/c = 4$ to those at $b/c = 2$ and $b/c = 6$, holding the tag length constant ($L = 5$). The treatment condition varies in terms of network topology: regular networks (RG); small-world networks (SW), and random networks (RN). Each replication has 5,000 time steps as with the experiments under mutation in the previous chapters. 100 replications are executed for each network topology.

We examine whether there are significant differences in the dynamics of the local reinforcement of cooperation, its global diffusion, and the invasion by mutant defectors across those three societies with the following measures: the first emergence time of universal cooperation; how often mutant defectors after their emergence constitute the majority of the population; and the frequency of the transition from universal cooperation to universal defection.

Table 6.4. Average Clustering Coefficients and Average Path Lengths of Regular, Small-world, and Random Networks ($\mu = .00$)

ACC	N	Mean	SD	Min	Max	Post-hoc Test
RG		.6429	.0000	.643	.643	
SW	3000	.1027	.0094	.081	.134	All pairs ***
RN		.0798	.0104	.046	.119	
APL	**N**	**Mean**	**SD**	**Min**	**Max**	**Post-hoc Test**
RG		6.6970	.0000	6.697	6.697	RG vs. SW *** RG vs. RN ***
SW	3000	2.4377	.0007	2.433	2.438	
RN		2.4367	.0470	2.277	2.614	

Note: ** $p < .05$; *** $p < .01$.

Table 6.4 and Table 6.5 present the average clustering coefficients (ACC) and the average path lengths (APL) of three static networks. In the absence imitation errors, the average clustering coefficient is highest in RG, second highest in SW, and lowest in RN at each experimental group holding *b/c* and *L* constant ($p = .00$). There is no mean difference in the average path lengths between SW and RN ($p = .351$). In the presence of mutation errors, we find the same patterns in both ACC and APL across three network topologies. The average difference in APL between SW and RN is not statistically significant (*p* = .862).

Table 6.5. Average Clustering Coefficients and Average Path Lengths of Regular, Small-world, and Random Networks (μ = .01)

ACC	N	Mean	SD	Min	Max	Post-hoc Test
RG	300	.6429	.0000	.643	.643	All pairs ***
SW		.1028	.0010	.081	.133	
RN		.0798	.0109	.045	.109	
APL	**N**	**Mean**	**SD**	**Min**	**Max**	**Post-hoc Test**
RG	300	6.6970	.0000	6.697	6.697	RG vs. SW *** RG vs. RN ***
SW		2.4377	.0007	2.435	2.438	
RN		2.4364	.0482	2.330	2.608	

Note: ** $p < .05$; *** $p < .01$.

Supplementary Experiments

We want to compare the outcomes from Model 4 with those from Model 1 because agents change their tolerance in a step-wise manner in the models in this chapter and the next chapter as well. It is likely that the average tolerance is higher in Model 4 due to a slower downward change in tolerance, but it is lower because of a slower upward change in tolerance. We are particularly interested in whether or not these forces in opposite directions will be cancelled out.

Table 6.6. Parameter Setting for Sensitivity Test of Model 4.

Parameters	Values or Ranges
Number of agents	100
Interaction space	Torus
Number of adjacent neighbors	8
Benefit-to-cost ratio	2, 4, 6, 8, 10
Tag length	0, 2, 4, 6, 8, 10
Imitation error	0
Condition for cooperation	$\mid t_A - t_B \mid < T_A$
Payoff-based imitation rules	Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies her tags and adjusts his tolerance toward her level by one unit.

The likelihood of the survival of cooperation, the average tolerance, and the average social distance will be compared across those two models under the same experimental conditions (Table 6.6). Each experiment is run until societies reach either universal cooperation or universal defection. Otherwise, it is run for 1,000 time steps. 100 replications are taken for each condition.

6.3. Results

Main Experiments

Table 6.7 presents the likelihoods of the survival of cooperation and universal cooperation in societies with different network topologies. All societies have completely mutable markers, but agents in them adjust tolerance levels towards those of more successful neighbors in a step-wise manner. Consistent with the dynamics on the torus presented at the first row in Table 6.10 (See Supplementary Experiments), there is no chance of the survival of cooperation in spite of network reciprocity unless the benefit-to-cost ratio is higher than the average number of neighbors regardless of network topology when altruists play a one-shot Prisoner's Dilemma game with defectors. We observe that it sometimes occurs that altruists win against defectors on highly clustered regular networks lacking in small-world-ness and societies can reach universal cooperation.

Emergent societies are more likely to attain the state of universal cooperation when making a distinction between 'us' and 'them' is available. However, universal cooperation more frequently happens on regular networks than on small-world networks or random networks since discriminators can defeat defectors more easily due to higher degrees of clustering and longer paths. These advantages of regular networks become more noticeable in societies where cultural markers are less differentiated and cooperation is relatively costly.

Table 6.7. Likelihood of Survival of Cooperation and Universal Cooperation in Model 4 (Networks)

	b/c				
L	2	4	6	8	10
0	0/0/0 (0/0/0)	0/0/0 (0/0/0)	0/0/0 (0/0/0)	0/0/0 (0/0/0)	13/0/0 (13/0/0)
2	51/14/22 (51/14/22)	76/27/32 (75/27/32)	82/16/30 (80/16/30)	95/26/54 (91/26/54)	100/65/70 (100/65/70)
4	100/84/82 (100/84/82)	100/72/71 (99/72/71)	100/81/80 (96/81/80)	100/92/91 (99/90/89)	100/98/99 (100/96/98)
6	100/88/86 (99/88/86)	100/88/88 (99/88/88)	100/96/94 (99/95/88)	100/95/98 (96/91/95)	100/98/98 (100/98/96)
8	100/94/80 (100/94/80)	100/94/94 (98/94/94)	100/98/88 (100/94/88)	100/100/94 (99/97/91)	100/100/99 (99/99/97)
10	100/91/91 (96/91/91)	100/93/95 (99/93/95)	100/98/97 (99/97/95)	100/100/100 (98/96/97)	100/100/100 (97/98/97)

Note: The number at the first row represents how many times out of 100 trials cooperators survive in the absence of imitation errors. The number in parentheses at the second row indicates the likelihood of universal cooperation. Within each row, regular networks (RG), small-world networks (SW), and random networks (RN) from the left to the right. For examples, when $L = 6$ and $b/c = 6$, the possibility of the survival of cooperation is 100% (RG), 96% (SW), and 94% (RN). The chance of universal cooperation is 99% (RG), 95% (SW), and 88% (RN).

As is presented in Figure 6.1, cultural diversity tends to decrease over time since agents imitate markers of more successful neighbors, but emergent cooperative societies at equilibrium are more likely to retain cultural diversity as cooperation becomes less costly and the tag length becomes longer. However, when holding the benefit-to-cost ratio of cooperation and the complexity of culture *L*, we find that agents assimilate into local villages significantly much faster on regular networks because of higher degrees of clustering than that on small-world networks and random networks.

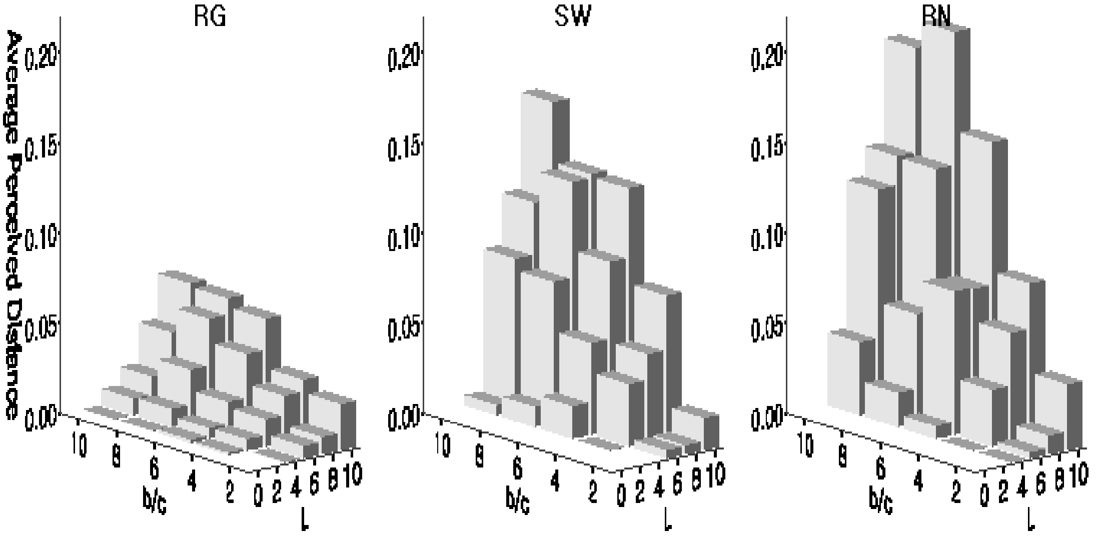


Figure 6.1. Average Perceived Distance at Cooperative Equilibrium in Model 4
Note: Regular networks (left); small-world networks (middle); random networks (right).

Figure 6.2 shows the average of tolerance in the population at the cooperative equilibrium. Agents learn intolerance very quickly from more successful neighbors because they have to adapt themselves to changing local environments where cultural heterogeneity is increasingly eroded which serves as a guide for their discriminating interactions to others. Regardless of network topology, it is most likely to happen that the overwhelming majority are those who have the most discriminating one among all possible cooperative strategies. However, conditional cooperators with higher levels of tolerance are more likely to survive as the tag length becomes longer and the benefit-to-cost ratio gets higher.

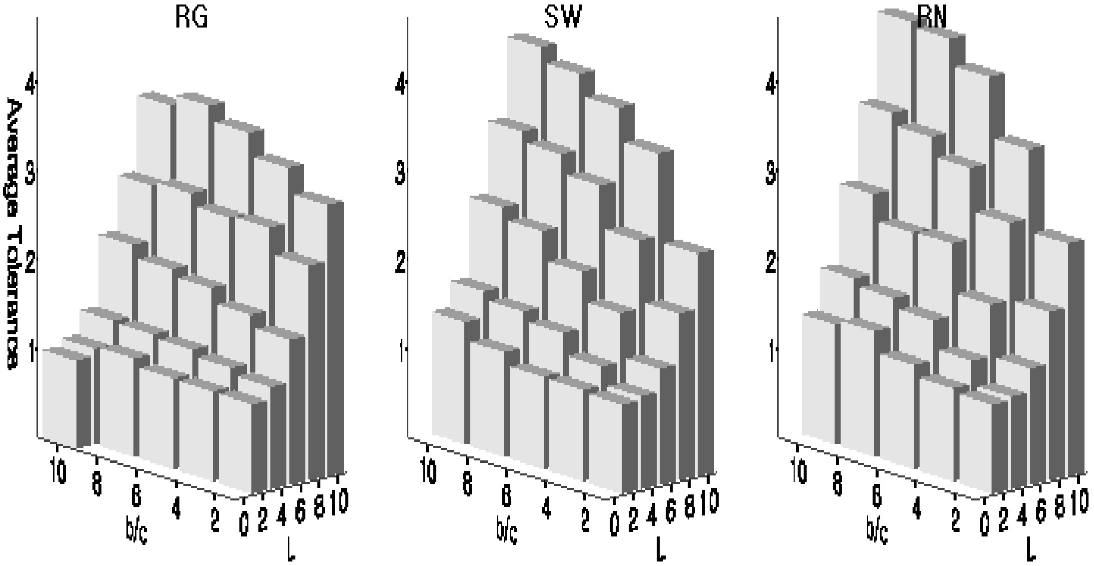


Figure 6.2. Average Tolerance at Cooperative Equilibrium in Model 4.
Note: Regular networks (left); small-world networks (middle); random networks (right).

In particular, cooperative agents with the strongest parochialism are more favored on regular networks than on small-world networks and random networks because the local convergence of cultural markers are faster in those ring lattices. Consequently, the average tolerance at the cooperative equilibrium on regular networks is lower than that on the other two networks under the same conditions of the benefit-to-cost ratio and the complexity of culture.

We take a robust regression of the average tolerance at the cooperative equilibrium on the benefit-to-cost ratio, the tag length, and network topology. The iteratively reweighted least squares procedure in STATA is used because the data are seriously affected by non-normality and heteroskedasticity rather than by influential outliers. Since we do not want to impose any particular pattern in the relationship between dependent and independent variables, we generate four dummy variables of the *b/c* ratio, four dummy variables of the tag length, and two dummy variables of network topology, SW and RN, as is in the left panel of Table 6.8.

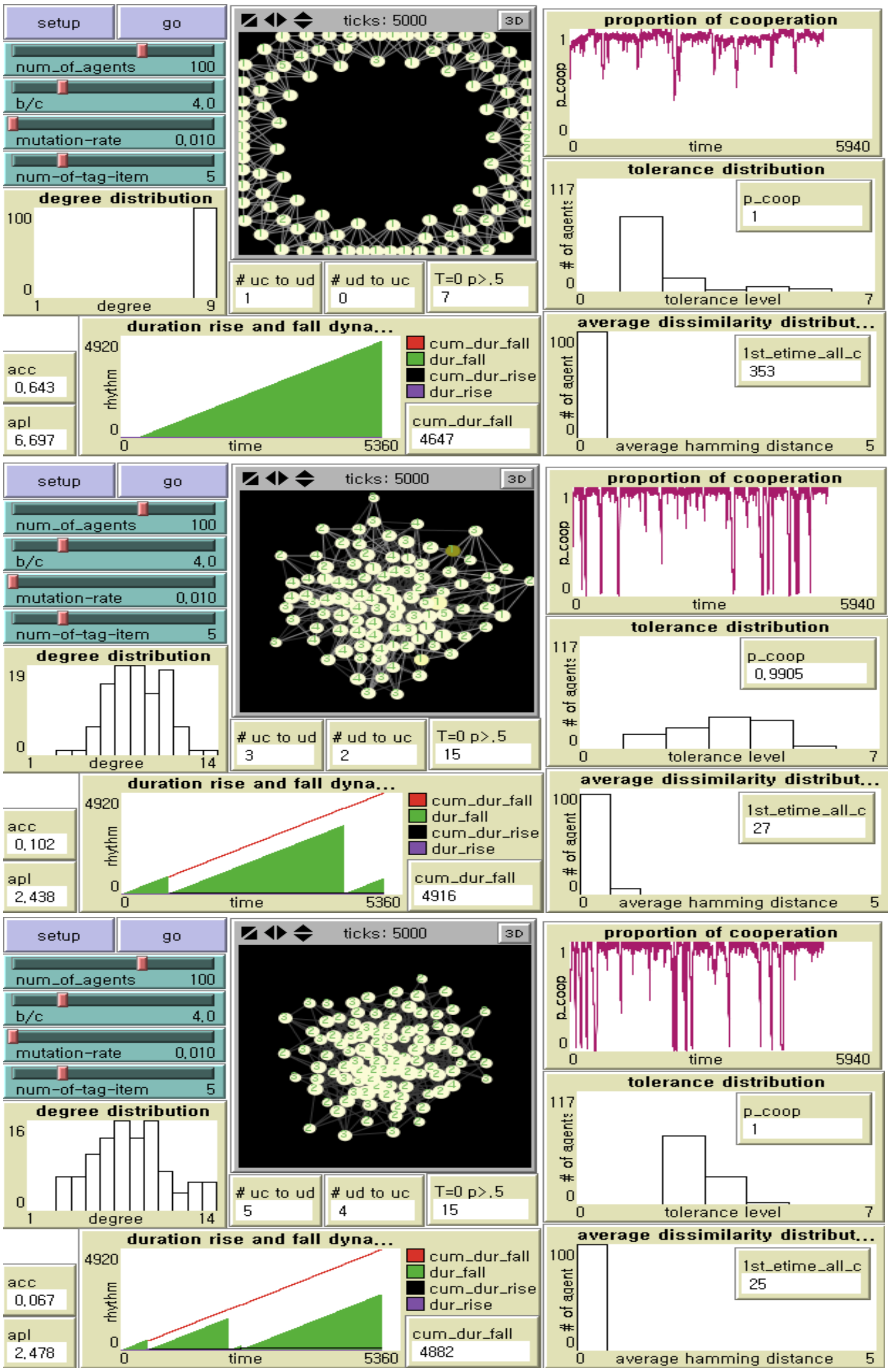
Table 6.8. Robust Regression on Average Tolerance at Cooperative Equilibrium

Variable	*b*	SE	Variable	*b*	SE
b/*c* = 4 (dummy)	.4117**	.0241	*b*/*c* = 4 (dummy)	.4117**	.0241
b/*c* = 6 (dummy)	.6704**	.0240	*b*/*c* = 6 (dummy)	.6697**	.0240
b/*c* = 8 (dummy)	.7912**	.0236	*b*/*c* = 8 (dummy)	.7909**	.0236
b/*c* = 10 (dummy)	.8615**	.0234	*b*/*c* = 10 (dummy)	.8610**	.0234
L = 4 (dummy)	.3050**	.0271	*L* = 4 (dummy)	.3023**	.0271
L = 6 (dummy)	.9264**	.0269	*L* = 6 (dummy)	.9235**	.0269
L = 8 (dummy)	1.7273**	.0268	*L* = 8 (dummy)	1.7233**	.0268
L = 10 (dummy)	2.5304**	.0268	*L* = 10 (dummy)	2.5265**	.0268
SW (dummy)	.1398**	.0181	ACC	-1.8226**	.5739
RN (dummy)	.2344**	.0179	APL	.1921**	.0744
Intercept	.3964		Intercept	.2843	
Probability > *F*	0.0000		Probability > *F*	0.0000	
N	6448		*N*	6448	

Note: * $p < .05$; ** $p < .01$. The reference groups are *b/c* = 2, *L* = 2 (in both models), and RG (in the left model). The OLS regression does not provide significantly different results. Adjusted R^2 are .7005 (Left) and .6991 (Right) according to the OLS regression.

First, the higher benefit-to-cost ratio, the higher tolerance at the cooperative equilibrium. Controlling for the effects of the tag length and network topology, all the average tolerance differences between each of four societies with cooperation more costly and the reference society (*b/c* = 2) are statistically significant. Next, the longer tag length, the higher tolerance in emergent cooperative societies. Holding all other variables constant, all four societies with longer tag strings are significantly more tolerant of cultural diversity than the reference society (*L* = 2). Lastly, we also find that the average tolerance at the cooperative equilibrium is significantly higher in random networks and small-world networks than in regular networks when controlling for the effects of all other variables.

In order to separate the effect of average clustering from the effect of small-world-ness (global reachability), we set another model in the right panel of Table 6.8. The average tolerance at the cooperative equilibrium is significantly affected by both network properties, controlling for all other variables. 0.2 point increase in the average clustering coefficient lowers the average tolerance by approximately 0.4. It also turns out that as the average path length increases by one unit, the average tolerance goes up by approximately 0.2. These two effects are consistent with the results presented in Figure 6.4. In sum, the higher clustering and the more easily globally-reachable, it is more likely that emergent cooperative societies are grounded on stronger parochialism.


(a)

ticks: 5000

num_of_agents 100
b/c 4.0
mutation-rate 0.010
num-of-tag-item 5
acc 0.643
apl 6.697
# uc to ud 1
# ud to uc 0
T=0 p>.5 7
p_coop 1
1st_etime_all_c 353
cum_dur_fall 4647

(b)

ticks: 5000

num_of_agents 100
b/c 4.0
mutation-rate 0.010
num-of-tag-item 5
acc 0.102
apl 2.438
# uc to ud 3
# ud to uc 2
T=0 p>.5 15
p_coop 0.9905
1st_etime_all_c 27
cum_dur_fall 4916

(c)

ticks: 5000

num_of_agents 100
b/c 4.0
mutation-rate 0.010
num-of-tag-item 5
acc 0.067
apl 2.478
# uc to ud 5
# ud to uc 4
T=0 p>.5 15
p_coop 1
1st_etime_all_c 25
cum_dur_fall 4882

Figure 6.3. Dynamics of Tag-based Cooperation in Model 4 across Network Topologies

Note: $b/c = 4$, $L = 5$, and $\mu = .01$. Regular (a); Small-world (b); and Random (c). The number in each agent indicates her tolerance level. The brightness of each node is proportional to how many neighbors with whom she cooperates out of the total number of neighbors.

Tag-based cooperative societies are not evolutionarily robust in the presence of imitation errors, but the dynamics of the local reinforcement of parochial cooperation, its global diffusion, and the invasion by defectors significantly vary across different network topologies. We capture a typical run of the simulation on regular networks in the panel (a), small-world networks in the panel (b), and random networks in the panel (c) of Figure 6.3.

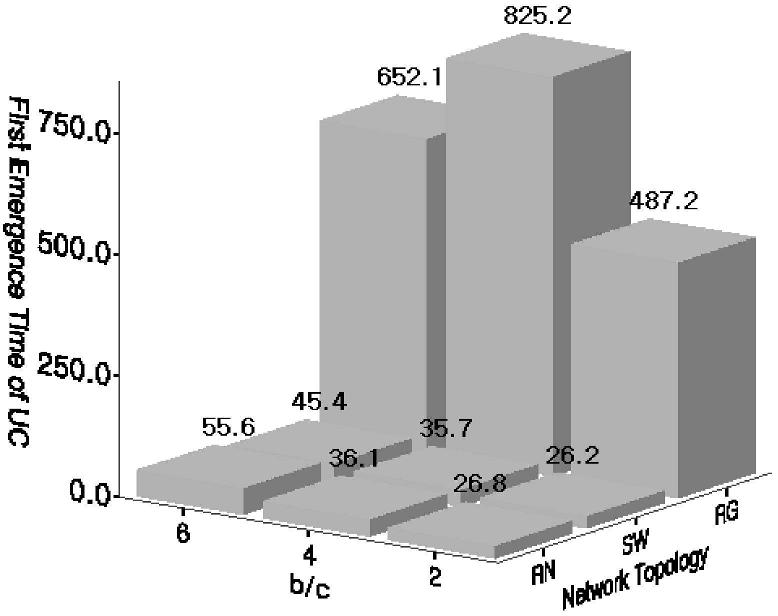


Figure 6.4. First Emergence Time of Universal Cooperation

We record the first emergence time of universal cooperation (e.g. 353, 27, and 25 from *1st_etime_all_c* in each panel of Figure 6.3). Figure 6.4 displays the average time step when societies reach the state of universal cooperation. The local convergence of tolerance and cultural markers is much faster on regular networks with high degrees of clustering, but it takes much longer for local cooperation to be globalized because of their longer path lengths when holding the benefit-to-cost ratio constant. On the contrary, there are no significant differences in the first emergence time of universal cooperation between small-world networks and random networks across the *b/c* ratios under experiment.

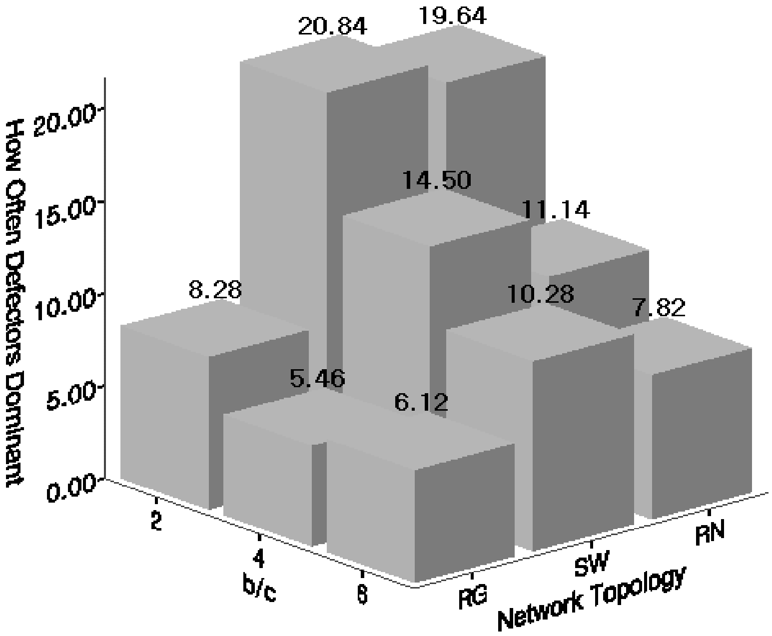


Figure 6.5. How Often Defectors Successfully Form Majority

Next, we measure the frequency that indiscriminate defectors becomes the majority in the population (e.g. 7, 15, and 15 from $T = 0\ p > .5$ in each panel of Figure 6.3). As is shown in Figure 6.5, mutant defectors with tolerably similar markers are less likely to become the majority in the population on regular networks than on small-world networks and random networks. Emergent cooperative societies are more frequently attacked by those defectors as cooperation becomes more costly, but the efficiency of the invasion by defectors is more seriously affected by the benefit-to-cost ratio on small-world networks and random networks than on regular networks. It is statistically significant ($\alpha = .01$) that defectors are more successful in forming the majority in the population after their emergence on small-world networks than on random networks at *b/c* = 4 and *b/c* = 6.

Table 6.9. OLS Regression on How Often Defectors Successfully Form Majority

Variable	*b*	SE	Beta
b/*c* = 4 (dummy)	-5.859**	.392	-.401
b/*c* = 6 (dummy)	-8.148**	.392	-.558
ACC	51.549**	12.315	1.949
APL	-8.414**	1.596	-2.454
Intercept	34.502		
Probability > *F*	.0000		
N	900		

Note: * $p < .05$; ** $p < .01$. The reference group is *b/c* = 2. Adjusted $R^2 = .528$.

According to Table 6.9, the benefit-to-cost ratio significantly affects whether mutant defectors displaying tolerably similar markers can become the majority in the population by triggering a downward spiral of cooperation. Controlling for the effects of average clustering and global reachability, societies with less costly cooperation are more successful in hindering the invasion by those defectors compared to the reference society (*b/c* = 2). Holding the *b/c* ratio constant, either societies with higher degrees of clustering or those with more cross-cutting ties are more susceptible to the invasion by mutant defectors. For example, 0.2 point increase in the average clustering coefficient or one unit of decrease in the average path length heightens the frequency that defectors constitute more than half of the population by approximately 10.

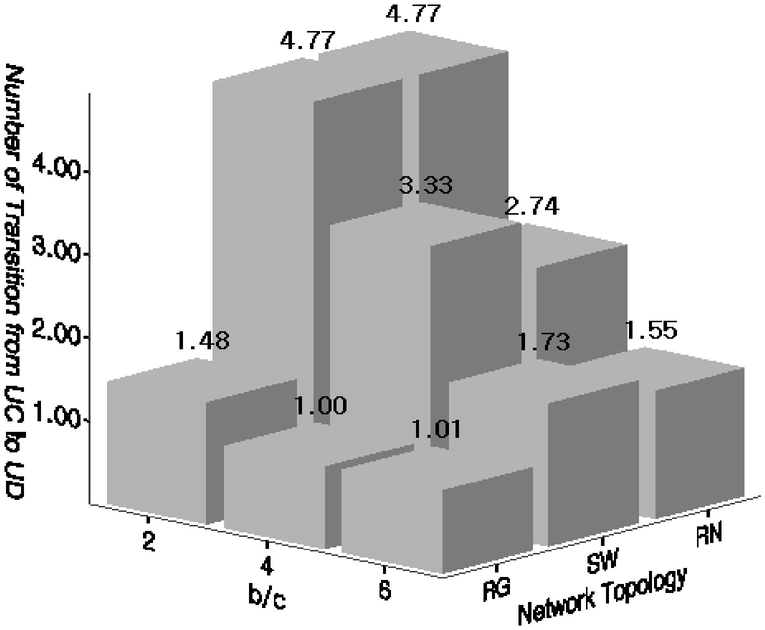


Figure 6.6. Frequency of Transition from Universal Cooperation to Universal Defection

Lastly, we record the number of the half downward cycles from universal cooperation to universal defection (e.g. 1, 3, and 5 from *# of uc to ud* in each panel of Figure 6.3). As is in Figure 6.6, regular networks are less likely to experience a complete destruction of universal cooperation because very highly clustered societies tend to be repaired by re-emerging local clusters of parochial cooperators in the middle of the invasion by mutant defectors. For the same reason, societies with relatively high degrees of clustering (SW) are more robust than their counterparts (RN) although defectors on small-world networks constitute the majority more successfully than those on random networks (Figure 6.5). The average occurrence of the transition from universal cooperation to universal defection does not show a significant difference between small-world networks and random networks not only at $b/c = 2$ ($\alpha = .01$) but also at $b/c = 6$ ($\alpha = .05$).

Supplementary Experiments

As is presented in Table 6.10, we find no significant differences in the likelihoods of the survival of cooperation and universal cooperation between societies where markers are completely mutable, but agents adjust tolerance levels towards those of more successful neighbors in a step-wise manner (Model 4) and societies with completely mutable tags and genetically transmissible tolerance (Model 1).

First, altruists cannot win against defectors if the benefit-to-cost ratio does not exceed the average number of neighbors in structured populations consisting of them alone ($L = 0$). Polymorphism, the co-existence of those two agents, is otherwise possible, whereas there is no chance of universal cooperation even at $b/c = 10$ without ‘tagging.’

However, tag-based local interaction and local learning significantly increase the chance of the survival of cooperation and universal cooperation as well. The longer the tag length, the more likely it is that parochial cooperators defeat not only defectors but also altruists. Making a distinction between ‘us’ and ‘them’ with four-length markers is enough for emergent societies to avoiding falling into the trap of mutual betrayal up to a 90% chance within the whole range of the *b/c* ratios under experiment.

Table 6.10. Likelihood of Survival of Cooperation and Universal Cooperation in Model 4 (Torus)

	b/c				
L	2	4	6	8	10
0	0 0	0 0	0 0	0 0	46 (0) 43 (0)
2	30 (30) 23 (22)	60 (58) 56 (50)	68 (60) 73 (63)	88 (61) 62 (50)	99 (54) 88 (46)
4	98 (89) 100 (89)	90 (78) 100 (81)	94 (74) 98 (85)	99 (70) 96 (81)	100 (77) 98 (70)
6	99 (87) 100 (81)	99 (88) 100 (80)	99 (82) 100 (91)	100 (78) 98 (82)	100 (82) 100 (87)
8	99 (86) 100 (87)	99 (89) 100 (84)	100 (83) 100 (87)	100 (89) 100 (90)	100 (88) 100 (79)
10	97 (81) 100 (87)	99 (89) 100 (95)	100 (92) 100 (89)	100 (84) 100 (84)	100 (87) 100 (86)

Note: The number at each cell represents the possibility that societies reach the cooperative equilibrium, that is, how many times out of 100 trials cooperators ($T \geq 1$) survives in the absence of imitation errors. The number in parentheses indicates the likelihood of universal cooperation. In each cell, the numbers at the first row (Model 4) and those at the second row (Model 1) from Table 4.4.

It does not necessarily happen that the most discriminating agents dominate a completely homogeneous population to take the lead in universal cooperation, as is indicated by the discrepancy between the likelihood of the survival of cooperation and the likelihood of universal cooperation. We observe cooperative societies sometimes emerge in which tribes with different sets of markers co-exist without penetrating one another under various spatial patterns as presented in Figure 4.3 through Figure 4.6.

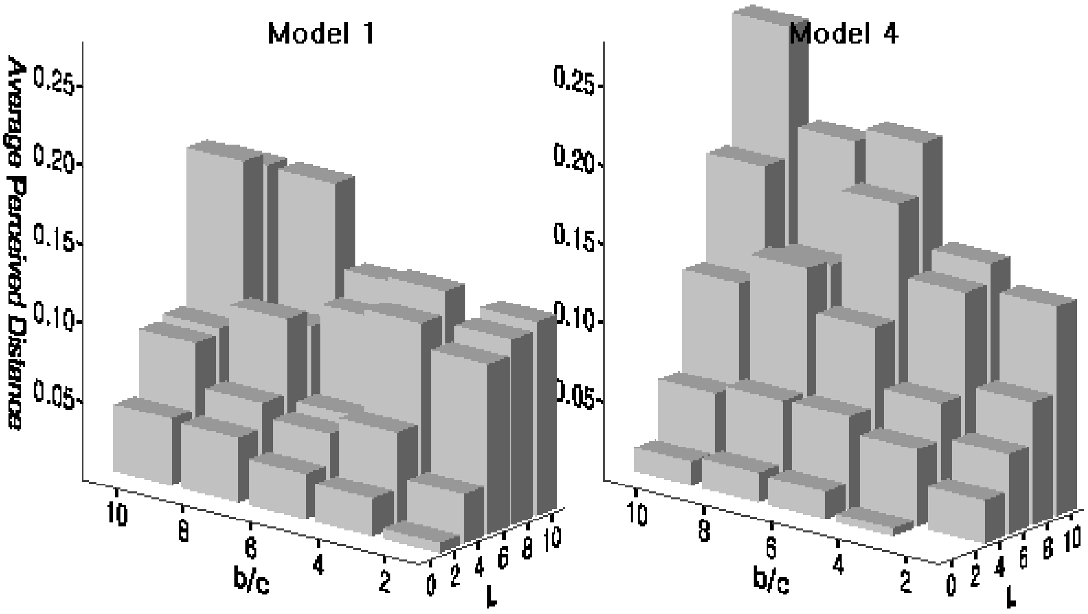


Figure 6.7. Average Perceived Distance at Cooperative Equilibrium in Model 1 and 4

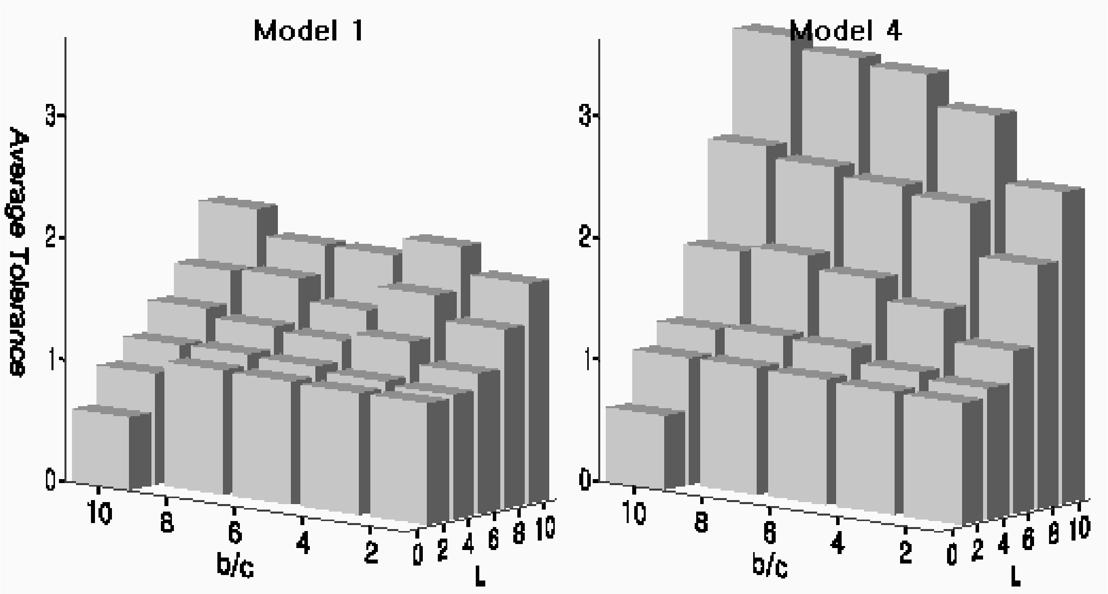


Figure 6.8. Average Tolerance at Cooperative Equilibrium in Model 1 and 4

Next, we compare the average dissimilarity and the average tolerance at the cooperative equilibrium across two societies (Figure 6.7 and Figure 6.8). The overall tendency is not different from one society to the other: as agents have longer tags, cooperative societies tend to be more heterogeneous and less parochial. More tolerant agents are less likely to perish and cultural diversity is thus more likely to be maintained in societies of concern in the following two chapters where agents relatively slowly learn tolerance from more successful neighbors. However, it turns out that there are no statistically significant differences in those tendencies between two societies when agents have relatively short tags ($L = 2$ or 4) at $\alpha = .05$ when controlling for the benefit-to-cost ratio, except in the average dissimilarity at $L = 4$ and $b/c = 10$.

6.4. Concluding Remarks

There are no significant differences in the survival of cooperation across three tag-based societies with different network topologies. Also, emergent tag-based societies can maintain society-wide cooperation only with significant losses of tolerance and cultural diversity, regardless of network topology. Nonetheless, we find that the degree of parochialism on average is stronger in regular networks because the local convergence of cultural markers is faster in highly clustered societies. The likelihood of universal cooperation is, therefore, higher in those societies. Agents learn intolerance more slowly in small-world networks and random networks. More tolerant agents who cooperate with culturally diverse others are more likely to be preserved in less cohesive networks.

None of tag-based societies is stable in the face of deviants displaying tolerably similar markers, but we find that the dynamics of the local reinforcement of tag-based cooperation, its global diffusion, and cascades of non-cooperation triggered by those defectors differ from one network topology to another depending on local clustering and global reachability. First, local cooperation is reinforced more quickly on regular networks with higher degrees of clustering. Next, it takes much longer for parochial societies to reach universal cooperation on regular networks with fewer short cuts than on the other two ‘small-world’ networks. Lastly, societies shaped by regular networks with very long path lengths are more robust because discriminating egoists more frequently are organized into cooperative groups due to high clustering, and they impede a complete destruction of cooperation by defectors facing fewer cross-cutting ties.

We conclude that high clustering on average contributes to the rapid formation of cooperative clusters. However, existing studies do not consider its negative effects on the robustness of cooperation in one-shot interactions. Group members embedded in cohesive ties tend to trust each other, but such clustered groups are more easily perturbed by defectors with tolerably similar markers (i.e. local cascades of non-cooperation). Clustering-driven social capital is not always good for the institutionalization of cooperation in sizeable groups without reciprocity and sanctions.

Cooperators in societies should be able to recruit defectors at greater distances to achieve high levels of cooperation. However, defectors can invade cooperative clusters more efficiently through cross-cutting ties. In these aspects, global reachability is a double-edged sword, as Cassar (2007) and Hanaki, Peterhansl, Dodds, and Watts (2007) address it. Consistent with our hypotheses at the beginning, we uncover that a long path length may delay the accomplishment of society-wide cooperation. On the other side, it provides favorable conditions for the stable evolution of cooperation by slowing down the speed at which defectors that disrupt signals of trustworthiness traverse.

Chapter 7: Co-evolutionary Dynamics of Parochial Cooperation and Networks

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7.1. Problem Statement

Our experiments in the previous chapters indicate that strong parochialism and cultural assimilation is characteristic of emergent cooperative societies unless the benefits of cooperation are relatively high, the tag space (*L*) is sufficiently large from the beginning, cultural heterogeneity is exogenously induced by immicable markers (Chapter 5), or societies have long path lengths (Chapter 6). In particular, the co-existence of less tolerant agents with more tolerant agents (polymorphism) is rarely observed in emergent cooperative societies.

Our focus in this chapter is on the option that agents can terminate the current relationships and choose new partners – instead of learning – from the "non-forced/ selective play" (Vanberg and Congleton, 1992; Orbell and Dawes, 1991) paradigm. We combine the action approach with the selection approach: the artificial societies that we explore below are ones in which agents learn both cultural markers and tolerance from more successful neighbors. Alternatively, they may break ties with dissimilar neighbors and form new ties to similar new partners selected either by referral, or from the larger society.

There is no risk of network disconnection in the previous chapter since agents play the game with the same set of neighboring partners in fixed networks. Back to the fourth question raised in Chapter 2, if agents select interaction partners based on homophily preference (“birds of the same tags flock together”), societies, however, may be segregated into highly homogeneous factions (e.g. Schelling’s model of residential segregation). This leads to a dilemma of integration in a Durkheimian sense: local integration requires cohesive ties (strong ties), whereas global integration necessitates cross-cutting ties (weak ties). We stress here that this dilemma is consistent with the trade-off relationship between the local reinforcement of cooperation and its global diffusion discussed in the previous chapter.

As addressed in the previous chapter, Granovetter (1973) proposes a solution to this dilemma, a small-world network as the optimization of strong ties (Colemanian social capital in this chapter) and weak ties (Burtian social capital in this chapter). Some studies (e.g. Eguíliz, Zimmermann, Cela-Conde, and San Miguel, 2005) observe that evolving small-world networks – where agents play the different roles such as “leaders,” “conformists,” and “exploiters” named by Eguíliz et al. (2005) – strongly promote the evolution of cooperation. However, some others contend that scale-free networks are highly conducive to globalized cooperation (e.g. Santos and Pacheco, 2005; Li, Zhang, and Hu, 2007). Suffice to say here that those studies, either cooperation in fixed networks or cooperation in endogenous networks, do not consider its evolutionary dynamics in the presence of the invasion by emerging defectors.

Given our joint model of emergent order and emergent structure, we seek to understand the effects of network plasticity and transitive closure bias in the selection of new partners on the evolution of parochial cooperation and network topology. A particular interest is whether variation in plasticity and closure bias makes possible stable cooperative societies in the face of defectors that avoid the tendency toward reduced cultural diversity and high intolerance.

Tag-based Actions and Tag-based Selection: Parochialism and Homophily

There are two distinctive approaches in existing models of tag-based societies. It is useful to differentiate what actions to choose (i.e. the action strategy) from how to select partners (i.e. the selection strategy) following Yamagishi, Hayashi, and Jin (1994). In one usage of tags, agent has tag-mediated perception of dissimilarity to interaction partners. Tolerance serves as a proxy strategy. Agent can use different strategies toward different partners depending on whether or not her perceived distances to her partners are less than her tolerance level (Riolo et al., 2001; Choi et al., 2006). Agents globally interact with a few randomly selected others (e.g. Riolo et al., 2001) or locally with adjacent neighbors on the lattice (e.g. Choi et al., 2006). Either global or local interaction is forced without so-called the “exit option” (Orbell and Dawes, 1993).

Tagging may play another role in the evolution of cooperation by affecting how to select partners. In this approach, it is the chance of interactions that is influenced by ‘tagging’ (Riolo, 1997; Hales, 2000; Hales, 2004; Hales and Edmonds, 2003; Edmonds and Hales, 2005). This usage is closer to the original meaning of tagging as a pervasive mechanism which facilitates selective interactions through aggregation and boundary formation in complex adaptive systems (Holland, 1993; Holland, 1995). For instance, agents move around to search the population for identical partners (e.g. Hales, 2000; Hales, 2004; Hales and Edmonds, 2003; Edmonds and Hales, 2005). Either no interaction (i.e. 'unforced play') or interaction with any of others randomly selected (i.e. 'forced play') is implemented if there is not any identical partner (Edmonds and Hales, 2005). In Riolo (1997), the chance of interaction between agent A and B is $1 - | t_A - t_B |^p$ given that agents have real-number tags $t \in [0, 1]$. A single fixed value of "pickiness," $p = 0.2$, is used, instead of endogenous tolerance. Strategies are not based on tag-based perception in these models, where which agents do not have tolerance (as a proxy for strategy in the present study). For example, unconditional cooperation and unconditional defection are taken in Hales and Edmonds (2003) and Hales (2004). Riolo (1997) employs stochastic strategies represented by triple real numbers.

Issues in Existing Models of Cooperation on Dynamic Networks

Research on "emergent order" (institutional order embedded in networks – dynamics on networks) has been done separately from research on "emergent structure" (network evolution – network dynamics) until recently (Macy and Willer, 2002), but models of the co-evolutionary dynamics of cooperation and networks in social dilemma games have indeed become a major research focus (Eguíliz et al., 2005; Santos, Pachecco, Lenaerts, 2006; Hanaki, Peterhansl, Dodds, and Watts, 2007; Buskens, Corten, and Weesie, 2008; Fu, Hauert, Nowak, and Wang, 2008). In such artificial societies, adaptively learning or rational agents interact and are influenced by their neighbors, as in fixed multi-agent games. In addition, agents may break ties to existing neighbors and form new ties. The interplay of influence of the network embedding on the agent and the agent's (strategic) rewiring of their network positions give rise to the co-evolution of agent traits in the population and the topology of the network. In other words, the focus is on how (pro-social) norms co-evolve with on-going relationships in which agents are embedded, who are neither over-socialized nor under-socialized (Granovetter, 1985).

In such co-evolutionary models, the essence of the theory lies in the rules by which agents interact with, change their strategies, and break and make ties with interaction partners. In (evolutionary) game theoretical approaches, agents imitate higher-scoring-strategies in the neighborhood at the previous round (i.e. influence). However, there are inconsistencies between how to interact with partners (i.e. action) and how to choose them (i.e. selection): agents use a single strategy, which they copy from more successful neighbors, toward all neighbors at the next round (e.g. 'always' cooperate and 'always' defect), while they choose partners reading image scores (Fu et al., 2008), randomly (Eguíliz et al., 2005), or based on a myopic calculation of expected benefits and costs (Hanaki et al., 2007). Furthermore, both tie dissolution and tie construction is unilateral (e.g. Fu et al., 2008), or tie breaking is consensual and tie making is unilateral (e.g. Eguíliz et al., 2005). Neither is realistic.

In more classical game theoretical approaches, a consistency between the action strategy and the selection strategy is maintained given that boundedly or perfectly rational agents attempt to maximize their utilities (e.g. Buskens et al., 2008). But, adaptively learning agents in our study imitate cultural tags of interaction partners who are more successful and modify tolerance toward their tolerance levels: they do not have complete knowledge about the status of the network and they cannot consider all possible choices of strategy, tie formation, and its deletion: they do not change their tolerance as a proxy strategy to maximize utility; and they do not manage their ties strategically in a forward-looking manner. Cultural tags play a role in interaction: agents help similar alters, but do not if their perceived social distances towards alters are bigger than their tolerance levels. Cultural tags also play a role in selection. Agents break the old ties unilaterally with dissimilar others and create new ties to similar others. For a new tie to be formed, however, the difference between the two agents must fall within the tolerance of both agents. That is, new ties are formed by mutual consent.

We need to address here some important differences between our model in this chapter and existing studies of cooperation on dynamic networks. In their models, partner switching tends to accelerate preferential association among cooperators. First, both defectors and cooperators are inclined to terminate the relationship with defectors because they gain nothing from their own kind. Second, defectors attempt to make new ties to cooperators, while cooperators want to hang around with their own kind. Regarding building new links, it is strongly assumed that agents are always able to recognize new partners as defectors or cooperators. Otherwise, agents believe that other players will continue with their current strategy. Agents presumably have information about the strategies of new partners at the previous round particularly when they are chosen by referral. Without any information, agents can construct new relationships with randomly selected partners.

Those assumptions and rules can be reasonable for repeated interactions, but we question how agents know who are cooperators and who are defectors in one-shot interactions. In our models, as is addressed earlier, tolerance is an exact predictor of a predisposition to cooperation (i.e. the higher tolerance, the more likely to cooperate; the lower tolerance, the less likely to cooperate), but tolerance is not observable in tag-based societies. If tolerance is visible, there is no risk of invasion by mutant defectors because existing cooperators are able to notice whether or not mutant defectors exploit them.

Tolerance can be another plausible heuristic for partner change, but it leads to an inconsistency between the action rule and the selection rule. The former is driven by tag-based similarity perception and parochial cooperation, whereas the latter is based on partner selection by reading tolerance. Besides, there will be a strong built-in bias toward cooperation by breaking ties with less tolerant neighbors (i.e. they are more likely to defect) and creating new ones with more tolerant players (i.e. they are more likely to cooperate). We cannot overemphasize here that parochial agents in tag-based societies, instead, rely on tag-based similarity to predict behaviors of interaction partners: they cooperate with similar others in the shared belief that 'in-group members will help each other.' Very often, however, tag-based similarity does not exactly predict behavioral predispositions. This is why existing cooperators are supposed to accept all mutants, as long as they have tolerably similar tags, as in-group. But, unfortunately, some of them turn out to be those who have lower levels of tolerance and they are therefore more likely to exploit others.

As is in existing models of cooperation on dynamic networks, if cooperators can at least break ties with mutant defectors, instead of being influenced by them, then cooperative societies will definitely become more stable. However, even if opportunities of switching partners are provided, parochial agents in the present study cannot break ties with those who are predisposed to defect (i.e. players with lower levels of tolerance) in favor of those who are predisposed to cooperate (i.e. players with higher levels of tolerance). The only thing they can do is to break ties with out-group in search for in-group based on their homophily preferences (i.e. 'birds of a 'cue' flock together').

Two Faces of Social Capital

Social capital indicates an advantage people can obtain due to their location in a social network. Coleman (1990a) stresses that if a dense network of social relations between the group members provides favorable conditions for the emergence of norms to make their collective actions possible: "Because social relationships consist of obligations and expectations. . . and because each actor continues to control some events in which the other is interested, there exists . . . leverage which can be used for the purpose of developing sanctions" (Ibid: 270). On the contrary, Burt (1992) highlights another aspect of social capital to maintain that the entrepreneurship of individuals takes advantages of structural holes between clustered groups.

As is summarized in Table 7.1, closure and bridging are complementary features of social capital (Burt, 2005; Burger and Buskens, 2009), but it is yet to be fully understood how those opposite two forces shaping network evolution affect the dynamics of cooperation, especially both in the setting of one-shot interactions without reciprocity and in the presence of mutant defectors. Following our discussion in the previous chapter, cooperation is more likely to be locally reinforced in societies of highly clustered networks. However, such societies are more vulnerable to local cascades of non-cooperation in the presence of defectors displaying tolerably similar cultural markers. Also, local integration necessitates cohesive ties – strong ties in Granovetter (1973), but global integration requires cross-cutting ties (i.e. "the strength of weak ties"). Cooperation is less likely to be fully blown in networks with longer path lengths, but it can be more stable in those networks where defectors have more difficulties in penetrating every corner of the society.

Table 7.1. Two Faces of Social Capital: Closure and Bridging

	Closure	Bridging
Features	More closed, exclusive Redundant, strong ties	More open, inclusive Non-redundant, weak ties
Measure	Average clustering coefficient	Average path length
Partner selection	Making new ties to neighbors-of-neighbors	Making new ties with agents at greater distances
Effects on cooperation	Local reinforcement (+) Cascades of non-cooperation (-)	Global expansion (+) Defectors diffuse rapidly (-)

How Network Plasticity and Closure Matter

Our agents either interact with the agents in their current neighborhood, or break a tie and form a new one, rather than doing both at the same time. The likelihood of these alternatives is exogenous (e.g. Santo et al., 2006; Fu et al., 2008), which we call 'network plasticity' (i.e. the relative likelihood of homophily-based partner selection versus adopting cultural traits of more successful interaction partners).

If an agent chooses to break ties, they search for new partners with varying degrees of a transitive closure bias (Granovetter, 1973; Watts, 1999), which is treated exogenously (e.g. Hanaki et al., 2007; Fu et al., 2008): agents may form new ties, by mutual consent, with neighbors-of-neighbors (high clustering) or random other agents at greater distances.

We are concerned with the consequences of variation in network plasticity and homophily-driven triadic closure on the demography of agents: how much tag diversity is there in the population?; and how tolerant are agents of cultural differences? We also examine the topology of evolving networks in which agents are embedded: under what conditions do ‘small-world’ networks emerge?; and what are the shape of evolved networks in terms of clustering, path length, and the degree distribution? Finally, we focus on the stability of parochial cooperation including the level of global cooperation: how frequently do mutant defectors lead to the collapse of global cooperation; how often does defection become the dominant culture?; and how is it possible that parochial cooperation is significantly more robust on evolving networks?

7.2. Experimental Design

Main Experiment

We focus on an intermediate case ($b/c = 4$ and $L = 4$), as is the same as the main experiments in the presence of imitation errors in the previous chapter (Table 7.2). All conditions of the main experiments include two sources of stochastic errors – imitation errors ('cultural perturbation') and tie-rewiring errors ('network perturbation'). The final design for the main experiment does not consist of the 6 by 5 (q by p) factorial, but rather the truncated version shown in Table 7.3.

Table 7.2. Parameter Setting of Main Experiments on Model 5

Parameters	Values/ Ranges
Number of agents	100
Benefit-to-cost ratio	4
Tag length	4
Erdös-Rényi probability	.06
Error	.01 for both imitation and tie rewiring
Network plasticity (p)	10 through 50 with the interval of 10
Closure (q)	0 through 50 with the interval of 10
Condition for cooperation	$\mid t_A - t_B \mid < T_A$
Payoff-based imitation rules	Given one neighbor randomly chosen, if her score is higher than an ego, the ego copies her tags and adjusts his tolerance toward her level by one unit.

Table 7.3. Design of Main Experiments on Model 5

	p				
q	10	20	30	40	50
0	▨	▨	▨	▨	▨
10	▨	▨	▨	▨	▨
20	▨	▨	▨	▨	---
30	▨	▨	▨	---	---
40	▨	▨	---	---	---
50	▨	---	---	---	---

Notes: Models in which changing partners is more common than learning cultural traits from more successful neighbors (i.e. $p > 50$) almost always result in disconnected structures within 2,000 time steps even at the minimal level of clustering in our experimental setting ($q = 10$). Even at $p \leq 50$, when agents are quite likely to break ties with dissimilar others and form new ties from among the neighbors of remaining neighbors, there is a strong tendency for society to dissolve into separate tribes (---s in this table). We restrict our attention to lower levels of plasticity and clustering, where the population remains connected.

In each of the 20 remaining conditions (i.e. shaded areas in Table 7.3), 100 replications are performed. $G_{(i,j)}$ hereafter denotes the experimental group at $p = i$ and $q = j$. Each trial is run for 2,000 time steps. All outcome measures will be taken only between time point 1,000 and time point 2,000 to allow the model to reach its characteristic state from the varying initial conditions.

7.3. Results

We have already shown the dynamics of parochial cooperation on static random networks in Figure 6.2, but we should address its several aspects. Beginning with the lower right in Figure 7.1, the first point is about a random drift toward more tolerance. This is indicated by an increase in the yellow areas (Plot of 'Evolution of Tolerance' in lower right, where 'Yellows' for $2 \leq T \leq 4$ and 'Blue' for $T = 5$). As long as the majority of less parochial agents have the same tag strings as those of the strongest discriminators (i.e. $T = 1$), societies can achieve a high level of global cooperation without a significant increase in tag diversity.

Second, even relatively low rates of perturbation have big impacts on the long-run dynamics of parochial cooperation. Once parochial agents (i.e. $1 \leq T \leq 5$) cooperate with, and are exploited by intolerant mutants, global cooperation collapses. The chance of a transition to a "betrayal society" increases whenever the demography gradually changes toward the co-existence of cooperators with different levels of tolerance. A significant increase in more tolerant agents in the population ('cultural drift' equivalent to 'genetic drift' in evolutionary biology) makes global cooperation more vulnerable (cf. Young and Foster, 1996).

Third, 'betrayal societies' are rather quickly repaired when agents err in learning from neighbors. Since defectors do not benefit from each other, once perturbations create discriminating cooperators, other agents preferentially interact with them and learn tags and tolerance from each other, they can reconstruct a new cooperative society. However, the reconstructed societies do not increase significantly in cultural diversity (Plot of 'Average Dissimilarity Distribution').

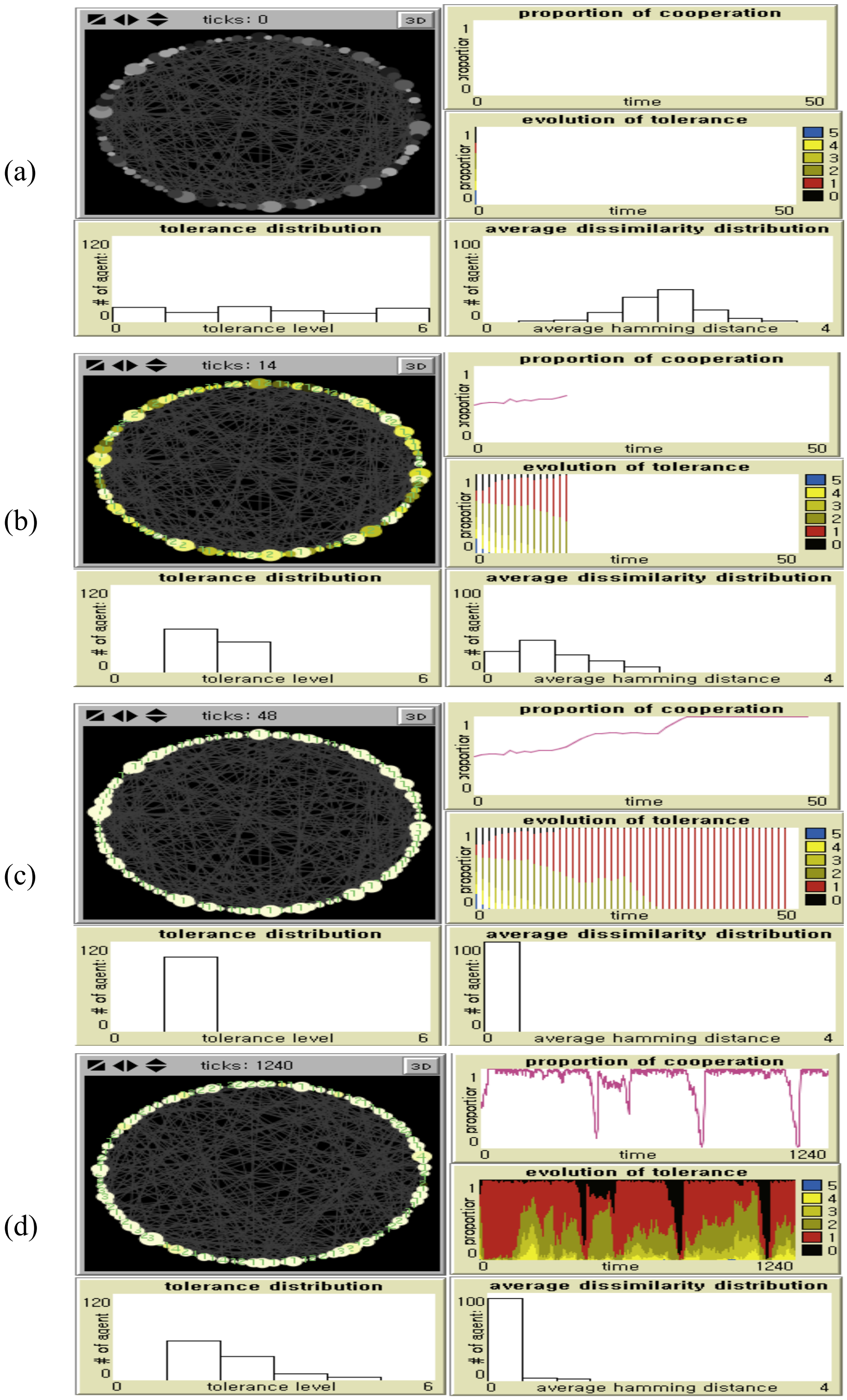


Figure 7.1. Dynamics of Tag-based Cooperation on Static Random Network

Notes: A typical run of the simulation. Numbers in each node indicate tolerance levels. The node size and its brightness are proportional to agent degree and to the proportion of neighbors with whom each agent cooperates, respectively. $N = 100$, $b/c = 4$, $L = 4$, $k = 6$, $p = 0$, and $\mu = .01$ after 50 time-steps.

Homogeneity and Tolerance.

On fixed random networks cooperation can be sustained, but only with a loss of diversity. Results from the main experiments show that societies with greater plasticity are more likely to retain global diversity than those in which payoff-based learning outweighs partner selection. To the extent that agents move about, global diversity is protected against the emergence of a single dominant culture. Also, when new partners are selected from among neighbors of neighbors (i.e. stronger closure bias), there is an additional modest tendency toward sustaining diversity. The clustering effects on cultural diversity are significant ($\alpha = .05$) at $G_{(10, 50)}$, $G_{(20, 40)}$, and $G_{(30, 30)}$ compared to $G_{(10, 0)}$, $G_{(20, 0)}$, and $G_{(30, 0)}$ respectively.

In societies where tolerance is learned from successful neighbors on random static networks, there is a strong tendency for tolerance of cultural differences to erode. In the main experiments, we find that the tendency toward lower levels of tolerance is not much affected by network plasticity. There are, however, the strong clustering effects on agent's learning intolerance. As is shown in Table 7.4, the most discriminating cooperators still predominate in societies with more plasticity. However, it is also true that agents are less likely to learn intolerance on evolved networks with higher clustering. The average tolerance is significantly higher ($\alpha = .05$) at $G_{(10, 10)}$ through $\mathrm{G}_{(10, 50)}$, $G_{(20, 20)}$ through $G_{(20, 40)}$, $G_{(30, 20)}$ and $G_{(30, 30)}$, $G_{(40, 20)}$, and $G_{(50, 10)}$ compared to each reference experimental group $G_{(i, 0)}$.

Table 7.4. Proportions of Agents by Level of Tolerance at Varying Levels of Plasticity and Closure Bias

G_{ij}	$T = 5$	$T = 4$	$T = 3$	$T = 2$	$T = 1$	$T = 0$
$G_{(10, 0)}$	.0032(.0021)	.030(.016)	.11(.036)	.27(.047)	.50(.060)	.10(.054)
$G_{(10, 10)}$	.0030(.0018)	.033(.020)	.12(.036)	.28(.046)	.48(.061)	.091(.047)
$G_{(10, 20)}$	.0035(.0024)	.036(.018)	.12(.041)	.28(.050)	.48(.066)	.071(.043)
$G_{(10, 30)}$	.0038(.0028)	.038(.021)	.12(.037)	.28(.046)	.48(.065)	.075(.049)
$G_{(10, 40)}$	.0046(.0048)	.035(.021)	.13(.042)	.29(.050)	.46(.073)	.086(.046)
$G_{(10, 50)}$	.0048(.0046)	.041(.020)	.13(.041)	.29(.047)	.47(.071)	.065(.048)
$G_{(20, 0)}$	.0036(.0024)	.030(.015)	.11(.038)	.26(.048)	.50(.065)	.095(.046)
$G_{(20, 10)}$	.0037(.0053)	.033(.016)	.12(.041)	.28(.052)	.47(.072)	.089(.046)
$G_{(20, 20)}$	.0048(.0023)	.034(.019)	.13(.041)	.29(.057)	.47(.071)	.074(.050)
$G_{(20, 30)}$	.0037(.0021)	.035(.021)	.12(.041)	.29(.054)	.48(.073)	.072(.046)
$G_{(20, 40)}$	.0042(.0031)	.040(.025)	.13(.042)	.30(.055)	.47(.082)	.057(.039)
$G_{(30, 0)}$	.0041(.0028)	.026(.013)	.11(.039)	.28(.050)	.49(.068)	.092(.051)
$G_{(30, 10)}$	.0039(.0027)	.031(.017)	.12(.048)	.29(.055)	.47(.073)	.092(.053)
$G_{(30, 20)}$	.0051(.0049)	.033(.018)	.12(.045)	.29(.090)	.48(.074)	.073(.048)
$G_{(30, 30)}$	.0056(.0048)	.036(.023)	.12(.041)	.29(.061)	.48(.085)	.070(.046)
$G_{(40, 0)}$	.0044(.0024)	.027(.018)	.10(.041)	.28(.058)	.49(.074)	.10(.058)
$G_{(40, 10)}$	.0044(.0036)	.031(.017)	.11(.042)	.29(.059)	.48(.070)	.090(.056)
$G_{(40, 20)}$	.0048(.0020)	.033(.019)	.12(.043)	.29(.056)	.49(.081)	.067(.049)
$G_{(50, 0)}$	.0049(.0019)	.025(.013)	.10(.035)	.29(.063)	.49(.068)	.098(.055)
$G_{(50, 10)}$	.0050(.0018)	.028(.012)	.10(.038)	.29(.059)	.49(.069)	.082(.054)

Note: The numbers in each cell indicate Mean (Standard deviation). The shaded areas denote the groups in which the average tolerance is significantly higher or lower than their reference groups $G_{(i, 0)}$s.

Network Topologies

Unsurprisingly, for any given level of plasticity, the greater the tendency to select new interaction partners from among neighbors-of-neighbors, the greater the clustering of the overall network. Also unsurprisingly, as the tendency to clustering (q) increases, average path lengths in the whole population increase. As the joint effects of network plasticity and a bias of triadic closure continue, the density of local clusters increases at a decreasing rate, while the density of ties between clusters declines. At the extreme, high biases toward transitive partner selection result in the graph becoming disconnected.

A small-world network is a graph with n vertices and average degree k that exhibits the average path length $APL \approx APL_{\mathrm{random}}(n,k)$, but the average clustering coefficient $ACC >> ACC_{\mathrm{random}} \approx k/n$ (Watts, 1999). For each of the conditions of the main experiment, tests were performed if the mean average clustering coefficients (and the mean average path lengths) of 100 evolved networks are significantly greater than (and differ significantly from) the mean average clustering coefficients and (the mean average path lengths) of 100 random networks. Only one condition of the experiment ($p = 10$ and $q = 10$) satisfy the small-world properties. Evolved networks in all other groups cannot be classified as “small-world” because they display longer average path lengths than those of small-world networks (Table 7.5 and Table 7.6).

Table 7.5 Average Clustering Coefficients of Evolved Networks

	p				
q	10	20	30	40	50
0	.0532(.00909)	.0531(.00969)	.0520(.00797)	.0531(.00783)	.0597(.01036)
10	.0693(.01257)	.0696(.01192)	.0676(.01118)	.0702(.01009)	.0715(.01123)
20	.0826(.01491)	.0853(.01403)	.0869(.01410)	.0913(.01841)	
30	.1001(.01263)	.1041(.01647)	.1083(.02490)		
40	.1214(.01599)	.1333(.02673)			
50	.1425(.02035)				

Note: The numbers in each cell indicate Mean (Standard deviation).

Table 7.6 Average Path Lengths of Evolved Networks

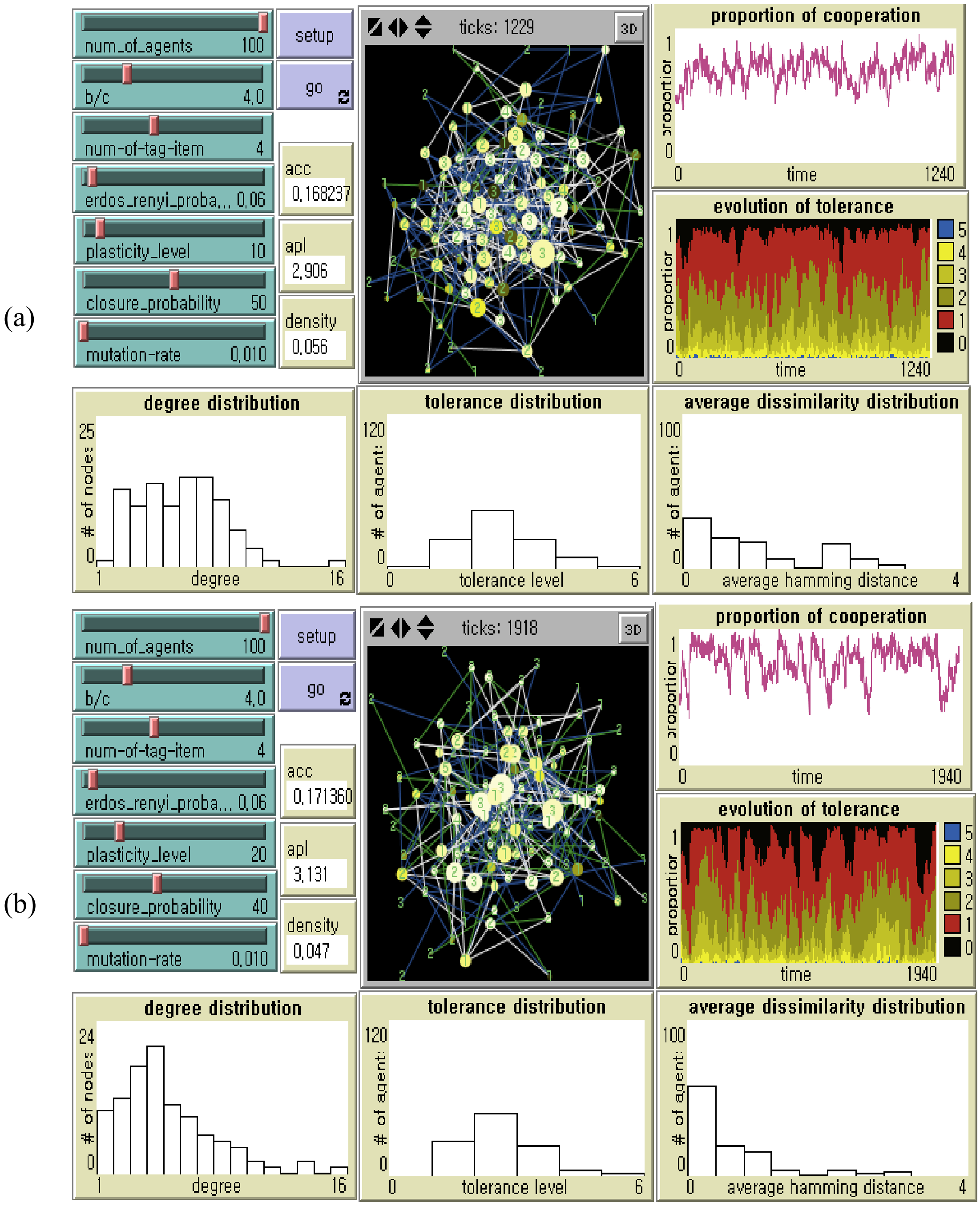
	p				
q	10	20	30	40	50
0	2.734(.07222)	2.757(.07062)	2.767(.07069)	2.760(.07079)	2.755(.07565)
10	2.771(.07134)	2.795(.07620)	2.829(.08917)	2.839(.09609)	2.841(.10145)
20	2.819(.08873)	2.839(.09527)	2.924(.10892)	3.002(0.1097)	
30	2.844(.08643)	2.913(.10805)	3.074(.15484)		
40	2.873(.09434)	3.069(.15669)			
50	2.939(.12120)				

Note: The numbers in each cell indicate Mean (Standard deviation).

When plasticity is present, there is a modest tendency for evolved networks to move toward more unequal distributions of agent degree. This effect is stronger, the higher the tendency to transitive closure in partner selection. The clustering effects on the maximum degree are significant ($\alpha = .05$) at $G_{(10, 40)}$ and $G_{(20, 30)}$ to $G_{(20, 40)}$ compared to $G_{(10, 0)}$ and $G_{(20, 0)}$, respectively. More tolerant agents are able to find new partners, while less tolerant agents are less successful in rewiring their networks and consequently, there is a modest tendency for more tolerant agents to acquire greater social capital. Clustering does not always ($\alpha = .05$) affect the evolution of 'hubs' with tolerance higher than the minimal tolerance for parochial cooperation ($T = 1$), except $G_{(10, 50)}$. Nonetheless, the overall trend is that the most highly connected actors are those who have somewhat higher degrees of tolerance. Accentuating this tendency, there are statistically significant tendencies ($\alpha = .05$) for the average degree of unconditional defectors and the most discriminating cooperators to decline with increasing closure in the selection of new interaction partners.

The Robustness of Cooperation.

We investigate the effects of network plasticity and clustering on the stability of parochial cooperation by examining the average frequency of cascades toward "betrayal society" (i.e. universal non-cooperation) once universal cooperation has been established. As network plasticity increases, cooperation generally becomes more stable. And, in general, as clustering in forming new ties increases, cooperation becomes more stable. The reasons for these results are two-fold. Breaks in the cooperative culture of a given local cluster take longer to be transmitted to other groups on evolved networks with weaker degrees of global penetration. Additionally, high clustering makes it easier for discriminating mutant cooperators to re-enforce one another's propensity to cooperate, which leads to more rapid "repair" of local breaks in cooperation.



(a)

num_of_agents 100
b/c 4,0
num-of-tag-item 4
erdos_renyi_proba... 0,06
plasticity_level 10
closure_probability 50
mutation-rate 0,010
acc 0,168237
apl 2,906
density 0,056
ticks: 1229

(b)

num_of_agents 100
b/c 4,0
num-of-tag-item 4
erdos_renyi_proba... 0,06
plasticity_level 20
closure_probability 40
mutation-rate 0,010
acc 0,171360
apl 3,131
density 0,047
ticks: 1918

Figure 7.2. Dynamics of Tag-based Cooperation on Evolving Network

Note: A typical run of the simulation with $p = 10$, $q = 50$ in Panel (a) and $p = 20$, $q = 40$ in Panel (b). Numbers in each node indicate tolerance levels. Node size is proportional to degree. Node brightness is proportional to the proportion of neighbors with whom each agent cooperates.

Figure 7.2 shows typical examples of moderately plastic (*p* = 10 and 20) evolving networks with a relatively high tendency to transitive tie-making (*q* = 50 and 40). The patterns at time-step = 1,229 in Panel (a) and 1,918 in Panel (b) contrast notably from those of the static random network shown in Figure 7.1. Although the rates of perturbation are the same, plastic networks with transitive closure characteristically display more frequent (i.e. the increased size of Black in plot of 'Evolution of Tolerance') – but much less severe cycles toward "betrayal society." The average levels of agent tolerance and the diversity of culture in society are also much greater than in static society. We also find that there is a tendency for the degree distribution to become unequal, particularly when more tolerant agents successfully accumulate social capital, as is indicated by Plot of 'Degree Distribution' and the average size of more tolerant nodes.

7.4. Concluding Remarks

We investigate the dynamics of tag-based parochial cooperation in societies, where actors are not only influenced by successful neighbors but also free to change their interaction partners by dropping ties to dissimilar neighbors and making new ties to similar others with a closure bias. We find that, if social mobility and clustering are too high, societies tend to devolve into cohesive, but disconnected, sub-populations. If social mobility and clustering are too low, there are no significant differences between societies with random network topologies at the degree of closure = 0% and partly mobile societies: parochial cooperation is propelled mostly by the strongest discriminators; a highly homogeneous population is needed for globalized cooperation; and parochial cooperation is not robust against mutant defectors. These patterns in the dynamics of cooperation are not fundamentally different from those in static societies where tags are completely mutable. In particular, small-world networks are norm-generating, but not norm-sustaining: their high degrees of clustering foster the local reinforcement of parochial cooperation, whereas defectors can travel more quickly through relatively short paths.

There is, however, a part of the parameter space between these two outcomes: $G_{(10, 50)}$ and $G_{(20, 40)}$. It is on evolving networks with moderately high local clustering and fairly low global penetration that the long-run dynamics of parochial cooperation manifest significantly different results. The mean average clustering coefficients and the mean average path lengths of 100 evolved networks are .143 (.134) and 2.939 (3.069), and the standard deviations are .0204 (.0267) and .121 (.157) at the first (second) experimental condition). Here, parochial cooperation is globally more stable in the face of mutant defectors although the invasion of the core by defectors sometimes seriously perturbs cooperative relations at the local level; and emergent societies retain relatively high tolerance and more cultural diversity.

How is this possible? First of all, structural conditions – high clustering and reduced global penetration – lessen the likelihood of a successful invasion by mutant defectors – the disruptive effects of an apparent ‘in-group’ member betraying others. Mutant defectors more frequently attack existing cooperative societies with increased tolerance to trigger non-cooperation, but local clusters of parochial cooperators quickly re-emerge to inhibit cascades of betrayal. Defectors are less likely to become the majority because it is more difficult for them to traverse networks with long path lengths. Meanwhile, it more frequently happens that newly emerging tolerant agents of diverse tags preferentially interact with and benefit from each other, instead of being absorbed into cooperative clusters of stronger parochialism and highly homogenized culture. Agents with strong parochialism promote local homogeneity since they are more likely to restrict the pool of acceptable neighbors and potential partners, while agents who display moderate degrees of tolerance construct inclusive ties to culturally diverse others. This tendency becomes stronger as clustering increases: evolving networks are characterized by a moderate inequality in social capital because less parochial agents build outward social networks more easily than intolerant agents. To the extent that all these processes reinforce each other immediately after invasion by mutant defectors significantly destructs the established parochial institutional orders and networks, a new cooperative society of high tolerance and more cultural diversity can emerge.

Chapter 8: Discussion and Conclusions

Relatively robust and high levels of cooperation in human societies are commonly observed empirically, but have been a challenge to research on a multi-agent one-shot Prisoner's Dilemma game. Societies composed of altruists who always help others are readily undermined by indiscriminating defectors under the force of natural selection. Recent theories notice that it is not realistic for agents to play the game with randomly matched partners in a pairwise manner. They demonstrate that cooperation can be sustained even in populations purely consisting of indiscriminating altruists and defectors if agents simply interact with immediate neighbors and leave offspring in proportion to fitness in their neighborhood. This reciprocation through network helps altruists preferentially interact with their own kind while avoiding defectors. However, the effect of spatiality operates only if the benefits of cooperation are relatively high and the number of neighboring interaction partners is limited.

The population in the classical models of a spatial evolutionary Prisoner's Dilemma game is idealistic since it is purely composed of two groups of indiscriminators: those who always cooperate toward others with the highest level of trust and those who always refuse to do that with the lowest level of trust. Some other studies pay due attention to the roles of discriminators in the evolution of cooperation in human societies. They verify that cooperation is more likely to prosper as the number of agents increases who use conditional strategies depending on the trustworthiness of partners even in unstructured populations where agents interact with randomly selected partners. However, emergent cooperative societies are highly susceptible to those who fake signals of trustworthiness but are predisposed to defect toward others. Pairwise random interaction is another limitation of extant models of cooperation through signaling because it is not realistic. Human agents may have relatively stable sets of interaction partners, as is assumed in the classical model of network reciprocity. Also, they may switch partners based on their preferences under a certain level of social mobility.

Theoretically informed by existing research highlighting the importance of networks and signals (as “heuristic cues”) in the evolution of cooperation, the current study inquires into cultural bases and structural foundations of cooperation in human societies as complex systems. Social structure has three dimensions in our study. First, culture is a set of shared beliefs and available strategies for Weberian social action, the action taking into account the behavior of others in game theory. Second, institution is conceived as behavioral regularity from a bottom-up perspective in the sense that institutionalization occurs through a reciprocal typification of habitualized actions. Third, network as the relational dimension provides an interpersonal setting of actions. Human agents embedded in on-going relationships interact with one another.

The present study investigates the evolutionary dynamics of cooperation in artificial societies in which agents have tags and tolerance. In the setting of a one-shot Prisoner's Dilemma, they simultaneously interact with neighbors, and they either imitate tags and tolerance of more successful neighbors or break and make ties with others. The theoretical question under study is thus how individuals sharing cultural elements in the Blau Space ("the tag space") create network patterns of social relations which simultaneously affect the evolution of cultural groups, and how emerging networks of social groups come into play in the institutionalization of cooperation and its deinstitutionalization.

The current research offers a list of findings and propositions to further understanding of the evolution of cooperation as institutional order when societies are situated in the Prisoner's Dilemma. In Chapter 4, we reconfirm the received finding that altruists alone can beat defectors even in a one-shot game where agents interact with the same set of adjacent neighbors if the benefit-to-cost ratio of cooperation is higher relative to the average number of neighbors. Cooperation otherwise cannot survive. We demonstrate that it holds true, regardless of network topology.

Second, we manipulate the population to have not only altruists and defectors but also the discriminators who categorize partners into 'us' and 'them' by reading tags as observable markers. Since tolerance is not an observable trait in tag-based societies, tags serve as heuristic cues for how to interact with neighbors. Egoistically, those discriminators cooperate only with neighbors who have tolerably similar markers, and otherwise decline to cooperate. We discover that reading markers and cooperating only with trustworthy partners significantly facilitates the survival of cooperation. This implies that ethnocentric egoists can be even necessary to trigger and maintain cooperation when helping others is relatively costly.

Third, we ask how society-wide cooperation is possible from local interactions among agents who have limited tolerance for cooperating with others who they see as different from themselves. Such parochial cooperation stops at group boundaries. Emergent cooperative societies do not consist of relatively tolerant agents including altruists with the highest level of tolerance, who trust heterogeneous neighbors. Tolerance for diversity is rather rapidly eroded in emerging societies with an increasing loss of heterogeneity. Agents become more discriminating against perceived out-group, but high levels of global cooperation are still possible in increasingly homogenized populations. Most of time, the most discriminating egoists form the vast majority of the population. They are those who are willing to cooperate only toward neighbors with exactly the same markers.

Emergent parochial societies are, however, unstable in the presence of mutant defectors with tolerably similar tags. There occur downward spirals of cooperation that lead to a society of mutual betrayal once those defectors perturb "secret handshaking" among parochial cooperators. This generally indicates that cooperation on the basis of sending and receiving exclusive signals is highly efficient, but it is not successful in terms of stability – such cooperation fails to continue once free-riders can easily learn to fake signals of trustworthiness.

In Chapter 5, we point out that the evolutionary instability of tag-based parochial cooperation is partly because tags are completely changeable. Conceptualizing tags as cultural markers as a simple form of identities (rather than modeling them as genetically inheritable traits), we build one society where each agent has one immutable marker at the same dimension ('caste society') and the other society where such an immutable marker in different dimensions ('modern society').

Cooperative agents with the strongest parochialism are still in the majority of the population in those two societies. But, tag-based cooperation is significantly stable in a modern society despite the fact that agents in it are more tolerant enough to accept a broader range of defectors as in-group. We find that persistent cultural heterogeneity in such a modern society helps agents continue to make distinction between ‘us’ and ‘them,’ with none of identities constantly predominant in the society as a whole. It is characterized by loosely coupled small-sized groups (tribes) with different cultural identities.

We know that when markers are completely mutable, tag-based parochial cooperation is inevitably vulnerable to defectors displaying tolerably similar markers. The following two chapters intend to seek structural solutions to efficient and stable cooperative societies promoting the diversity of tags and tolerance. We first investigate the effects of network topology on the evolution of cooperation in tag-based societies in Chapter 6. We present that the dynamics of the local reinforcement of parochial cooperation, its global diffusion, and cascades of non-cooperation triggered by defectors are significantly affected by the interplay of clustering and global reachability.

Parochial cooperation diffuses more slowly in regular networks, but it becomes more robust against indistinguishable mutant defectors in them than in small-world networks and random networks. It is because high degrees of clustering promote the rapid formation of local cooperative clusters, while long average path lengths render the invasion by mutant defectors less efficient.

In Chapter 7, we finally examine the co-evolution of three dimensions of social structure: cooperation as its institutional dimension, tags and tolerance as its cultural dimension, and social network as its relational dimension: how does cooperation as a behavioral regularity evolves with “CatNets” named by White (Tilly, 1978: 63) as groups of (cultural) categories plus networks? In artificial societies under investigation, agents not only take discriminating actions toward neighbors, but they also have a homophily preference for socializing with the members of one’s group. Agents have the option of either imitate tags and tolerance of more successful neighbors or switching partners based on the homophily preference with varying probabilities of network plasticity. They break ties with out-group neighbors in search for similar others either from neighbors-of-neighbors (Colemanian cohesive ties) or at greater distances (Burtian cross-cutting ties) with varying degrees of closure.

We find that, if social mobility and clustering are too high, societies devolve into cohesive, but disconnected, sub-populations. If social mobility and clustering are too low, there are no significant differences between static societies and partly mobile societies: parochial cooperation is propelled mostly by the strongest discriminators; a highly homogeneous population is needed for globalized cooperation; and parochial cooperation is not robust against mutant defectors. There is, however, a part of the parameter space between these two outcomes where global cooperation is possible without network disintegration despite that emergent societies are not highly homogenous. With moderately high clustering and fairly low global penetration (reachability), society-wide and stable cooperation is achievable in emerging hierarchical networks of cultural groups that acquire differential shares of social capital and economic capital even though cultural markers are completely mimicable.

The current study has broader significance for studying group processes and market dynamics. First, the tag-based partner identification (‘tagging’) in our study is consonant with socio-psychological theories of group membership as social identities (Hogg, 2006). People tend to make distinctions between ‘us’ and ‘them’ through ‘categorization’ (Tajfel, 1974) as a cognitive process of classifying stimuli on the basis of ‘similarities’ between them (Turner, 1982).

Social psychologists have been interested in how the intergroup-outgroup bias influences cooperation since the ‘minimal group’ experiments in the 1970s. They have observed a consistent pattern of results that ‘belonging to a pre-assigned group’ positively affects the level of cooperation. Simple categorization is enough to create in-group favoritism, and human subjects in those experiments maximize their group-level rewards. For examples, Kramer and Brewer (1984) and Brewer and Kramer (1986) conclude that when subjects see themselves as in-group members, they are more likely to contribute to the public goods even at the cost of individual gains.

Cooperation may increase when human subjects expect that its benefits will be shared with in-group members. The classical minimal group experiments do not consider the expectation of reciprocity among in-group members as a confounding factor, however. In this aspect, cooperation can emerge (and prosper) when subjects begin to expect enduring benefits from in-group favoritism (and continue to have such egoistic expectations). Our research rather demonstrates the evolution of cooperation in one-shot interactions without the expectation of in-group reciprocity. Cultural groups, rather than they are pre-assigned, emerge as cultural markers, albeit meaningless at the beginning, become salient through the reinforcement of the disproportionate benefits of parochial interaction. They dissolve in the face of in-group deviants who disturb self-enforcing labeling that promotes within-group solidarity. In this aspect, our study shows cognitive and socio-psychological bases of stratification, and vice versa.

Economic sociologists have proposed to conceptualize markets as social structures. Economic actors are neither over-socialized nor under-socialized (Granovetter, 1985). How economic exchanges are embedded in on-going networks is one of the core questions in economic sociology: “The anonymous market of neoclassical models is virtually nonexistent in economic life and transactions of all kinds are rife with the social connection described (Granovetter, 1985: 495).” In these respects, the current study provides a game theoretical view of market dynamics – systematic processes of adaptive learning and networking by agents who interact with neighboring partners without perfect information about costs and opportunities to be found.

Macy and Sato (2002)[1] undertake a computational research on trust, signaling, parochialism, and market formation in the setting of Prisoner’s Dilemma game. They begin with an interesting question raised by Yamagishi and Yamagishi (1994): why are Japanese businesses more likely to shun better deals in the open market in favor of established suppliers in their local markets? Why do more individualistic Americans show higher trust than more collectivistic Japanese?

They conclude that Japanese businesses try to minimize the transaction cost by decreasing the chance of being cheated by strangers, while they must pay the opportunity cost by reducing the pool of potential transaction partners. A global market is maintained when agents learn trust to cooperate with strangers within a middle range of social mobility – which is neither too low to disturb a parochial equilibrium nor too high to disturb a signaling equilibrium.

From a different angle, our study examines the conditions under which a global market evolves out of repeated interactions among economic actors facing one-shot transactions and sending and receiving signals of trustworthiness with limited tolerance toward outside strangers. Markets consisting of more tolerant agents who trust diverse others can easily establish large-scaled cooperative relations, but they are more likely to be cheated by free-riders. Parochial agents are indispensible for the evolution of costly cooperation in one-shot exchanges, but global cooperation is possible only when agents in markets are highly homogenous. Emergent markets based on parochial cooperation may not be robust against free-riders who fake signals of trustworthiness. Also, they tend to become fragmented when parochial agents are more likely to socialize with similar others.

We suggest that a global market can evolve consisting of more exclusive parochial networks driven by local search (i.e. the closedness of cohesive ties) and more inclusive networks by global search (i.e. the openness of cross-cutting ties) within a certain range of social mobility. In such a global market at dynamic equilibrium, the transaction cost and the opportunity cost may be balanced so that global efficiency can be achieved. Also, an emerging market can be relatively stable against those who learn to fake signals of trustworthiness.

Endnotes

Chapter 1

1 The multi-agent Prisoner's Dilemma game in the present study is not the same as the so-called N-person Prisoner's Dilemma game (e.g. the tragedy of the commons and the public goods game). It is also different from the trust game as a one-sided Prisoner's Dilemma game in which agents sequentially interact with each other.

Chapter 2

1 Perrin (1975; 1976; 1995) rather emphasizes similarities between Spencer's sociology and Durkheim's. Spencer frequently stresses that institutions arise not by design but by incidental growth. Spencer discusses the concept of unintended consequences. Spencer makes a distinction between causal analysis and functional analysis. He does consistently underline the importance of the microfoundations of social integration such as rituals and ceremonies even in complex societies.

2 Parsons ([1934]1990) can be seen as an attempt to establish a footing for the subjective approach to institutions based on a theory of rational action, opposing the objective approach, according to Coleman (1990b: 333-334). However, "Parsons later abandoned his attempt to develop a social theory based on a theory of rational action; from *The Social System* (1951) onward, his theoretical efforts took the form of classification schemes for social systems and other macro-social phenomena" (Ibid: 335). Similarly, Sawyer (2005: 41-2) points out that Parsons draws heavily on emergence concepts in *The Structure of Social Action* (1937), but he turns to a structural-functional theory of systems in *The Social System*. The concepts of values and norms in his earlier works is closer to scripts and rules (Alexander, 1987).

3 Coleman’s Boat model consists of three processes (Hedström and Swedberg, 1998: 21-3): situational (how macro-level events or conditions affect the individual); action-formation (how the individual assimilated the impact of macro-level events); and transformational (how a number of individuals, through their actions and interactions, generate macro-level outcomes).

4 Another promising approach to institutional analysis is taken by practitioners of the neo-functionalism. See Alexander and Colomy (1985) and Colomy (1986; 1990; 1998).

5 Schűtz as a core member of the Austrian school of economics seeks to synthesize rational choice theory and phenomenology albeit not addressed in the sociological literature with the exception of Prendergast (1986). “Several writers have interpreted Schűtz as a rational-choice theorist. However, we think it probable that most social scientists familiar with Schűtz neglect his rational-choice side, viewing him instead as a hermeneutic or ‘interpretive’ theorist” (Koppl and Whitman, 2004: 303). Foss (1996) emphasizes that Schűtzian insights can be a corrective to the problem with the classical game theory that it throws away information as common knowledge which players need in order to take into account each other’s choice of actions. The Austrian school of economics agrees that the market as a core institution is the outcome of human action as opposed to human design. It is decentralized and primarily constituted through local knowledge about costs and opportunities to be found. Accordingly, the market dynamics is a systematic process of mutual discovery by participants without perfect information (Langlois, 1992).

6 Veblen argues that economics should be reconstructed as a post-Darwinian science because Darwinism would contribute significantly to our understanding of social evolution – the origins, growth, persistence, and variation of institutions in particular – without relying on any version of teleology (Hodgson, 2003).

7 “The generalized Tit-for-Tat” is applicable to large-sized populations: each actor calculates the fraction of her neighborhood that cooperated at the last round, if this fraction is greater than a cut-off point, cooperate, and otherwise, defect (Watts, 1999).

For example, when the cut-off point is 0.5, agents will cooperate if cooperation is the majority strategy at the last round among their local neighbors, and otherwise decline to cooperate. However, we note that each agent indiscriminately use a single strategy, cooperate or defect, toward all of her neighbors.

8 What shared genes are to the biology of altruism, empathy is to the psychology of altruism. In the same way that genes connect people physically, empathy connects them emotionally. Just as sociobiologists suggest that altruistic dispositions evolve when they foster the propagation of shared genes, so psychologists propose that individuals are motivated to help others when it enhances their shared affective state (Krebs, 1987: 104). Empathy may therefore serve as a proximal psychological mechanism intervening between phenotype matching and altruism. People are more strongly motivated to tell those who are truly trustworthy from those who pretend to be trustworthy. Therefore, cooperators have a strong incentive to send the signals of their trustworthiness that cannot easily be imitated by free-riders who want to exploit them. Frank (1988) maintains that emotional signals such as sympathy and compassion enable cooperation between strangers in human societies since such moral sentiments are difficult to fake.

9 We note here the weakness of the ‘green-beard’ altruism – which is not resistant to individuals who have the gene displaying the ‘green-beard’ phenotype but not the gene coding altruism (Hamilton, 1964; Dawkins, 1976; Van Baalen and Jansen, 2003).

Chapter 3

1 Synchronous updating assumes a global clock so that all agents update their status at the same time in each time-step (i.e. non-overlapping generations). As a well known example, Huberman and Glance (1993) demonstrate that the results of Nowak and May’s model (1992) could have changed significantly if they had used asynchronous updating, that is, updating a randomly selected agent at a time (i.e. overlapping

generations). Substantively, asynchronous updating "might seem at odds with the original Prisoner's Dilemma game, where both players decide simultaneously and find out about each other's actions only in retrospect. However, synchronous updating is quite degenerate in any kind of distributed, multiplayer context where it is virtually inconceivable that everyone would decide upon their next action at the same time, every time' (Watts, 1999: 209). However, "substantial but distinct regions of the parameter space lead to the persistence of cooperators with both synchronous and asynchronous updating" (Nowak and Sigmund, 2000: 140). Also, either fully synchronized updating or fully asynchronized one is idealistic. Rather, the reality may be somewhere in between.

2 Some studies use real-number tags (e.g. Riolo, 1997; Riolo et al., 2001) while others use binary tags (e.g. Hales, 2000; Hales, 2004; Edmonds and Hales, 2005; Choi et al., 2006) or integer tags (e.g. Hales and Edmonds, 2003). Real-number tags are not realistic in the sense that human agents cannot make such fine-grained distinctions. Either integer tags with a single bit (e.g. $t \in [1, 2, \ldots, 500]$ in Hales and Edmonds (2003)) or long-winded binary tags (e.g. $L \geq 32$ in Hales (2000), Hales (2004), and Edmonds and Hales (2005)) are also somewhat problematic, given the experimental result that human agents use a small number of dimensions on average to construct their identities, for instance, 5.4 in the context of international relations (Rousseau and van der Veen, 2005).

3 The Hamming Distance indicates that agents count the presence or absence of attributes across a certain number of dimensions available. The average of Hamming Distance across the whole population (or all local neighbors) can be regarded as the mean perceived social distances. '1 – Standardized Hamming Distance' is the same as the 'Simple Matching Index' (Hanneman and Riddle, 2005) which is a common measure of similarity in social network analysis.

4 In our model, unlike Riolo et al. (2001), *i* will defect in spite of no difference between two tags as long as T_i is 0 (i.e. "always defect"). In the same way, *i* will cooperate as long as T_i is $L + 1$ (i.e. "always cooperate") given that the maximum tag

difference is L. As Roberts and Sherratt (2002: 500) and Edmonds and Hales (2003) point it out, Riolo et al. (2001) would have had lower levels of cooperation if a ‘strict tolerance’ rule $HD_{ij} < T_i$ had been used.

5 An ego of $T \geq 1$ cooperates with others as long as their tags are identical to its own, as in Riolo et al. (2001).

6 We employ the same payoff matrix as that in Riolo et al. (2001), but $b/c = 2$ in our model, for example, is equivalent to the cost-to-benefit ratio=0.5 in Riolo et al. (2001) because $b = 1$ is fixed in their model.

7 The ‘selected bias’ method for reproduction (i.e. “higher than or equal to” instead of “higher than”) is another factor that contributes to higher donation rates in Riolo et al. (2001). See Edmonds and Hales (2003).

8 The classical rule of strategy updating in evolutionary games on networks is that agent i randomly selects one of her neighbors j, and then agent i adopts agent j’s strategy when $\pi_i < \pi_j$ with the probability W influenced by the total payoff difference between the two agents: $W_{i \leftarrow j} = \dfrac{1}{1 + \exp[-\beta(\pi_j - \pi_i)]}$ (Santos et al., 2006; Fu et al., 2007). Here, the parameter β as an inverse temperature in statistical physics reflects the strength of selection. $\beta \to 0$ leads to neutral drift, while $\beta \to \infty$ corresponds to the imitation dynamics where agent i’s strategy is replaced by agent j’s strategy. Our model assumes that $\beta \to \infty$. This deterministic updating rule of tags and tolerance leads to a more rapid homogenization of the population than stochastic updating rules. In this way, we put the feasibility of alternative cooperative societies to a stricter test. However, we acknowledge that using the accumulated payoff in the formula may be problematic since agents in our model have different numbers of neighbors (i.e. heterogeneous, not homogeneous), unlike those on the torus. Either using the accumulated payoff divided by the number of ties or introducing costly ties is an alternative approach that considers the average rate of return on investment (i.e. economic capital per social capital).

9 Agent's tolerance has limited effects on agent's degree in the model. Agents can break ties only if they can find new partners. For example, unconditional defectors perceive all players as out-group, but they do not continue to lose their ties.

10 Given 100 agents and $k = 6$ in Chapter 7, an ego's choice for selecting new partners outside neighbors of her neighbors can be restricted. This is why we use $r \in N^2{}_i + h \in N$ and $h \notin N^2{}_i$ instead of $r \in N^2{}_i + h \in N$ which is closer to the original meaning of closure-biased random selection.

11 See Santos et al. (2006) and Fu et al. (2008). They define $W = \tau_e / \tau_a$. Hence, with $W \rightarrow 0$, the evolution of cooperation on static graphs is recovered; and with increasing W, agents promptly adjust their co-players. $W = 1$ is equivalent to p = 50(%) in our study since a strategy update event is chosen with probability $(1 + W)^{-1}$ and a network update event is selected otherwise. In Eguíliz et al. (2005: 989), for values of social plasticity $z << 1$, strategies change much faster than network evolution (a situation similar to the frozen network of $z = 0$), while for $z = 1$, strategies and network evolve at the same rate (fluid social network). We note here that network changes without strategy updating either at $W \rightarrow \infty$ or $z \rightarrow \infty$ in their studies. This is equivalent to p = 100(%) in our research.

Chapter 4

1 Ohtsuki et al. (2006) introduce three different rules of strategy updating: 'death-birth updating'; 'birth-death updating'; and 'imitation updating.' For death-birth updating, at each time step a random individual is selected to die, and then her neighbors compete for the empty site proportional to their fitness. For birth-death updating, at each time step an individual is chosen for reproduction proportional to fitness, and then the offspring replaces a randomly selected neighbor. For imitation updating, at each time step a random individual is chosen to update her strategy; she will stay with her own strategy or imitate one of her neighbors proportional to fitness.

They verify that cooperation can survive if the benefit-to-cost ratio exceeds the average number of neighbors in structured populations of altruists and defectors when the death-birth updating rule is applied: $b/c > k$. The birth-death rule does not favor cooperation. It holds true that $b/c > k + 2$ under the imitation updating rule. Our finding is that $b/c > k$. However, we should point out that the imitation rule in Ohtsuki et al. (2006) is not the same with the strategy updating rule in our models explained in Endnote 8 of Chapter 3.

Chapter 6

1 It should be also noted here that as the tag length gets longer, there is less chance that mutant defectors are introduced who have similar tags within the tolerance range of a dominant group of cooperators, when controlling for the mutation rate. This is another reason why we select an intermediate tag length ($L = 5$).

Chapter 8

1 Macy and Sato's model rests on different assumptions. First, the Prisoner's Dilemma game in their model has the "exit" option ($T > R > E \geq P > S$, given the exit payoff E). Second, dyadic interactions are assumed, whereas agents interact with multiple (neighboring) partners in our model. Third, agents stochastically either behave parochially or cooperate if their partner cooperates, and otherwise defect (i.e. signal reading). In our model, agents read tags and cooperate only with perceived in-group members, given that tolerance (as a proxy for strategy) is not observable in societies. Fourth, each agent has a vector of three propensities for entering a global market or not, cooperating or not, and trusting or not. Each agent in our model has predispositions for parochial cooperation and homophilic association, but social mobility and clustering (local versus global search) are exogenous. Fifth, agents'

propensities are updated through social learning and reinforcement learning (based on the Bush-Mosteller algorithm). Payoff-based imitation is used in our model. Sixth, agents are not able to mimic signals. Instead, random moving, exogenously implemented (i.e. social mobility), generates newcomers (strangers). Defectors with tolerably similar tags are born due to mutation (i.e. an error in payoff-based imitation) in our model in which agents basically play a one-shot game. Therefore, strictly saying, neither Macy and Sato’s model nor our model consider those who (intentionally) learn to fake signals of trustworthiness.

Appendix: NetLogo Code for Models

The original codes are copied in the following order:

Variable declaration

```
globals [
  ;; the following global variables are used in all models
  go?
  proportion_cooperation_list
  tolerance_list
  average_hamming_distance_list
  homophily_list_coop ;; local homophily in tolerance
  homophily_coop ;; local homophily in tolerance
  homophily_list_distance ;; local homophily in tags
  homophily_distance ;; local homophily in tags
```

```
   number_rewired ;; for small-world network generation in Model 4

   tol_dependent_degree_list ;; used only in Model 5

   ;; the following global variables are used both in Model 4 and Model 5
   clustering-coefficient
   clustering-coefficient-of-lattice
   average-path-length
   average-path-length-of-lattice
   infinity
   average_degree
   density
   cooperation_history
   first_emergence_time_all_coop
   first_emergence_time_all_defect
   first_emergence_time_either
   phase
   cum_duration_fall
   duration_fall
   cum_duration_rise
   duration_rise
   count_fall
   count_rise
   mode_tolerance_list_history
   count_zero_block
]

turtles-own [
   score
   tag-list
   tolerance
   average_hamming_distance
   dissimilarity_list
   neighbor_list
   temp-score
   temp-strategy
   strategy-list
   neighborhood
   sus-list ;; susceptibility for Model 2 and Model 3

   ;; the following variables are used in Model 4 and Model 5
   node-clustering-coefficient
   distance-from-other-turtles
]

;; the following procedures are used in Model 4
links-own [
   rewire-one?
]
```

Setup

Chapter 4 and 5

```
to setup
   ca
   ask patches [ create-agents ]
   ask turtles [
      set neighborhood turtles-on neighbors ;; Moore neighborhood
      set neighbor_list sort [ who ] of neighborhood
      similarity-perception
   ]
   update-plot
end
```

A. Model 1 (Genetic inheritance)

```
to create-agents
   sprout 1 [
      set tag-list [ ]
      let i 0
      while [ i < num-of-tag-item ]
      [
         set tag-list fput random 2 tag-list
         set i i + 1
      ]
      let l num-of-tag-item
      set tolerance random ( l + 2 )
      set shape "circle"
   ]
end
```

B. Model 2 (Caste societies)

```
to create-agents
   sprout 1 [
      set tag-list [ ]
      set sus-list [ ]
      let i 0
      while [ i < num-of-tag-item ]
      [
         set tag-list fput random 2 tag-list
         set sus-list fput 0 sus-list
         set i i + 1
      ]
      set sus-list replace-item 0 sus-list 1 ;; the first item does not change
      let l num-of-tag-item
      set tolerance random ( l + 2 )
      set shape "circle"
   ]
end
```

C. Model 3 (Modern societies)

```
to create-agents
   sprout 1 [
      set tag-list [ ]
      set sus-list [ ]
      let i 0
      while [ i < num-of-tag-item ]
      [
         set tag-list fput random 2 tag-list
         set sus-list fput 0 sus-list
         set i i + 1
      ]
      set sus-list replace-item ( random num-of-tag-item ) sus-list 1
                                 ;; the item including 1 in the suslist does not change
      let l num-of-tag-item
      set tolerance random ( l + 2 )
      set shape "circle"
   ]
end
```

Chapter 6 and 7

```
to setup
   ca
   set infinity 999
   set-default-shape turtles "circle"
   make-nodes-links initial_network ;; a random network by default for Model 5
   no-display
   set clustering-coefficient-of-lattice clustering-coefficient
   set average-path-length-of-lattice average-path-length
   ask turtles [
      set neighbor_list sort [ who ] of link-neighbors
      similarity-perception
   ]
   update-plot
   display
end

to make-nodes-net
   crt num_of_agents [
      set tag-list [ ]
      let i 0
      while [ i < num-of-tag-item ]
      [ set tag-list fput random 2 tag-list
        set i i + 1
      ]
      let j 0
      while [ j < num_of_agents ]
      [ let l num-of-tag-item
        set tolerance random ( l + 2 )
        set j j + 1
```

```
    ]
    layout-circle ( sort turtles ) max-pxcor - 1
  ]
end
```

A. Model 4 (Static networks with different topologies)

```
;; the procedures for calculating the average clustering coefficient and the average path length
  are not presented below because we follow those in the NetLogo Small Worlds model by
  Wilenski (2005): to-report do-calculations… end; to-report in-neighborhood? [ hood ]…
  end; to find-clustering-coefficient… end; and to find-path-lengths… end.

to make-nodes-links [ initial ]
  if ( initial = "random-network" ) [
    make-nodes-net
    if ( erdos_renyi_probability = 0 or erdos_renyi_probability = 1 ) [ stop ]
    ask turtles [
      create-links-with turtles with [self > myself and random-float 1.0 <=
        erdos_renyi_probability ]
      [ set color grey – 3 ]
    ]
    let success? not any? turtles with [ count my-links = 0 ]
    set success? do-calculations
    ifelse average-path-length = 999 [
      setup ;; if there is any isolate by any chance, setup again
      clear-all-plots
    ] [
      ask turtles [ set size ( size + 0.10 * count my-links ) ]
      set success? do-calculations
    ]
  ]
  if ( initial = "regular-network" ) [
    make-nodes-net
    ring-lattice
    ask turtles [ set size ( size + 0.10 * count my-links ) ]
    let success? true
    set success? do-calculations
  ]
  if ( initial = "small-world-network" ) [
    make-nodes-net
    ring-lattice
    rewiring
  ]
end

to ring-lattice
  let i 0
  while [i < count turtles ]
  [
    make-edge turtle i turtle ( (i + 1) mod count turtles )
    make-edge turtle i turtle ( (i + 2) mod count turtles )
    make-edge turtle i turtle ( (i + 3) mod count turtles )
```

```
      make-edge turtle i turtle ( (i + 4) mod count turtles )
      set i i + 1
   ]
end

to make-edge [ node1 node2 ]
   ask node1 [ create-link-with node2 [ set rewire-one? false ]
   ]
end

;; the average clustering coefficient and the average path length from 1000 random graphs are
0.08001 and 2.43586. Their standard deviation are 0.010216 and 0.048826, respectively.
;; z-test (one-tail) : [ 0.08001 - ACC from a small-world network ] / ( 0.010216 / sqrt 1000 ) =
-1.645 (alpha level is 0.05)
;; z-test (two-tail) : [ 2.43586 - APL from the same small-world network ] / ( 0.048826 / sqrt
1000 ) = 1.96 (alpha level is 0.05)
;; rewiring is allowed until both conditions are satisfied.

to rewiring
   set number_rewired 0
   while [ number_rewired < 200 ] [
      let potential-edges links with [ not rewire-one? ]
      if any? potential-edges [
         ask one-of potential-edges [
            let node1 end1
            if [ count link-neighbors ] of end1 < ( count turtles – 1 )
            [
               let node2 one-of turtles with [ ( self != node1 ) and ( not link-neighbor? node1 ) ]
               ask node1 [ create-link-with node2 [ set color grey - 3 set rewire-one? true ] ]
               set number_rewired number_rewired + 1
               die
            ]
         ]
      ]
   ]
   let success? true
   set success? do-calculations
   while [ ( average-path-length < 2.4333201 or average-path-length > 2.4383999 ) or
            clustering-coefficient < 0.0805414 ] [
      let potential-edges links with [ not rewire-one? ]
      if any? potential-edges [
         ask one-of potential-edges [
            let node1 end1
            if [ count link-neighbors ] of end1 < (count turtles - 1)
               [
               let node2 one-of turtles with [ ( self != node1 ) and ( not link-neighbor? node1 ) ]
               ask node1 [ create-link-with node2 [ set color grey - 3    set rewire-one? true ] ]
               set number_rewired number_rewired + 1
               die
            ]
         ]
      ]
```

```
    set success? do-calculations
    if number_rewired = 400 [ ;; if a small-world network satisfying both conditions is not
                                          generated, then another try
      setup
      clear-all-plots
    ]
  ]
  ask turtles [ set size ( size + 0.10 * count my-links ) ]
  set clustering-coefficient-of-lattice clustering-coefficient
  set average-path-length-of-lattice average-path-length
]
end
```

Go

```
to go
  set go? true
  ask turtles [ similarity-perception ]
  ask turtles [ interaction]
  ask turtles [ payoff ]
  ask turtles [ tag-tolerance-update ]
  tick
  update-plot
end
```

Similarity perception

```
;; if count link-neighbors = 0 [ set average_hamming_distance 0 ] in Model 5
to similarity-perception
  set dissimilarity_list [ ]
  let j 0
  while [ j < 8 ] ;; while [ j < count link-neighbors ] for Model 4 and 5
  [
    let b length filter [ ? = true ] ( map [ ?1 = 1 and ?2 = 0 ]
      [ tag-list ] of self [ tag-list ] of turtle item j neighbor_list )
    let c length filter [ ? = true ] ( map [ ?1 = 0 and ?2 = 1 ]
      [ tag-list ] of self [ tag-list ] of turtle item j neighbor_list )
    set dissimilarity_list lput ( b + c ) dissimilarity_list
    set j j + 1
  ]
  set average_hamming_distance mean dissimilarity_list
end
```

Interaction

```
to interaction
  set temp-score [ ]
  set strategy-list [ ]
  let j 0
  while [ j < 8 ] [ ;; while [ j < count link-neighbors ] [ for Model 4 and 5
    let partner turtle item j neighbor_list
```

```
        let ego self
        let p position [ who ] of ego [ neighbor_list ] of partner
        ask partner [
          ifelse [ tolerance ] of partner > item p [ dissimilarity_list ] of partner [
            set temp-strategy true ;; partner j cooperates toward the ego
          ] [
            set temp-strategy false ;; partner j declines to cooperate toward the ego
          ]
        ]
        ifelse [ tolerance ] of ego > item j [ dissimilarity_list ] of ego [
          set [ temp-strategy ] of ego true ;; the ego cooperates toward partner j
          set strategy-list lput 1 strategy-list
          ifelse [ temp-strategy ] of partner = true [
            set temp-score fput ( b/c - 1 ) temp-score ;; reward for mutual cooperation
          ] [
            set temp-score fput ( - 1 ) temp-score ;; sucker's payoff
          ]
        ] [
          set [ temp-strategy ] of ego false ;; the ego does not cooperate toward partner j
          set strategy-list lput 0 strategy-list
          ifelse [ temp-strategy ] of partner = true [
            set temp-score fput b/c temp-score ;; temptation to defect
          ] [
            set temp-score fput 0 temp-score ;; punishment for mutual defection
          ]
        ]
        set j j + 1
      ]
    end
```

Payoff calculation

```
to payoff
  set score 0
  set score sum temp-score
end
```

Reproduction (Payoff-based imitation)

Model 1 (Genetic inheritance)

```
to tag-tolerance-update
  let reference one-of turtles-on neighbors
  let what-to-compare [ score ] of reference
  let self-score [ score ] of self
  ifelse mutation-rate > random-float 1.0 [
    set tag-list [ ]
    let j 0
    while [ j < num-of-tag-item ]
    [ set tag-list fput random 2 tag-list
      set j j + 1
    ]
```

```
        set tolerance random ( num-of-tag-item + 2 )
    ] [
        if what-to-compare > self-score [
            set tag-list [ ]
            set tag-list [ tag-list ] of reference
            set tolerance [ tolerance ] of reference
        ]
    ]
end
```

Model 2 (Caste societies)

```
to tag-tolerance-update
    let reference one-of turtles-on neighbors
    let what-to-compare [ score ] of reference
    let self-score [ score ] of self
    ifelse mutation-rate > random-float 1.0 [
        let a item 0 tag-list
        set tag-list [ ]
        let j 0
        while [ j < num-of-tag-item ]
        [ set tag-list fput random 2 tag-list
          set j j + 1
        ]
        set tag-list replace-item 0 tag-list a
        set tolerance random ( num-of-tag-item + 2 )
    ] [
        if what-to-compare > self-score [
            let a item 0 tag-list
            set tag-list [ ]
            set tag-list [ tag-list ] of reference
            set tag-list replace-item 0 tag-list a
            set tolerance [ tolerance ] of reference
        ]
    ]
end
```

Model 3 (Modern societies)

```
to tag-tolerance-update
    let reference one-of turtles-on neighbors
    let what-to-compare [ score ] of reference
    let self-score [ score ] of self
    ifelse mutation-rate > random-float 1.0 [
        let p position 1 sus-list
        let a item p tag-list
        set tag-list [ ]
        let j 0
        while [ j < num-of-tag-item ]
        [ set tag-list fput random 2 tag-list
          set j j + 1
        ]
```

```
        set tag-list replace-item p tag-list a
        set tolerance random ( num-of-tag-item + 2 )
    ] [
        if what-to-compare > self-score [
            let p position 1 sus-list
            let a item p tag-list
            set tag-list [ ]
            set tag-list [ tag-list ] of reference
            set tag-list replace-item p tag-list a
            set tolerance [ tolerance ] of reference
        ]
    ]
end
```

Faster-mutating-tag-based Societies

```
to tag-tolerance-update
    let reference one-of turtles-on neighbors
    let what-to-compare [ score ] of reference
    let self-score [ score ] of self
    let a random-float 1.0
    ifelse mutation-rate * mu_factor > a [
        set tag-list [ ]
        let j 0
        while [ j < num-of-tag-item ]
        [ set tag-list fput random 2 tag-list
          set j j + 1
        ]
    ] [
        if what-to-compare > self-score [
            set tag-list [ ]
            set tag-list [ tag-list ] of reference
        ]
    ]
    ifelse mutation-rate > a [
        set tolerance random ( num-of-tag-item + 2 )
    ] [
        if what-to-compare > self-score [
            set tolerance [ tolerance ] of reference
        ]
    ]
end
```

Model 4 and Model 5 (A step-wise change of tolerance)

```
to tag-tolerance-update
    let reference one-of link-neighbors
    let what-to-compare [ score ] of reference
    let self-score [ score ] of self
    ifelse mutation-rate > random-float 1.0 [
```

```
      set tag-list [ ]
      let j 0
      while [ j < num-of-tag-item ]
      [ set tag-list fput random 2 tag-list
        set j j + 1
      ]
      set tolerance random ( num-of-tag-item + 2 )
   ] [
      if what-to-compare > self-score [
         set tag-list [ ]
         set tag-list [ tag-list ] of reference
         ifelse tolerance > [ tolerance ] of reference [
            ifelse tolerance = 0 [
               set tolerance tolerance
            ] [
               set tolerance tolerance - 1
            ]
         ] [
            ifelse tolerance = [ tolerance ] of reference [
               set tolerance [ tolerance ] of reference
            ] [
               ifelse tolerance = num-of-tag-item + 1 [
                  set tolerance tolerance
               ] [
                  set tolerance tolerance + 1
               ]
            ]
         ]
      ]
   ]
end
```

Model 5 (Evolution of culture and networks)

```
;; the mutation rates, mu1 and mu2, are controlled as 0.01 for cultural perturbation and network perturbation,
;; given the codes below, the following values were selected in our experiments.
;; at p=10, mu1=1/90; mu2=1/10
;; at p=20, mu1=1/80; mu2=1/20
;; at p=30, mu1=1/70; mu2=1/30
;; at p=40, mu1=1/60; mu2=1/40
;; at p=50, mu1=1/50; mu2=1/50
;; if network plasticity = 0, if the mutation rate is 0.01 given N=100, one agent errs in imitating tags and tolerance.
;; if network plasticity = 50 given the same mutation rate (0.01), the chance of cultural perturbation would decrease, which accordingly reduces the frequency of the emergence of mutant defectors (i.e. conditional probability).
;; to avoid this issue, regardless of different levels of network plasticity, we model that one agent experiences cultural perturbation, and one agent experiences network perturbation per round.
```

```
to tag-tolerance-update
  let p random 100
  let m random-float 1.0
  ifelse ( p < network_plasticity and p >= 0 ) [
    ifelse mu1 > m [
      ifelse count link-neighbors != 0 [
        random_breaking_making
      ] [
        random_making
      ]
    ] [
      ifelse count link-neighbors != 0 [
        breaking_if_outgroup_making_if_ingroup
      ] [
        making_if_ingroup
      ]
    ]
  ] [
    ifelse mu2 > m [
      ifelse count link-neighbors != 0 [
        set tag-list [ ]
        let j 0
        while [ j < num-of-tag-item ]
        [ set tag-list fput random 2 tag-list
          set j j + 1
        ]
        set tolerance random ( num-of-tag-item + 2 )
      ] [
        stop
      ]
    ] [
      ifelse count link-neighbors != 0 [
        let reference one-of link-neighbors
        let what-to-compare [ score ] of reference
        let self-score [ score ] of self
        if what-to-compare > self-score [
          set tag-list [ ]
          set tag-list [ tag-list ] of reference
          ifelse tolerance > [ tolerance ] of reference [
            ifelse tolerance = 0 [
              set tolerance tolerance
            ] [
              set tolerance tolerance - 1
            ]
          ] [
            ifelse tolerance = [ tolerance ] of reference [
              set tolerance [ tolerance ] of reference
            ] [
              ifelse tolerance = num-of-tag-item + 1 [
                set tolerance tolerance
              ] [
                set tolerance tolerance + 1
```

```
                     ]
                  ]
               ]
            ]
         ] [
            stop
         ]
      ]
   ]
end

to random_breaking_making
   let node1 one-of link-neighbors
   let f [ who ] of node1
   let node3 self
   let g [ who ] of node3
   ifelse ( node1 = nobody ) [
      stop
   ] [
      let node2 one-of turtles with [ ( not link-neighbor? node3 ) and ( self != node3 )]
      let h [ who ] of node2
      ask node3 [ create-link-with node2 [ set color green - 1 ] ]
      ask link [ who ] of node3 [ who ] of node1 [ die ]
      set [ neighbor_list ] of self fput h [ neighbor_list ] of self
      set [ neighbor_list ] of self sort remove f [ neighbor_list ] of self
      set [ neighbor_list ] of node2 sort fput g [ neighbor_list ] of node2
      set [ neighbor_list ] of node1 sort remove g [ neighbor_list ] of node1
   ]
end

to random_making
   let node1 self
   let b [ who ] of node1
   let node2 one-of turtles with [ ( not link-neighbor? node1 ) and ( self != node1 ) ]
   let a [ who ] of node2
   ask node1 [ create-link-with node2 [ set color green - 1 ] ]
   set [ neighbor_list ] of self sort fput a [ neighbor_list ] of self
   set [ neighbor_list ] of node2 sort fput b [ neighbor_list ] of node2
end

to breaking_if_outgroup_making_if_ingroup
   let node1 one-of link-neighbors
   let b length filter [ ? = true ] ( map [ ?1 = 1 and ?2 = 0 ]
      [ tag-list ] of self [ tag-list ] of node1 )
   let c length filter [ ? = true ] ( map [ ?1 = 0 and ?2 = 1 ]
      [ tag-list ] of self [ tag-list ] of node1 )
   let dis1 ( b + c )
   ifelse dis1 >= [ tolerance ] of self [
      let f [ who ] of node1
      let node3 self
      let g [ who ] of node3
      ifelse ( node1 = nobody ) [
```

```
      stop
    ] [
      let q random 100
      ifelse ( q < closure_probability and q >= 0 ) [
        set target one-of link-neighbors
        ifelse count [ link-neighbors ] of target >= 2 [
          let node2 one-of other [ link-neighbors ] of target
          let a length filter [ ? = true ] ( map [ ?1 = 1 and ?2 = 0 ]
            [ tag-list ] of self [ tag-list ] of node2 )
          let d length filter [ ? = true ] ( map [ ?1 = 0 and ?2 = 1 ]
            [ tag-list ] of self [ tag-list ] of node2 )
          let dis2 ( a + d )
          ifelse ( dis2 < [ tolerance ] of self ) and ( dis2 < [ tolerance ] of node2 ) [
            let h [ who ] of node2
            ask node3 [ create-link-with node2 [ set color white - 1 ] ]
            ask link [ who ] of node3 [ who ] of node1 [ die ]
            set [ neighbor_list ] of self sort fput h [ neighbor_list ] of node3
            set [ neighbor_list ] of self sort remove f [ neighbor_list ] of self
            set [ neighbor_list ] of node2 sort fput g [ neighbor_list ] of node2
            set [ neighbor_list ] of node1 sort remove g [ neighbor_list ] of node1
          ] [
            stop
          ]
        ] [
          stop
        ]
      ] [
        let node2 one-of turtles with [ ( not link-neighbor? node3 ) and ( self != node3 )
          and ( not member? self [ link-neighbors ] of link-neighbors ) ]
        let a length filter [ ? = true ] ( map [ ?1 = 1 and ?2 = 0 ]
          [ tag-list ] of self [ tag-list ] of node2 )
        let d length filter [ ? = true ] ( map [ ?1 = 0 and ?2 = 1 ]
          [ tag-list ] of self [ tag-list ] of node2 )
        let dis2 ( a + d )
        ifelse ( dis2 < [ tolerance ] of self ) and ( dis2 < [ tolerance ] of node2 ) [
          let h [ who ] of node2
          ask node3 [ create-link-with node2 [ set color blue - 1 ] ]
          ask link [ who ] of node3 [ who ] of node1 [ die ]
          set [ neighbor_list ] of self sort fput h [ neighbor_list ] of self
          set [ neighbor_list ] of self sort remove f [ neighbor_list ] of self
          set [ neighbor_list ] of node2 sort fput g [ neighbor_list ] of node2
          set [ neighbor_list ] of node1 sort remove g [ neighbor_list ] of node1
        ] [
          stop
        ]
      ]
     ]
   ] [
    stop
  ]
end
```

```
to making_if_ingroup
   let node1 self
   let b [ who ] of node1
   let node2 one-of turtles with [ ( not link-neighbor? node1 ) and ( self != node1 ) and
      ( not member? self [ link-neighbors ] of link-neighbors ) ]
   let a length filter [ ? = true ] ( map [ ?1 = 1 and ?2 = 0 ]
      [ tag-list ] of self [ tag-list ] of node2 )
   let d length filter [ ? = true ] ( map [ ?1 = 0 and ?2 = 1 ]
      [ tag-list ] of self [ tag-list ] of node2 )
   let dis2 ( a + d )
   ifelse ( dis2 < [ tolerance ] of self ) and ( dis2 < [ tolerance ] of node2 ) [
      let c [ who ] of node2
      ask node1 [ create-link-with node2 [ set color blue - 1 ] ]
      set [ neighbor_list ] of self sort fput c [ neighbor_list ] of node1
      set [ neighbor_list ] of node2 sort fput b [ neighbor_list ] of node2
   ] [
      stop
   ]
end
```

Plotting

```
;; the calculate the frequency of an item in the given list, the following codes are used.
to-report occurrences [x the-list]
   report reduce
      [ ifelse-value ( ?2 = x ) [ ?1 + 1 ] [ ?1 ] ] ( fput 0 the-list )
end

;; the following procedures are used in all models for plotting.
to update-plot
   set-current-plot "tolerance distribution"
   plot-pen-reset
   set-plot-x-range 0 num-of-tag-item + 2
   set-plot-y-range 0 round ( count turtles / ( num-of-tag-item + 1 ) + 100 )
   set-histogram-num-bars ( num-of-tag-item + 2 )
   histogram [ tolerance ] of turtles

   set-current-plot "average dissimilarity distribution"
   plot-pen-reset
   ifelse num-of-tag-item = 0 [
      set-plot-x-range 0 1
   ] [
      set-plot-x-range 0 num-of-tag-item
   ]
   set-plot-y-range 0 count turtles
   set-histogram-num-bars 10
   histogram [ average_hamming_distance ] of turtles

   set tolerance_list [ tolerance ] of turtles
   set average_hamming_distance_list [ average_hamming_distance ] of turtles
```

```
ifelse count turtles with [ tolerance >= 1 ] >= 1 [
   let i 0
   set homophily_list_coop [ ]
   while [ i < count turtles ] [
      ask turtle i [
         let z [ tolerance ] of self
         if z >= 1 [
            set homophily_list_coop fput ( count neighborhood with [ tolerance = z ] /
            count [ neighborhood ] of self ) homophily_list_coop
         ]
      ]
      set i i + 1
   ]
   set homophily_coop sum homophily_list_coop / count turtles with [ tolerance >= 1 ]
] [
   set homophily_coop 0
]

let i 0
set homophily_list_distance [ ]
while [ i < count turtles ] [
   ask turtle i [
      let z [ average_hamming_distance ] of self
      set homophily_list_distance fput ( count neighborhood with
         [ average_hamming_distance = z ] / count [ neighborhood ] of self )
         homophily_list_distance
   ]
   set i i + 1
]
set homophily_distance sum homophily_list_distance / count turtles

set-current-plot "local homophily"
set-current-plot-pen "tol"
plotxy ticks homophily_coop
set-current-plot-pen "tag"
plotxy ticks homophily_distance

ifelse go? = true [
   set proportion_cooperation_list [ ]
   let j 0
   while [ j < count turtles ]
   [
      set proportion_cooperation_list fput ( ( sum [ strategy-list ] of turtle j ) / 8 )
         proportion_cooperation_list
      set j j + 1
   ]
   set-current-plot "proportion of cooperation"
   plot ( sum proportion_cooperation_list ) / count turtles
] [
   set proportion_cooperation_list [ 0 ]
]
```

```
;; the following codes are used only for Model 4 and Model 5.
  ifelse member? 0 modes tolerance_list and member? 1 modes tolerance_list [
    set mode_tolerance_list_history fput 0 mode_tolerance_list_history
  ] [
    set mode_tolerance_list_history fput ( mean modes tolerance_list )
      mode_tolerance_list_history
  ]
  if ( length mode_tolerance_list_history > 2 ) [
    ifelse item 0 mode_tolerance_list_history = 0 and item 1 mode_tolerance_list_history =
        0 and ( item 2 mode_tolerance_list_history != 0 ) [
      set count_zero_block count_zero_block + 1
    ] [
      set count_zero_block count_zero_block
    ]
  ]

  let max-degree max [ count link-neighbors ] of turtles
  set-current-plot "degree distribution"
  plot-pen-reset
  set-plot-x-range 1 ( max-degree + 1 )
  histogram [ count link-neighbors ] of turtles

  set average_degree ( count links * 2 ) / count turtles
  set density ( 2 * count links ) / ( ( count turtles ) * ( count turtles - 1 ) )

  ifelse go? = true [
    set cooperation_history fput ( sum proportion_cooperation_list / count turtles )
      cooperation_history
    if ( occurrences 1 cooperation_history = 1 and first cooperation_history = 1 ) [
      set first_emergence_time_all_coop ticks - 1
    ;; considering that the list, cooperation_history, at the beginning is a blank array
      set first_emergence_time_either ticks - 1
      set phase 1
      set count_fall 1
    ]
    if ( occurrences 0 cooperation_history = 1 and first cooperation_history = 0 ) [
      set first_emergence_time_all_defect ticks - 1
   ;; otherwise, the second emergence time would replace the first one
      set first_emergence_time_either ticks - 1
      set phase 0
      set count_rise 1
    ]
    if ( sum proportion_cooperation_list / count turtles > 0 and sum
        proportion_cooperation_list / count turtles < 1 ) and
        ( first_emergence_time_either = 0 ) [
      set phase 2
    ]
  ] [
    set proportion_cooperation_list [ 0 ]
    set cooperation_history [ ]
    set phase 2
  ]
```

```
ifelse ( phase = 1 ) [
   ifelse ( sum proportion_cooperation_list / count turtles != 0 ) and ( ticks >
         first_emergence_time_either ) [ ;;and ( occurrences 1 cooperation_history >= 1 ) [
      set phase 1
      set cum_duration_fall cum_duration_fall + 1
      set duration_fall duration_fall + 1
      set count_rise count_rise
      set cum_duration_rise cum_duration_rise
      set duration_rise 0
   ] [
      set phase 0
      set cum_duration_fall cum_duration_fall
      set duration_fall 0
      set count_rise count_rise + 1
] [
   if ( phase = 0 ) [
      ifelse ( sum proportion_cooperation_list / count turtles != 1 ) and ( ticks >
           first_emergence_time_either ) [ ;;and ( occurrences 0 cooperation_history >= 1 ) [
         set phase 0
         set cum_duration_rise cum_duration_rise + 1
         set duration_rise duration_rise + 1
         set count_fall count_fall
         set cum_duration_fall cum_duration_fall
         set duration_fall 0
      ] [
         set phase 1
         set cum_duration_rise cum_duration_rise
         set duration_rise 0
         set count_fall count_fall + 1
      ]
   ]
]

set-current-plot "duration rise and fall dynamics"
set-current-plot-pen "cum_dur_fall"
plot cum_duration_fall
set-current-plot-pen "dur_fall"
plot duration_fall
set-current-plot-pen "cum_dur_rise"
plot cum_duration_rise
set-current-plot-pen "dur_rise"
plot duration_rise

;; the following codes are used in order to calculate the tolerance-dependent degree in Model
5 under the experimental condition of L = 4.
let i 0
set tol_dependent_degree_list [ ]
while [ i < 6 ] [
   let pool turtles with [ tolerance = i ]
      ifelse ( any? pool with [ length new_neighbor_list != 0 ] ) [
         set tol_dependent_degree_list lput mean [ length new_neighbor_list ] of turtles with
```

```
          [ tolerance = i ] tol_dependent_degree_list
      ] [
        set tol_dependent_degree_list lput 0 tol_dependent_degree_list
      ]
      set i i + 1
    ]
    set tol_dependent_degree_list tol_dependent_degree_list

;; the following codes are used to draw the plot of tides of tolerance in Model 5 given L = 5.
  if num-of-tag-item = 4 [
    set-current-plot "evolution of tolerance"
    let tot 0
    set-plot-y-range 0 1
    set-current-plot-pen "5"
    plot-pen-up plotxy ticks tot
    set tot tot + ( count turtles with [ tolerance = 5 ] / count turtles )
    plot-pen-down plotxy ticks tot
    set-current-plot-pen "4"
    plot-pen-up plotxy ticks tot
    set tot tot + ( count turtles with [ tolerance = 4 ] / count turtles )
    plot-pen-down plotxy ticks tot
    set-current-plot-pen "3"
    plot-pen-up plotxy ticks tot
    set tot tot + ( count turtles with [ tolerance = 3 ] / count turtles )
    plot-pen-down plotxy ticks tot
    set-current-plot-pen "2"
    plot-pen-up plotxy ticks tot
    set tot tot + ( count turtles with [ tolerance = 2] / count turtles )
    plot-pen-down plotxy ticks tot
    set-current-plot-pen "1"
    plot-pen-up plotxy ticks tot
    set tot tot + ( count turtles with [ tolerance = 1 ] / count turtles )
    plot-pen-down plotxy ticks tot
    set-current-plot-pen "0"
    plot-pen-up plotxy ticks tot
    set tot tot + ( count turtles with [ tolerance = 0 ] / count turtles )
    plot-pen-down plotxy ticks tot
  ]
end
```

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