Ecological action: a network approach

Tiziano Distefano* and Pietro Guarnieri[1]*

August 26, 2019

Abstract

This paper contributes to the issue of collective action by advancing an epistemology of agency based on the idea that individuals' propensity to act (attitudes) depends on relevant features of their social context. To this purpose, we develop a network model that links the probability that an agent joins collective action to the characteristics of the social structure, which is, in turn, shaped by the activation of collective actions within it. Our underlying assumption is that preferences for collective action are not only an individual endowment, but crucially depend on collective processes, that affect preference formation and characterize rationality as ecological.

1 Introduction

Since the seminal work of Elinor Ostrom (Ostrom, 1990) the role of institutions and social relationships in fostering collective action has been widely acknowledged also in economics. However, methodological individualism (Hodgson, 1986, 2007) still play as the paradigm grounding the theoretical discussion of conditions of possibility and limits (in terms of social dilemmas) of collective actions (Forsyth and Johnson, 2014). This paradigm can be identified in two features of the standard argument. First, a bottom-up framework where collective actions are thought only as the *result* of individuals' decisions and interactions. Second, the assumption that individuals' attitudes – summarized in the notion of preferences – are given as an individual endowment and do not change during the process of collective action itself (Bardhan and Ray, 2006).

This paper contributes to the collective action literature by interpreting collective action as the coevolution between agents' motivations to join collective actions and the features of their social environment – that is affected by the implementation of collective action itself. To this purpose, it relies on theories of *endogenous preferences* (Gerber and Jackson, 1993; Bowles, 1998; O'Hara and Stagl, 2002), *ecological rationality* (Bartlett, 1986; Smith, 2003; Todd and Gigerenzer, 2012) and *collective agency* (Gilbert, 2006) to place individuals decision-making in the context of emerging social relationships. In particular, our epistemological approach highlights a mutual and endogenous relationship between individual attitudes – i.e. motivations and evaluations that provide individual with reasons to act towards the purposes of the collective action – and the (relative) position of agents within the network of social relations. The main hypothesis is that, while individual agency has the power to affect the social conditions by creating social ties, social conditions feedback on the formation of those individual predispositions that manifest themselves through agency.

Accordingly, collective agency emerges through dynamics that prove to be self-reinforcing or self-defeating depending on the interplay between individual attitudes and social features – so overcoming the agency/structure duality (Davis, 2010). These dynamics are investigated by applying network modelling which has been extensively applied to social contexts (Borgatti

*University of Pisa, Department of Economics and Management, via C. Ridolfi, 10, 56124 Pisa (Italy).
[1]Corresponding author's e-mail: tiziano.distefano@ec.unipi.it

and Halgin, 2011) to analyse several aspects, such as: social epidemiology (El-Sayed et al., 2012), governance (Pittman and Armitage, 2019), local communities (Banerjee et al., 2012), and ecological behaviours (Gaaff and Reinhard, 2012).

Our model allows for describing the dynamic of repeated social interactions, where the exchange of information and knowledge across agents, within a given network of relations (e.g., in households, urban contexts, firms, associations, social networks, and so on), might influence (positively or negatively) the individual attitudes toward collective action. The model captures both the individual evolution of preferences – expressed as the propensity to undertake actions – over time and the variations of the distribution parameters, determined by the emergence of different collective actions at local level. In particular, the proposed model is able to account for dynamics of convergence and of divergence. The interplay between the micro- (bottom-up) and macro- (top-down) dimensions results as an essential factor in shaping the direction and the effectiveness of interactive processes that, while building social structures, sustain collective action. Although simple, the model can reproduce non-trivial and realistic social phenomena determined by the coevolution of individual attitudes and social structures.

The present study is organized as follows. Section 2 presents the theoretical and epistemological framework that is developed in the analytical model. Section 3 explains the model into details. Section 4 shows the results of the simulations and Section 5 discusses them and draws the main conclusions.

2 Theoretical background

The theoretical background sustaining the proposed analytical model calls for several notions that we characterize in this Section to facilitate the interpretation of the features and outcomes of the model.

2.1 Attitudes and actions

We refer to "individual attitude" as a synthetic notion that covers several components of motivations towards collective actions, such as: beliefs, expectations, knowledge, preferences, normative orientations, psychological traits, world-views, and so on. In other words, these components – not further analysed in the model – constitute various motivational drivers that affect the individual probability of taking part in collective action. However, we conceive attitudes as intrinsically subject to change due to social processes. Hence, we focus on the structure of the social context – i.e. the network of relationships that connect individuals in the population – to account for attitude change. The underlying hypothesis is that individuals' actions, grounded in attitudes, establish relationships across individuals that, in turn, affect individuals' attitudes (and hence actions).

Figure 1 depicts the main features of our theoretical model where attitudes play a key role. As the overall set of individuals' motivations, attitudes act as the transmission channel of the dynamics involving collective actions. They both cause individual participation in collective actions and are affected by the consequences of collective actions in terms of social ties. The mechanism through which individual actions may shape social relationships is discussed in the following subsection.

2.2 Interaction and institutions

We conceptualise two types of actions counting as an individual contribution to collective action. These two types highlight that participation in collective action implies *per se* interactions across individuals. First, individual contribution to a collective action is a public act – i.e. an action

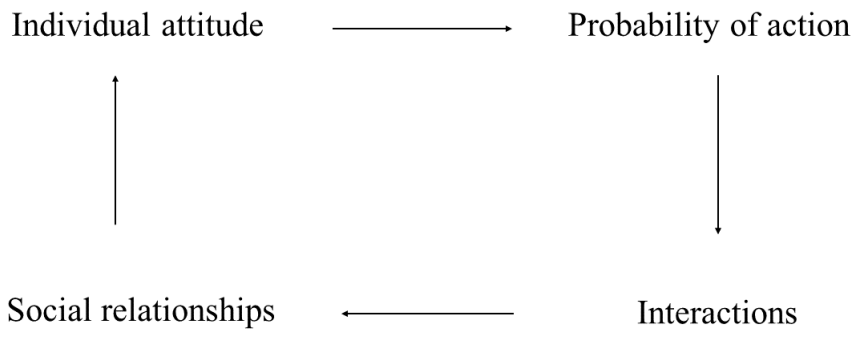

Figure 1: Attitudes update via network formation

that is publicly visible by other individuals (or at least some of its consequences).[1] Second, individuals (often) contribute to collective actions by communicating his/her own intentions or actions – e.g. to the purpose of persuading others to participate into collective actions themselves. Both types of actions imply an exchange of information and knowledge about others attitudes and willingness to act that influence mutual expectations and shared beliefs across individuals. On this ground, we assume that when two individuals interact above a certain threshold of frequency and/or intensity they establish a relationships for which they both believe that the other's participation in the collective action is more likely (than before interaction). In other words, when such interactions are effective the individuals believe to be in a group that is likely to contribute to the collective action.

The possibility that interactions actually lead to effective social relationships depends on two factors. On the one hand, they depend on the attitudes with which individuals enter the interaction. Since the attitude is reflected by the probability of acting toward a collective goal, effective interactions depends on the circumstance that the joint probability of acting is above a relevant threshold. On the other hand, it depends on the level of this threshold that we interpret in terms of the quality of institutional context in which such interactions occur. We take institutional context (i.e. formal or informal norms) as exogenous, and assume that when norms are in line with the purposes of the collective action the threshold that has to be overcome in order to form social relationship is low, or high otherwise. This implies that circumstances where the social norms favour the collective action are those where the individuals are more likely to form relationships and group to pursue it.

2.3 Social structures and attitude updating

The relationships resulting from interactions constitute a network whose properties identify the causality from the social context to individual attitudes that is the main focus of this study. In particular, interactions determine a distribution of relationships in the network representing how collective action spreads across individuals in the population.

We investigate two situations that may occur after interactions shape social relationships in the network. On the one hand, collective actions may result more frequent locally (i.e. only in some limited regions of the network) than overall in the global network. On the other hand, they may result less frequent in the local domains than in the global one. Accordingly, we build two indexes of relationships at the local and global level and study the effect of the two

[1] This interactive feature of individual participation in collective actions is particularly relevant in the case of actions that implies a duration in time and/or that are implemented in repeated occasions.

situations on the updating of individuals' attitude (and hence on the probability of participating into collective action).

To interpret the effects of the social context on individual attitudes we make two hypotheses concerning how individuals react to social circumstances. Accordingly, we single out two types of individuals, the *conformist* and the *principlist*. Then, we discuss two cases. In the first case, the global index revealing the overall diffusion of collective actions is higher than the local index, and individuals with low attitudes feel isolated. In this case, the conformist will try to adjust to the average behaviour in the network and will increase his/her probability; the principlist – who holds a low attitude since he/she does not agree with the purposes of the collective action – will strengthen his/her position so that his/her probability will further decrease. In the second case, the global index revealing the overall diffusion of collective actions is lower than the local index, and individuals with high attitudes feel isolated. In this case, the conformist will adapt to the average behaviour and will decrease his/her probability, while the principlist become even more convinced of his/her principles – in this case compliant with the purpose of the collective action – and will increase his/her probability.

3 Model

A Network is a system composed by n nodes (or agents) which may be connected by links. The number, weight, and the distribution of the links characterise the topological properties of the network. This framework allows to assess the evolution of complex systems through the computation of a class of indicators which measures relevant features of the structure of the network.

The network we analyse is unidirectional and un-weighted, since we assume that a) each interaction leading to a creation of a link between individual agents is bi-directional and b) that the quality and the intensity of each information exchanged is homogeneous across the network.[2]

Our main purpose is to explore in a simple framework the dynamics involving the distribution of agents' actions (i.e, collective action) and the influence of the social structure on individual attitudes. Hence, we minimise the number of behavioural assumptions and of parameters to provide the reader with the clearer evidence and interpretations.

3.1 Analytical tools

To build the local and global indexes referred in the previous section, we make reference to two basic notions of network theory, the *degree* and the *clustering*. We recall them to introduce the relative notations and analytical properties.

The local degree of agent j (d_j) is defined as the total number of connections ($a_{j,k}$) centered on j with any other node k, to say the total number of nodes $k \neq j$ belonging to the set of partners with which j creates a link (i.e., $k \, \epsilon \{J\}$). Namely (neglecting for the time specification)

$$d_j = \sum_{k \epsilon \{J\}} a_{j,k}, \qquad \overline{d} = n^{-1} \sum_j d_j \tag{1}$$

where $\overline{d}$ is the arithmetic mean and represents the average degree of each node. In our context, d_j represents a proxy of the global amount of information exchanged by agent j during the social interactive process.

A common feature of social networks is that if $a_{j,k} = 1$ and $a_{z,k} = 1$ then there is a heightened probability that vertex j will also be connected to vertex z ($a_{j,z} = 1$). This property,

[2]The case of leaders (nodes that are more important than others) and of different quality of the information – for instance, pieces of information more reliable than others – are out of the scope of the current study but might represent further improvements.

called clustering (or transitivity), means the presence of a heightened number of triangles in the network—sets of three vertices each of which is connected to each of the others (Newman, 2003).

In the context of our analysis, this indicator can be interpreted as a proxy of the quality and consistency of the information exchanged among agents. Indeed, if three vertexes form a connected triangle, then there is a sort of internal verification of the quality of the information exchanged. In other words, more isolated nodes might have less possibility to check the coherence of the information received.

Formally, the local clustering coefficient of vertex j is the ratio of the number of triangles connected to j ($\hat{c}_j$) to the number of triples among j's neighbours ($\tilde{c}_j$) (Watts and Strogatz, 1998). Namely

$$c_j = \frac{\hat{c}_j}{\hat{c}_j}, \qquad \overline{c} = n^{-1} \sum_j c_j \tag{2}$$

where $\overline{c}$ is the arithmetic mean indicating what we consider as the global index. Figure 2 shows an example to clarify. Let us consider a graph composed by $n = 7$ nodes with a total number of connections of 8 links (i.e., global degree in an unidirectional network is $d = 2^{-1} \sum_j \sum_k a_{j,k} = 8$). Let us focus on vertex j (blue dot) which has 3 connections (blue lines of panel a.). Vertex j forms 1 connected triangle ($\hat{c}_j = 1$, green lines of panel b.) among the three potential triples ($\tilde{c}_j = 3$, orange lines of panel c.). Hence, the local clustering coefficient of node j results in 1/3.

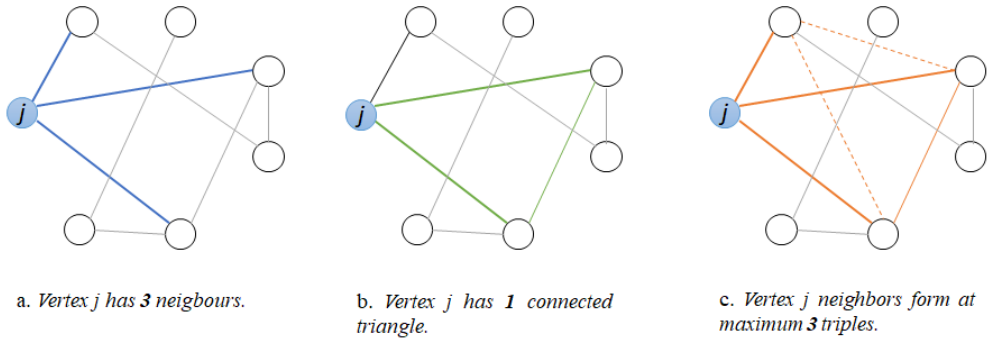

Figure 2: Graphical representation of local clustering coefficient for a generic vertex j.

3.2 Simulation procedure

The step-by-step simulation procedure, deriving from the causal diagram shown in Figure 1 is as follows:

1. *w*e assume that n agents interact over time;

2. we build the vector of initial probabilities of action p^0, with length n. The vector is set up on the base of a random Uniform distribution (i.e., $p^0 \sim U(0,1)$). This probability derives from the set of the overall motivational factors of individuals included in what we define as attitudes (i.e. tastes, norms, beliefs, and so on);

3. In each period $t > 1$, each agent is matched with anyone else, so that the joint probability[3] that j and k, with $j \neq k$, are connected is: $a_{jk}^{t+1} = p_j^t \cdot p_k^t$;

4. a connection is created if the joint probability is greater than an exogenous threshold ($s \in$ [0,1]) representing institutional norms. Hence, $a_{jk}^t = 1$ if and only if $a_{jk}^t \geq s$ and $a_{jk}^t = 0$ otherwise;

[3]In this case the underlying assumption is that there are no unobserved variables that affects the probability of a matching among agents, to say the product of probabilities is the joint probability of two i.i.d. variables.

5. we build the unweighted and unidirectional adjency matrix (A), with entries a_{jk}, $\forall j \neq k$ (note that self-loops are not allowed), as computed in the previous step;

6. we compute a network indicator (α) both at individual local level (α_j) and for the whole network ($\overline{\alpha}j$). The latter represents the global property of the network;

7. given the structure of the network the individual updates his/her attitude and hence the probability of further participating in collective actions. In particular, on the base of a comparison between the local (α) and the global ($\overline{\alpha}j$) indexes of social relationships we describe the two possible updating process respectively attributable to the two agents types of conformists and principlists:

Type A)

$$p_j^{t+1} = p_j^t \cdot u_{j,t}^A, \quad where \quad u_{j,t}^A = exp(+\alpha_{j,t} - \overline{\alpha}_t) \tag{3}$$

Type B)

$$p_j^{t+1} = p_j^t \cdot u_{j,t}^B, \quad where \quad u_{j,t}^B = exp(-\alpha_{j,t} + \overline{\alpha}_t) \tag{4}$$

Note that, in the case of type A) the probability increases if $\alpha_j > \overline{\alpha}$, and decreases otherwise, while in case B) the reverse condition holds. Note that the variable α represents a generic network index, which in our case can be either the cluster or the degree;[4]

8. iterating steps from 2. to 6. until the system converges (i.e., when the probability is no more updated, so that $\forall j$, $u_{j,t} = 1$).

The procedure described so far allows us to define an endogenous mechanism through which the individual attitudes are modified from social interaction and collective actions. The specific functional form is able to update the probability in a parsimonious way. Indeed, as explained below with some specific applications, the probability is only slightly modified round by round.[5] As introduced in the section about the theoretical background, the weight of the exponential is the difference between the topological characteristics of the individual participation in local groups and an analogous network indicator relative to the overall structure. The resulting dynamics is endogenous since both the local and the global property of the network emerge from the interactive process and depends on the structure of relationships generated by interactions, and depending on the individuals' probability of actions in turn.

3.3 Model Setting

Our analytical methodology is flexible and allows for studying the emergence of several distributions of collective actions under a variety of different interaction conditions. The core of our approach consists of 4 main modelling alternatives, given by the combination of the 2 types of agents (A and B) and 2 updating indicators (degree and clustering), both computed at the local and the global level. Moreover, we are able to vary a range of different initial conditions and of parameter values in order to provide robustness checks and to describe several realistic scenarios. Notably, the model can be set up with three alternative initial distributions (Uniform, Normal, and Gamma), and an exogenous threshold that can assume 9 values (s: 0.1, 0.2,..., 0.9),[6] Then the number of all modelling possibilities resulting from the combinations of these alternative settings is rather high (2x2x3x9 = 108). To ensure statistically robust outcomes, we run each

[4]Note that in case of the degree indicator we normalise the argument of the exponential law by the maximum degree so to have an indicator comparable with the clustering coefficient that assumes values in the range [0,1]. However, this condition does not affect the meaning of the results

[5]On average the individual probabilities are updated with little jumps (viz. $|\Delta p_j^t| \sim 20\%$).

[6]For the sake of completeness, we run all the simulations by varying s in the range [0.1, 0.9] with steps of 0.1. Since the results follow a gradual change, we opt to describe a reduced number of simulation.

scenario 50 times, from which we compute the arithmetic mean. For the sake of simplicity, we only show a sub-sample of the whole outcomes, by focusing on specific scenarios, where the number of agents (n) are kept constant, to make easier the interpretation of the results.

The results of numerical simulations, exposed in Section 4, are based on the values assumed by n and s and by the parameters of each distribution. Namely:

(a) $n = 1000$ agents;

(b) s can assume a low (0.2), middle (0.5), or high (0.8) value to test the impact of the institutional setting;

(c) sorting p^0 from the minimum value so that the initial ranking is preserved.[7] This procedure allows to compare the results through the different simulations and ensuring that the average is not affected by the initial random extraction;

(d) if the extracted initial probability is greater than 1, then $p_j^0 = 1$, while if it is negative then $p_j^0 = 0.01$. These conditions are necessary because all values must be in the admissible range, for the probability to be significant.

As it will be clear below, the last assumption is justified by the mode of interaction. Indeed, setting a minimum value of 0 entails that the agent can never be involved in the participation process. However, this condition does not avoid that, at the end of the process, an individual might end up with a zero probability. Finally, we show the average values coming from the 50 iterations in order to avoid arbitrary upshots due to a specific random extraction.

4 Results

Figure 3 shows the distribution of agents' probability at the end (time = T) of the interactive process.[8] In the case of a population composed only of *Type A)* individuals, we observe a clear *polarisation* process, characterised by a binomial distribution, where agents are either strongly motivated do join collective action (i.e., $p_j^T \simeq 1$) or careless with respect to it (i.e., $p_j^T \simeq 0$). As expected, the frequency of collective actions is higher when the institutional framework is more aligned (s low). As the threshold increases, the frequency shifts towards less contributions to the collective action in the population. In particular, when s is low about the 70%-80% of agents are strongly motivated to act, in the middle case the share falls to about the 50%, while in case of adverse institutional settingthey represent only a minority of about 20%.

These results are robust to the two network indicators applied in this study, although under the clustering coefficient the effects are stronger. This is the first insight that this indicator might be a good proxy of the information quality, as it will be clarified shortly. Interestingly, the interactive process does not always lead toward a predetermined direction, but it is tightly dependent on the contextual conditions. This entails that a higher level of participation and communication does not automatically translate in more collective actions if not paired with institutional intervention (Tavoni et al., 2011).

Bottom panels of Figure 3 report the outcomes for a population of only *Type B)* individuals, i.e. the *conformist* mode of updating by which, at least when the threshold is low, individuals tend to converge to a common behaviour. Indeed, this updating process tend to heighten the probability of agents with an initial low environmental attitude (i.e., below the mean), and *vice versa*. In other words, agent tend to conform to the dominant level of agency, which is grounded in s. Interestingly, the level of convergence changes depending on the type of the indicator. In the case of degree (most of the) agent converges to $\sqrt{s}$. This is explained by the rule of link creation.

[7] In other words, the agent in the first position will always be the one with the minimum probability and the last the one with the highest value.

[8] Note that, each iteration within the same type of scenario, might end up in a different time.

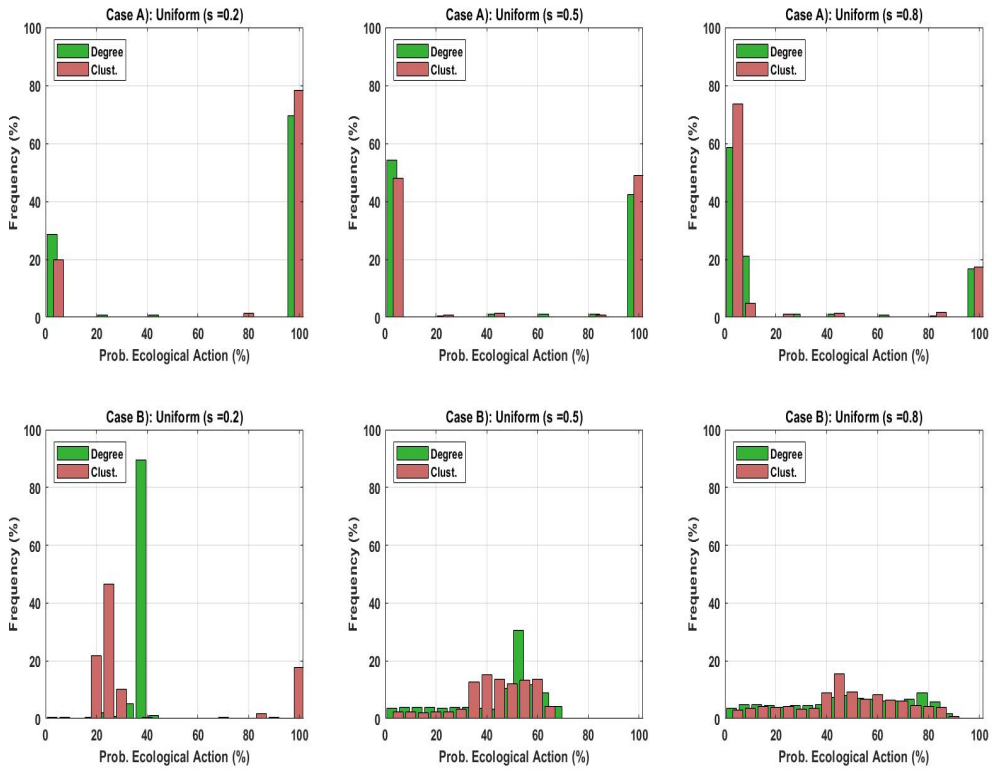

Figure 3: Final distribution of agents probability. *Frequency of attitudes towards collective action at the end of the simulation time. Updating processes based on degree (green bar) and clustering coefficient (red bar), for Types A (top) and B (bottom) and three thresholds (s): low (left), middle (central), and high (right).*

Since the activation of the link is directly dependent on the product of the individual probability, then when the majority of the agents reaches the square root of s the process stops, to say if $p_j^t \to \sqrt{s}$ and $p_k^t \to \sqrt{s}$, then $p_j^t \cdot p_j^t \to s$. Interestingly, in the case of the clustering coefficient, the individual probabilities are more concentrated around s (instead of $\sqrt{s}$), confirming that this indicator better captures the quality of information and then agents conform more precisely to the social norm. However, as s increases this is less evident because the number of interactions reduce. Higher thresholds hamper the creation of the connections, thus impeding that the probabilities are updated. Hence, the interaction process becomes less effective in changing the initial attitudes toward collective action. This leads to a final distribution of ecological actions more close to the initial (Uniform) distribution (as appear from the bottom-right panel of Figure 3).

Figure 4 plots the dynamic of the individual probability over time. For the sake of simplicity, we only plot ten representative agents, instead of all the sample of 1000 individuals, varying from a low (blue) to a high (orange) initial probability. This graphs highlight the complex dynamic behind the formation of the final distribution described above. They emerge non-trivial and heterogeneous behaviours peculiar of the complex systems.

For *Type A)* individuals (top two-rows panels) the presence of the threshold (dotted line) strongly affect the direction of the individual probability, since the larger part of those starting above the threshold ($p_j^0 > s$) ends up with an high p_j^T, and *vice versa*. However, the speed of convergence and the shape of paths change even within a specific setting. In some cases – e.g., degree updating with $s = 0.5$ (green line) and clustering updating with $s = 0.8$ (yellow line) – nodes are not attracted to an extreme value but, after an initial fluctuation, they stabilize toward an intermediate value.

The bottom two-rows panels show the outcomes for *Type B)* individuals. When s is low, most

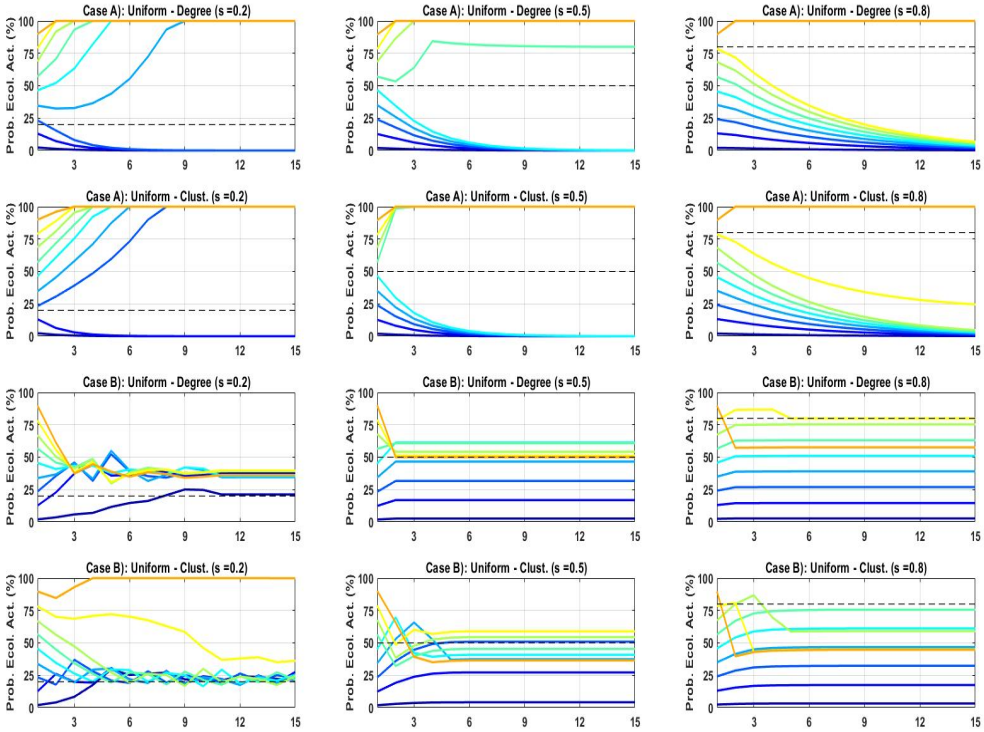

Figure 4: Path of individual probability. *Ten selected agents, from low (blue) to high (orange) initial probability, for Case A (top two-rows) and B (bottom two-rows) and three thresholds (s, dotted line): low (left), middle (central), and high (right).*

of the nodes fluctuate around s ($\sqrt{s}$) in case of clustering (degree). However, as above, some agents follow independent paths, thus conserving heterogeneous behaviours. On the contrary, when s increases the paths are more flat because, after an initial fluctuation, the interactive process do not affect anymore the individual pro-environmental attitude because the number of links drastically decreases.

5 Discussion and conclusions

The model proposed in this paper entails several analytical advantages, but also, limitations due to the tentative nature of the above illustrated settings. As any "paper-and-pencil" approach it represents an idealisation and abstraction of the real and detailed causal forces that shape social relations and individual behaviours. The main purpose of the current study is precisely to propose a simple and generalisable approach able to shed a light on the attitude formation and on a two-type of social process widely observed in the real world, such as *polarisation* and *conformism*. To do so, we decide to be agnostic about the individual decision process, thus avoiding to discuss rationality issues (i.e. the solution of social dilemmas, the formation of shared beliefs in collective agency). Hence, we deal with collective action at an intermediate scale in between the micro- and macro- level, through a statistical approach. The proposed framework is flexible, parsimonious and able to endogenously determine the dynamics of individual attitudes and behaviours that co-evolve with interactions and the emergence of social structures.

The limitations of the present work single out several points that will be possibly developed in further researches. These include: a) developing the analysis of modes of attitude updating by providing an analytical specification of the interaction of Type A and B in the population; b) the inclusion of frictions (e.g., geographical distance, bounded time and limited number of relations to be created); c) taking into account the memory of previous connections (i.e., friends tend to be

friends over time); d) the endogenous determination and evolution of the threshold (social norm); e) the inclusion of experts (node asymmetry and directional link) and heterogeneous relevance of the information exchanged (weighted link); f) calibrating the initial distribution with real data (e.g., from EU-Eurobarometro); g) testing the main model predictions via experiments.

To summarise the main outcomes of the present research, we underline that the numerical simulations determine several outcomes depending on the index of the updating process (degree or clustering) and on the institutional setting (parameter s). It results that a population of Types A) generates a *polarisation* process which ends up in a binomial distribution, with the population departed between individual with strong (viz. $p_j^T \sim 1$) and weak (viz. $p_j^T \sim 0$) attitudes toward collective action. Note that the interactive process does not necessarily determine a convergence toward actions that might be considered more 'desirable'. On the contrary, if institutions are not effective in creating the conditions to favour collective action (s high) then the system might end up with a majority of free riders (see top-right panel of Figure 3).

Instead, types B) might generate a converging process, with the majority of agents with behaviours close to the current norm (viz. $p_j^T \sim s$), only if the institutional setting is particularly favourable (s low). In this case, agents adapt to the given standard without strong impulse to change the situation. On the contrary, unfavourable institutions obstacle interactive process which stops early without generating a significant change in the initial individual attitudes (viz. $p_j^T \sim p_j^0$).

Both the discussed cases underline the relevance of the interplay between top-down institutional setting and the bottom-up collective action to the purpose of pursuing of social desiderata. Our model shows as the mutual influence between individuals' attitudes and the social relationships in which they develop is crucially mediated by the presence of institutional norms that determine the direction and the speed of the processes in the analysed dynamics.

References

Banerjee, S., A. M. Kwasnica, and J. S. Shortle (2012). Agglomeration bonus in small and large local networks: A laboratory examination of spatial coordination. *Ecological Economics 84*, 142–152.

Bardhan, P. and I. Ray (2006). Methodological approaches to the question of the commons. *Economic Development and Cultural Change 54*(3), 655–676.

Bartlett, R. V. (1986). Ecological rationality: Reason and environmental policy. *Environmental Ethics 8*(3), 221–239.

Borgatti, S. P. and D. S. Halgin (2011). On network theory. *Organization science 22*(5), 1168–1181.

Bowles, S. (1998). Endogenous preferences: The cultural consequences of markets and other economic institutions. *Journal of economic literature 36*(1), 75–111.

Davis, J. B. (2010). *Individuals and identity in economics.* Cambridge University Press.

El-Sayed, A. M., P. Scarborough, L. Seemann, and S. Galea (2012). Social network analysis and agent-based modeling in social epidemiology. *Epidemiologic Perspectives & Innovations 9*(1), 1.

Forsyth, T. and C. Johnson (2014). Elinor ostrom's legacy: governing the commons, and the rational choice controversy. *Development and Change 45*(5), 1093–1110.

Gaaff, A. and S. Reinhard (2012). Incorporating the value of ecological networks into cost–benefit analysis to improve spatially explicit land-use planning. *Ecological economics 73*, 66–74.

Gerber, E. R. and J. E. Jackson (1993). Endogenous preferences and the study of institutions. *American Political Science Review 87*(3), 639–656.

Gilbert, M. (2006). Rationality in collective action. *Philosophy of the social sciences 36*(1), 3–17.

Hodgson, G. (1986). Behind methodological individualism. *Cambridge Journal of Economics 10*(3), 211–224.

Hodgson, G. M. (2007). Meanings of methodological individualism. *Journal of Economic Methodology 14*(2), 211–226.

Newman, M. E. (2003). The structure and function of complex networks. *SIAM review 45*(2), 167–256.

Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action.* Cambridge university press.

O'Hara, S. U. and S. Stagl (2002). Endogenous preferences and sustainable development. *The Journal of Socio-Economics 31*(5), 511–527.

Pittman, J. and D. Armitage (2019). Network governance of land-sea social-ecological systems in the lesser antilles. *Ecological Economics 157*, 61–70.

Smith, V. L. (2003). Constructivist and ecological rationality in economics. *American economic review 93*(3), 465–508.

Tavoni, A., A. Dannenberg, G. Kallis, and A. Löschel (2011). Inequality, communication, and the avoidance of disastrous climate change in a public goods game. *Proceedings of the National Academy of Sciences 108*(29), 11825–11829.

Todd, P. M. and G. Gigerenzer (2012). *Ecological rationality: Intelligence in the world.* OUP USA.

Watts, D. J. and S. H. Strogatz (1998). Collective dynamics of 'small-world'networks. *nature 393*(6684), 440.