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**Tragedy of the Commons
and Evolutionary Games in
Social Networks:
The Economics of Social
Punishment**

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Tragedy of the Commons and Evolutionary Games in Social Networks: The Economics of Social Punishment

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Summary

This study revisits the problem of the tragedy of the commons. Extracting agents participate in an evolutionary game in a complex social network and are subject to social pressure if they do not comply with the social norms. Social pressure depends on the dynamics of the resource, the network and the population of compliers. We analyze the influence the network structure has on the agents' behavior and determine the economic value of the intangible good - social pressure. For a socially optimal management of the resource, an initially high share of compliers is necessary but is not sufficient. The analysis shows the extent to which the remaining level of the resource, the share of compliers and the size, density and local cohesiveness of the network contribute to overcoming the tragedy of the commons. The study suggests that the origin of the problem – shortsighted behavior - is also the starting point for a solution in the form of a one-time payment. A numerical analysis of a social network comprising 7500 agents and a realistic topological structure is performed using empirical data from the western La Mancha aquifer in Spain.

Keywords: Tragedy of the Commons, Cooperation, Evolutionary Game, Social Network, Social Punishment

JEL Classification: C71, D85, Q25

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Abstract

This study revisits the problem of the tragedy of the commons. Extracting agents participate in an evolutionary game in a complex social network and are subject to social pressure if they do not comply with the social norms. Social pressure depends on the dynamics of the resource, the network and the population of compliers. We analyze the influence the network structure has on the agents' behavior and determine the economic value of the intangible good - social pressure. For a socially optimal management of the resource, an initially high share of compliers is necessary but is not sufficient. The analysis shows the extent to which the remaining level of the resource, the share of compliers and the size, density and local cohesiveness of the network contribute to overcoming the tragedy of the commons. The study suggests that the origin of the problem – shortsighted behavior - is also the starting point for a solution in the form of a one-time payment. A numerical analysis of a social network comprising 7500 agents and a realistic topological structure is performed using empirical data from the western La Mancha aquifer in Spain.

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1. Introduction

The origin of the tragedy of the commons is often explained by the fact that a natural resource is owned by a community. Although the existing literature has recognized the importance of common property, little attention has been given to the underlying social relationships of the community. Such social relationships imply that, in particular, one agent's decisions are influenced by the choices the other agents make. The interaction between the agents is governed by the type and pattern of their connections within the social network. The influence single aspects of a social network have on the tragedy of the commons, such as the share of compliers to a social norm, the density or size of the network and the connectivity between agents, has been analyzed as isolated elements (Tavoni et al. 2012, Currarini et al. 2015)¹, however, the influence and dynamics of a realistic network and its many facets has, as yet, not been studied. The object of this study is to analyze agents' behavior by taking into account that they are interacting in a large, complex network that is close to real networks. This requires, among other elements, that the network structure is highly asymmetric, that the distribution of the number of the agents' links follows a power law, and that there is a large number of agents.

Among the single aspects analyzed in the literature, cohesiveness and the share of compliers stand out. The definition for cohesiveness is most frequently based on links between agents. However, in the case of cooperativeness or the exercise of social pressure, not only are the links between agents important, but so too are the agents' chosen strategies. If two compliers are linked, one can expect they will experience greater social pressure than if every complier were linked to a defector but not linked between themselves. For this reason, we propose a new connectivity measure that is based on links and the strategy chosen. We have called it 'local cohesiveness' and it considers the links between the compliers in the neighborhood of an agent. The share of

¹ Factors other than the elements of a social network, but which favor disposition to comply with social norms, have been studied intensively in economics and other social sciences. Wenegrat, B., L. Abrams, E. Castillo-Yee and I. J. Romine (1996). "Social norm compliance as a signaling system. I. Studies of fitness-related attributions consequent on everyday norm violations." *Ethology and Sociobiology* **17**(6): 403-416, Ostrom, E., T. Dietz, N. Dolsak, P. C. Stern, S. Stonich and E. U. Weber, Eds. (2002). *The Drama of the Commons*. Washington, National Academy Press, Hanaki, N., A. Peterhansl, P. S. Dodds and D. J. Watts (2007). "Cooperation in Evolving Social Networks." *Management Science* **53**(7): 1036-1050.

compliers is another single aspect that is often seen as an important driving force behind the dynamics of the network. That said, the share of compliers is independent of network size and density. As such, its indicative power to foresee a possible propagation of compliers within social networks is limited. The previous arguments suggest that merely focusing on the single aspects of the network does not offer a reliable instrument to accurately analyze the tragedy of the commons.

This study aims to contribute to a better understanding of underlying forces of the tragedy of the commons. To this end, we analyze to what extent macro and micro characteristics of social interaction support social norms that help to conserve natural resources (Jackson et al. 2017). While the community may own the natural resource, it either lacks the legal power to enforce the social norm or it is too costly to rely on any kind of formal contract. However, those members complying to the social norm may be able to place social pressure (e.g. social shunning or rejection) on those who do not adhere to it (Ali and Miller 2016). In our model, social pressure depends on the share of compliers, the state of the resource and local cohesiveness.

The results of a numerical study based on empirical data from the western La Mancha aquifer show that a critical level of the initial share of compliers is necessary to achieve a more socially-optimal management of the resource. Yet, our calculations demonstrate that the range of the critical level of share of compliers is between 0.4 and 0.96. Given this wide range, the share of compliers alone is not a good indicator of cooperativeness in the community. The results show to what extent the critical level depends on the size and density of the network, the state of the resource and the strength of local cohesiveness. Thus, one may find that a certain initial share of compliers is necessary, but not sufficient, to overcome the tragedy of the commons. While a higher network density may contribute to greater acceptance of the social norm, this increase in density is only relevant if the additional links strengthen local cohesiveness, otherwise they are redundant. The fact that new links might be redundant demonstrates that density alone is a poor indicator of the network characteristics that support cooperation. Moreover, if all other characteristics are equal, then the analysis shows that large networks are less capable than smaller networks in engendering adherence to a social norm. Yet, this shortcoming may be redressed by favoring the creation of new connections between compliers. New strategy-dependent links can be supported when workshops are

organized, meetings or courses are run or new institutions, such as complier associations, are set up. Another policy option to secure higher cooperation may consist of a one-time payment to defectors if they change their strategy. The rationale for a single payment is the fact that defectors are short-sighted. Once they have changed sides, the increased number of compliers hampers from them reverting. In this respect, although shortsightedness of defectors is often considered as the origin of the tragedy of the commons, it also offers a starting point for its solution.

Environmental economics contributed to general economics by establishing a foundation for and formalizing methods to measure the value of intangible goods and services, such as Nature's aesthetic values or a particular environmental resource's existence value. This work aims to contribute to the literature by analyzing the monetary value of social shunning using the case of the western La Mancha aquifer in Spain.

In Section 2, we present the rationale for the modeling approach. In Section 3, we introduce the different elements of the economic model based on an integrated social-biophysical system. In Section 4, we define a concept for equilibrium and analyze possible equilibria. Then, in Section 5, we analyze the economics of social pressure and discuss policy options for overcoming the tragedy of the commons. In Section 6, we briefly present details of the social network's structural elements and in Section 7, to analyze the effect the social network has on the tragedy of the commons, we present a numerical analysis for our groundwater resource case. The paper then closes with some conclusions.

2. Rationale for the modelling approach

A first attempt to analyze the interplay between the emergence of cooperation and social networks was based on the evolutionary-game-theoretic approach. In its initial phase, the evolutionary game-theoretic approach was based on the premise that every agent can randomly meet any other agent, i.e. all agents are directly linked to each other. In terms of a social network, one would talk about a complete network. While this approach (Bowles 2004) helped to understand the driving factors behind the emergence and preservation of cooperation, it does not take full account of the complexity, vicinity and segregation patterns that occur between agents when interacting in a real world social network. For this reason, (Nowak and May 1992, Szabó and Fáth 2007) introduced a simple spatial structure where agents can interact only with their immediate neighbors.

This new framework demonstrated that cooperation is evolutionarily viable within a narrow window of the specified parameters of the game. Yet, this approach neglects empirical evidence (Amaral et al. 2000, Jackson et al. 2017) showing that agents are grounded in strongly heterogeneous networks with a great diversity among their neighborhood structure. To overcome the topological identity of the agents and to break up the underlying symmetry of the network structure, (Santos and Pacheco 2005, Santos et al. 2006, Santos et al. 2012) analyzed the emergence of cooperation in non-regular networks. Their results show that scale-free networks actively support the emergence of cooperation.

In contrast to traditional ways of economic thinking, the evolutionary-game-theoretic framework assumes that the agents' rationality is limited and individual decisions are taken by comparing payoffs. The proportion of individuals choosing a particular behavior increases when the payoff for that behavior exceeds the average payoff in the population, and decreases when the reverse is true. Hence, behavior that performs badly from the individual's point of view is weeded out, while behavior that reaps benefits is imitated (Sethi and Somanathan 1996, Osés-Eraso and Viladrich-Grau 2007). Within the evolutionary-game-theoretic framework, little attention has been paid to how payoffs are determined. Payoffs could be based on short-term or long-term perspectives, depending on the degree of individual commitment to the interests of the collective. In a short-term perspective individual interests predominate, whereas a long-term perspective reflects the welfare of the collective. In the latter case, the payoff can be calculated as the outcome of a differential game. Finally, determining the optimal strategic response to, let us say, thousands of other agents (each of whom occupies a unique position in the social network) could, because of the complexity of the strategic decision problem, stretch the assumption of rationality beyond its limits. Therefore, the assumption of limited rationality seems reasonable to us if the social network is large and topologically complex.

Alternatively, economists have studied the behavior of agents constituting part of a social network within the framework of repeated games (Haag and Lagunoff 2006, Jackson 2016). This strand of the literature establishes that cooperation can be maintained throughout the game if the defecting agents are sanctioned and excluded from cooperative benefits forever. The infinitely repeated games are framed as bilateral

or multilateral prisoner dilemmas. While the results of these studies are interesting, their applicability to real life situations is limited because equilibrium is only found on the basis of grim trigger strategies within the set-ups of infinitely repeated prisoner dilemma type games (Jackson 2016). Examples of successful cooperation (Sethi and Somanathan 1996), however, show that these social networks are not based on grim strategies at all. Such repeated games are the repetition of static games and do not consider the evolution of a stock variable. Consequently, neither do they allow for the tragedy of the commons, where the evolution of a natural resource is a fundamental element of the problem being analyzed.

In view of these considerations, we suggest a new framework that combines the distinctive aspects of the three strands of the literature, i.e. an evolutionary game-theoretic approach based on the solutions to the differential games employed within a social network that accounts for the complexity of the interaction between agents.

3. The economic model

The economic model is based on three different components: the social network that defines the interaction between agents, the resource demand strategies and the agent's chosen strategy. In the following, we present the three components.

3.1 A social network as a graph

Our interest is in the interaction between n different members of a social network that can be described by a simple graph $N=(A,L)$ which consists of a finite set $A=1,\dots,n$, $n > 2$ of agents and a set L of links that are the unordered pairs of elements from A . The elements in set L consist of the values of the indicatrix link function $l: A \times A \rightarrow \{0,1\}$:

$$l(i, j) \equiv l_{i,j} = \begin{cases} 1; & (i, j) \in L \\ 0; & (i, j) \notin L \end{cases} .$$

For any pair of agents, i and j , the expression $l_{ij} = 1$ indicates that the two agents are neighbors, otherwise $l_{ij} = 0$., i.e. they know and relate to each other. By definition,

simple graphs are undirected so that $l_{ij} = 1 \Leftrightarrow l_{ji} = 1$.² If every agent is connected to all other agents, N forms a complete network. Finally, the degree $k_N(i) = k_i = \sum_j l_{ij}$ of an agent i is the number of links at i , i.e. the number of neighbors i has. Denote by $P(K = k) = p_k$ the degree distribution of N , that is the probability that an agent i in N chosen uniformly at random has exactly k neighbors.

3.2 Resource demand strategies

Each member of the social network has access to a common property resource. However, extraction based on the maximization of each member's private net benefits would, in the long-run, lead either to the depletion of the resource or to very low annual private net benefits. To overcome the tragedy of the commons, the members of the social network have reached a common understanding of the characteristics of a sustainable extraction path. Let us interpret this common understanding as a social norm. Adherence to the social norm is voluntary and every member of the social network may choose to follow the sustainable extraction path or not. Let us label the behavior of the agents that follow the sustainable extraction path as *compliers* and the behavior of all other agents as *defectors*.

Each member either 1) employs the extracted resource as the input to produce a single good or 2) commercializes it on the market. In any case, members need to adjust all other inputs to the extracted amount of the resource so that their net benefits are maximized. Let $w(t)$ denote the amount of the resource extracted at calendar time t .

The available amount of resource is denoted by $s(t)$ with $s(0) = s_0$. All other inputs are considered by the composite input $x(t)$. Hence, by solving the decision problem:

$\max_{x_i} \pi(x_i, w_i, s)$ each member i determines the optimal amount of the composite input

² Moreover, agents are not linked to themselves (self-loops), i.e. $l_{ii} = 0$, and there is no more than one link between agent i and j (uniqueness of the link). For each agent i , $N(i)$ denotes their neighborhood, i.e. the set of all neighbors. Agent i can observe the action of agent j if, and only if, $j \in N(i)$. Nonetheless, in our network N , for any agent i and j there is a finite sequence of agents a_1, \dots, a_K such that $a_1 = i, a_K = j$ and $a_{k+1} \in N(a_k)$ for $k = 1, \dots, K-1$. This means there are no isolated agents in N .

given a particular value of w and s . The solution to problem is denoted by $x_i^*(w,s)$. Once the optimal use of the composite input has been determined, each member, i , still has to decide whether or not to adhere to the social norm. Adherence to the social norm will support sustainable extraction, whereas non-adherence will lead to a non-sustainable extraction path. Non-coordinated individual behavior would result in a sustainable extraction path if all members were to consider stock dependent costs when determining the privately optimal extraction path. These costs will be fully considered if all the agents have a private planning horizon of sufficient length. Consequently, we define compliers as far-sighted agents with a planning horizon of $T \gg 1$ years, whereas defectors are short-sighted and their planning horizon is 1 year.³ We assume that the underlying reason for this shortsightedness is either related to socioeconomic factors (e.g. the agent's age) or is closely related to risk aversion. Each agent determines the privately optimal extraction path (resource demand function) based on the solution to the following decision problems. For compliers, the resource demand function is given by:

$$w_i^C(\xi, t, T, s(t)) = \underset{w_i(\xi)}{\operatorname{argmax}} \int_t^{t+T} e^{-r\xi} \pi(x_i^*(w(\xi), s(t)), w_i(\xi), s(t)) d\xi \quad (1)$$

subject to

$$\dot{s}(\xi) = g(s(\xi)) - \sum_i^{cn} w_i^C(\xi) - \sum_{cn+1}^n \bar{w}_i^D, \quad s(\xi) = s_t,$$

where r denotes the private intertemporal discount rate, \bar{w}_i^D for the resource that the defectors demand at time t , a dot over a variable the operator d/dt , c is the share of compliers within the population of all agents and $g(s(t))$ is the reproduction or growth function of the resource.

In other words, compliers consider the extraction by defectors as constant. The resource demand function (1) is the solution to an open-loop strategy. The rationale for open-loop strategies is that agents can commit to maintaining the established extraction profile at

³ Alternatively, we could have distinguished the behavior of compliers and defectors by the choice of different time preferences. Yet, the choice of different discount rates would have been more difficult since there is no natural orientation for its specification like generational succession or economic lifetime of an investment.

time t over the planning horizon T because they do not obtain any further information in the future, i.e. nothing about the remaining level of the resource, nor about the choice the other agents made. Yet, in the case of natural resource, agents can often see the state of the stock and consequently their extraction profile should depend on the natural resource level they observe. Hence, one could model the resource demand function as the solution to a feedback strategy where compliers' resource demand is a function of the remaining stock. Yet, given the large number of agents and the complexity of the social network, it is difficult to envision that every agent is playing a non-cooperative game against all the others. The reasons for this are threefold. Firstly, the required effort to solve this game is extremely high⁴, secondly the agents' rationality may be limited and, thirdly, compliers seek to implement a cooperative solution instead of a non-cooperative one. For these three reasons, we discard determining the resource demand as the solution to a feedback strategy and propose a modified open-loop strategy instead. Based on the circumstance that agents can frequently observe the level of stock remaining, we propose that they are allowed to amend their extraction profile after one year. In other words, the agents determine a new open-loop extraction profile based on the amount of the natural resource they see. This profile is maintained until the next revision period when new information about the level of the remaining stock is obtained.

In the defectors case, we assume that the length of their planning horizon is one year. Thus, their resource demand function is given by:

$$w_i^D(\xi, 1, s(t)) = \underset{w_i(\xi)}{\operatorname{argmax}} \int_t^{t+1} e^{-r\xi} \pi(x_i^*(w(\xi), s(t)), w_i(\xi), s(t)) d\xi \quad (2)$$

subject to:

$$\dot{s}(\xi) = g(s(\xi)) - \sum_i^{cn} \bar{w}_i^C - \sum_{cn+1}^n w_i^D(\xi), \quad s(t) = s_t,$$

where \bar{w}_i^C denotes the compliers' resource demand at time t . We assume that compliers and defectors differ only in respect to the length of their planning horizon, but not to their private discount rate.

⁴ This requires every agent solving a large system of partial differential equations.

3.3 Strategy choice - an evolutionary game-theoretic approach

Given our focus on the interaction between agents, we analyze how an arbitrary initial distribution of compliers and defectors evolves over time and how this changing distribution affects the evolution of the resource. At every moment of time, agents can change their strategy, i.e. from complier to defector, or vice versa. Strategy choice is based on the evolutionary game-theoretic approach (Sethi and Somanathan 1996, Osés-Eraso and Viladrich-Grau 2007). We assume that this decision is influenced by the following factors:

1. the difference between the net benefits of a defector and a complier (i.e. the defector's extra benefits) and
2. the interaction with other agents (network effects)

In the case of the first point, we assume that the larger the difference is between the maximal net benefits of complying with the strategy, given by, $\pi^C(x_i^*(w_i^C(\cdot), s(t)), w_i^C(\cdot), s(t))$ and not complying with the strategy, given by $\pi^D(x_j^*(w_j^D(\cdot), s(t)), w_j^D(\cdot), s(t))$, the greater the chance at moment t a complier will become a defector and a defector will not become a complier. The difference between $\pi^D - \pi^C$ is not only important for the agent's strategy, but also presents the magnitude of the loss defectors inflict on those members of the network who are adhering to the social norm. In the absence of an institution that is technically and legally in a position to punish defectors, compliers may retaliate for the defectors' abstraction of the common property resource through social shunning (ostracism) (Ali and Miller 2016).

In terms of social pressure, we assume that all agents are perfectly informed about the strategy choice their neighbors have made (complete monitoring) and that there is no time delay between detecting non-compliance and retaliation.⁵ To concentrate on the first-order dilemma of public goods (provision of cooperation), we suppose that retaliation is costless for the compliers. In doing so, we avoid the second-order dilemma of public goods since compliers do not have to agree on how to divide the costs of retaliation among themselves.

⁵ Social pressure is the application of the principle of reciprocity as the response to non-compliance of the social norm by defectors.

Social pressure and social punishment

If an agent defects, they will be exposed to social pressure from the compliers.⁶ However, making use of the social network suggests that social pressure on defector i depends on the number of compliers and defectors within their local neighborhood $N(i)$. Let us define the set of compliers within the neighborhood $N(i)$ by $N_c(i)$. Thus, the share of compliers, c_i , can be defined by $c_i = |N_c(i)|/|N(i)|$. This relationship is considered an important factor in determining social pressure because it measures the direct influence the neighborhood has on defector i (Haag and Lagunoff 2006, Jackson et al. 2012). The higher the number of compliers of neighborhood $N(i)$ is, the greater the social pressure on agent i . However, not only is the share of compliers, c_i , important in determining social pressure, but so too is the relationship between the agents who form part of the set $N_c(i)$. In the case that none of these agents is linked to another agent in this set, one can assume that the social pressure on defector i will not be as high as when each and every agent in set $N_c(i)$ is linked. In the first case, local cohesiveness between the agents in set $N_c(i)$ would be zero, whereas in the latter it would be one. Let us denote the cohesiveness among the compliers in the neighborhood by $\tau_{c_i} \in [0,1]$. This measures the degree of connectivity between the compliers in set $N_c(i)$. Haag and Lagunoff (2006) and Jackson et al. (2012) employed a different metric, independent of the agents' strategy choice, for connectivity. However, we used a more stringent measure of connectivity since the cohesiveness of compliers is important to analyze the tragedy of the commons. We denote the connectivity of all agents (compliers and defectors) in the neighborhood of agent i by τ_i . This measures how close the neighborhood of agent i is to a complete network.⁷ Alternatively, the measurement of cohesiveness for nodes or agents can also be measured on a network

⁶ Instead of the male and female possessive pronoun we use plural form to facilitate the reading.

⁷ The metrics employed by Jackson, M. O., T. Rodriguez-Barraquer and X. Tan (2012). "Social Capital and Social Quilts: Network Patterns of Favor Exchange." *American Economic Review* **102**(5): 1857-1897, is based on the definition of small, tree-like connected, complete networks (i.e. the so-called quilts). However, quilts (albeit interesting) are not compatible with the power law for large networks.

level. On this scale, we define transitivity or average local cohesiveness, as the average value of local cohesiveness, i.e. $\tau = \frac{1}{n} \sum_i^n \tau_i$. Finally, we assume, if the resource is abundant, the set of compliers $N_c(i)$ will exert less social pressure on defector i than if it were scarce.

Once the three key elements of social pressure have been introduced, we can then write the social pressure function as $\omega(s(t), c_i(t), \tau_{c_i}(t))$. As explained above, an increase in the stock reduces social pressure (i.e. $\partial\omega/\partial s < 0$), an increase in number of compliers in the neighborhood of defector i increases social pressure (i.e. $\partial\omega/\partial c_i > 0$), and an increase in the strength of social ties between compliers in the neighborhood of defector i raises social pressure (i.e. $\partial\omega/\partial \tau_{c_i} > 0$).

We assume that social punishment is directly related to the difference between the net benefits of the defector and the complier $\pi^D(\cdot) - \pi^C(\cdot)$. Since these extra benefits present the loss defectors inflict on compliers, any social punishment can be viewed as redemption for the privation suffered by the compliers. However, social punishment is not independent of social interaction among the agents and, therefore, we assume that the loss defectors inflict on the compliers is attenuated or aggravated by the strength of social pressure $\omega(s, c_i, \tau_{c_i})$. More precisely, the social pressure produced and the extra benefits the defector gains as a result of incomppliance, define the social punishment imposed and is written as:

$$\omega(\cdot)(\pi^D(\cdot) - \pi^C(\cdot)).(3)$$

Agent utility and a probabilistic model of strategy choice

We assume that the utility of agent i adhering to the social norm at moment t is given by:

$$U_i^C(t) = \pi^C(\cdot), (4)$$

and the utility of the same agent i not adhering to the social norm at moment t is given by:

$$U_i^D(t) = \pi^D(\cdot) - \left[\omega(s(t), c_i(t), \tau_{c_i}(t)) (\pi^D(\cdot) - \pi^C(\cdot)) \right]. \quad (5)$$

Equation (4) indicates that the utility of a complier is equal to their private net benefits.⁸ This depends on the amount of the extracted resource and the level of the stock. Equation (5) shows that the utility of a defector consists of the net benefits from resource exploitation minus social punishment and, likewise, depends on the amount of the resource extracted and the stock levels. However, it also depends on the position the defector holds within the social network and the characteristics/topology of the social network within their neighborhood.

At each time step, every agent decides whether to maintain their current strategy or not. For this purpose, every agent i compares the utility associated with their current strategy $U_i(t)$ with that of the alternative strategy $U_i'(t)$. The utility of a complier is independent of their position in the network or the characteristics/topology of the social network within their neighborhood. However, the decision to maintain or to change their current strategy depends on these very elements as they influence the alternative strategy's utility. The agent will probably adopt an alternative strategy if it proves more beneficial, $U_i'(t) > U_i(t)$, whereas if $U_i'(t) \leq U_i(t)$, the agent will maintain their current strategy. These inequalities also form our tie-breaker rule in the remainder of the study. In mathematical terms, the probability of a change in the current strategy adopted by agent i for a given level of stock, is considered proportional to the difference in the utilities. Let the probability that agent i changes from complier to defector be denoted by $p_i^C(t)$ given by:

$$p_i^C(t) = \begin{cases} \frac{U^D(t) - U^C(t)}{\max\{U^D(t) - U^C(t)\}} & , \text{ if } U^D(t) - U^C(t) > 0 \\ 0 & , \text{ if } U^D(t) - U^C(t) \leq 0 \end{cases}, \quad (6)$$

and let the probability that agent i changes from defector to complier be denoted by $p_i^D(t)$ given by:

⁸ Although this formulation implies that agents are risk neutral, we opted for this specification to simplify the model and to concentrate on the interaction between agents in a social network.

$$p_i^D(t) = \left\{ \begin{array}{ll} \frac{U^C(t) - U^D(t)}{\max\{U^D(t) - U^C(t)\}} & , \text{ if } U^C(t) - U^D(t) > 0 \\ 0 & , \text{ if } U^C(t) - U^D(t) \leq 0 \end{array} \right\}. (7)$$

The denominator of Equations (6) and (7) refers to the maximal difference between the utility of the different strategies for a given level of stock at time t . Since the value of U^C is independent of the neighborhood and varies only with the level of stock, $U^D(t) - U^C(t)$ is maximal if U^D is maximal. For a given level of stock, the maximum of U^D transpires, if social punishment is zero. In other words, there are no compliers in the neighborhood and consequently local cohesiveness is zero and $U^D = \pi^D$.

The decision to maintain the current strategy or to adopt the alternative one is a 0 - 1 decision in probabilities. For this purpose, using the inverse transform method we generated a random number that takes only the values of 0 or 1. Put simply, if $p_i^D = 0.8$, there is an eighty percent probability this method will generate a 1 and a twenty percent probability it will generate a 0. Thus, if the random number drawn is a 1, the defector will change their strategy. Otherwise they will not.⁹

All agents simultaneously decide which strategy to choose based on the current distribution of compliers and defectors within the social network, with the probability being p_i^C or p_i^D . We assume that agents do not act strategically, i.e. they do not consider the possible strategy choices of their neighbors when deciding on their own. Given the large size of the social network and the resulting huge set of possible constellations each player needs to consider to make a strategic choice, it would seem to be more realistic to base individual strategy-choice on non-strategic behavior as in (Gale and Kavir, 2003).

4. Equilibrium concept

⁹A number u is drawn randomly from the uniform distribution $Uni(0 < P_i \leq 1)$. If u is less than or equal to P_i , the outcome is associated with a 1 or with a 0 otherwise. This method is comparable to a forged coin where the probability of landing heads up (1) is P_i and tails up (0) $1 - P_i$.

For the dynamics of a resource and a non-structured population, (Sethi and Somanathan 1996, Osés-Eraso and Viladrich-Grau 2007) identified equilibrium conditions. In the absence of a natural resource (Santos and Pacheco 2005, Santos et al. 2006, Santos et al. 2012) used Monte Carlo techniques to identify a window of parameter values for an equilibrium of the dynamics of a population embedded in an asymmetric social network.

Observation 1: (Equilibria conditions):

Any steady state equilibrium concept requires the following three equilibria, a) equilibria with respect to the dynamics of the resource, b) changes in the choice of strategy adopted by the agents and c) the demand the agents make of the resource must be incentive-compatible with the equilibria with respect to the dynamics of the resource.

Equilibria a) demands that $\dot{s}(t) = 0$ which, in turn, requires that

$$g(s(t)) = \sum_i^c w_i^C(t) + \sum_{c+1}^n w_i^D(t). \quad (8)$$

Additional to Equation (8), none of the agents change their strategy, or the share of compliers c is constant must also hold.¹⁰ Hence, an equilibrium b) in expected values is achieved if:

$$\sum_i^{cn} p_i^C - \sum_{cn+1}^n p_j^D = 0. \quad (9)$$

Finally, equilibrium c) holds if there is a $w_i^C(t)$ and $w_i^D(t)$ that satisfies Equations (1), (2) and (8). In other words, the amount of extracted resource required satisfies the balance between reproduction and extraction (Equation (8)) also has to be optimal from

¹⁰ The share of compliers can be kept constant if none of the agent changes, i.e. $p_i^C = 0, p_j^D = 0, \forall i, j, i \neq j, i + j = n$ Moreover, there may be a dynamic equilibrium if $p_i^C \neq 0, p_j^D \neq 0, \forall i, \forall j, i + j < n, p_k^C = 0, p_l^D = 0, \text{ and } \forall k, \forall l, i + j + k + l = n$ (the share of compliers of all agents), is constant. This implies that strategy changes from compliers to defectors, or vice versa, cancel each other out for $i + j$ agents, meanwhile $k + l$ agents maintain their current strategy. None of these two equilibria are necessarily steady state equilibria.

an economic point of view for compliers and defectors. i.e. none of the agents changes their strategy.

Hence, an equilibrium is defined by Equations (1), (2), (8) and (9). Given the great number of agents and the large degree of freedom to satisfy conditions (8) and (9), an equilibrium, if it exists, is likely to be not unique and stable. In this case, while it is possible that the number of compliers and defectors is maintained for a certain period of time, the new constellation in some neighborhoods will induce agents to change their strategies. Thus, the equilibrium is likely to be only temporary.

From a social point of view, the all-defector equilibrium or any mix equilibrium would not be efficient because the social optima can only be achieved with the all-complier equilibrium. Therefore, the more compliers there are, the more efficient the resource management is. Consequently, low probabilities of the all-defector equilibrium or any mix equilibrium must be evaluated positively from a social point of view.¹¹

Observation 2: (Measurement of distance to a network equilibrium)

Let us denote $\hat{\omega}_i$ as the share of the complier- i 's (defector- i 's) extra benefits $\pi^D - \pi^C$ that have to be transformed into additional or reduced social pressure for an equilibrium to hold. The sum of the absolute values of all $\hat{\omega}_i$ defines the distance of the actual state of the network to that of an equilibrium state.

In defining measure $\hat{\omega}_i$, let us assume initially that an equilibrium exists. Therefore, the three above-mentioned conditions (resource, strategy changes and economic incentive) are satisfied and the value of social pressure is equal to $\bar{\omega}_i(\bar{s}, \bar{c}_i, \bar{\tau}_{c_i}), \forall i$, where the bar over a variable denotes its equilibrium value. Let us assume that no agent has the incentive to change their strategy choice, i.e. $p_i^C(t), p_i^D(t) = 0, \forall i$. Thus, using Equations (6) and (7) it holds that

¹¹ One should bear in mind that the interpretation of equilibrium employed in evolutionary game theory is different from that employed in non-cooperative game theory. In the latter, equilibrium provides guidance for the agent with respect to the choice of the strategy. In evolutionary game theory, however, an equilibrium simply describes a temporary or permanent steady state without offering directions for the choice of the strategy.

$$U_i^C = U_i^D \Rightarrow \pi^C = \pi^D - \bar{\omega}_i(\cdot)(\pi^D - \pi^C) \Rightarrow \bar{\omega}_i = 1. (10)$$

Therefore, provided that no agent has any incentive to change their current strategy, Equation (10) implies that $\bar{\omega}_i = 1$. However, if some agents do have incentives to change their current strategy, a network equilibrium can only be established if condition (9) holds. In this case, there may be a dynamic and, most likely, transitory equilibrium where the probability of the number of compliers and defectors who change their strategy is canceled out. So, for agents who change their strategies $p_i^C > 0$, $p_i^D > 0$ holds, which implies that the corresponding social pressure $\hat{\omega}_i$ is given by:

$$\begin{aligned} \max \{U^D(t) - U^C(t)\} p_i^C &= U^D - U^C = \pi^D - \hat{\omega}_i(\cdot)(\pi^D - \pi^C) - \pi^C \\ \frac{\max \{U^D(t) - U^C(t)\} p_i^C}{-(\pi^D - \pi^C)} &= \hat{\omega}_i(\cdot) - 1 \Rightarrow \hat{\omega}_i(\cdot) < 1 \\ \max \{U^D(t) - U^C(t)\} p_i^D &= U^C - U^D = \pi^C - (\pi^D - \hat{\omega}_i(\cdot)(\pi^D - \pi^C)) \quad (11) \\ \frac{\max \{U^D(t) - U^C(t)\} p_i^D}{(\pi^D - \pi^C)} &= \hat{\omega}_i(\cdot) - 1 \Rightarrow \hat{\omega}_i(\cdot) > 1. \end{aligned}$$

Equations (10) and (11) indicate the values social pressure may take for a dynamic network equilibrium to hold (Equation (9)).

Interpreting the value of $\hat{\omega}_i$ is straightforward as it indicates the lack/ excess of the social pressure needed for the agents to change their strategies. Thus, the term $0 < 1 - \hat{\omega}_i \leq 1$ denotes the additional share of *defector-i*'s extra benefits $\pi^D - \pi^C$ that have to be imposed on complier *i*, in the form of social pressure, for an equilibrium to hold. Faced with this additional social pressure, complier *i* loses any incentive to become a defector and thus, has no interest in changing their strategy. Likewise, the term $0 < \hat{\omega}_i - 1 \leq 1$ denotes the share of *defector-i*'s extra benefits $(\pi^D - \pi^C)$ that have to be passed on to defector *i* in the form of reduced social pressure for an equilibrium to hold. This reduction in social pressure eliminates defector *i*'s incentives to change their strategy. Thus, a $\hat{\omega}_i$ -value of 1 (0.6, 1.7) indicates that 0% (40%, -70%) of the defector's extra benefits should be transformed into additional or reduced social pressure to establish an equilibrium.

5. Economics of social pressure

Assume now that an equilibrium is not achieved by the bioeconomic system on its own. For instance, if the number of compliers is low, then little social pressure can be exercised. Hence, there is a strong likelihood that the number of defectors will rise and the biophysical system will drift along an unsustainable path which may lead to inefficient equilibrium or resource depletion.

5.1 Policy options

In this situation, the community may decide to impose a one-time payment (v_i) on the defector whose behavior has inflicted a loss on the compliers, so that the number of compliers rises which, in turn, induces more defectors to change their strategy and adhere to the social norm. Given that there is now a higher number of compliers, the resource is managed in a more sustainable way.

Observation 3: (One-time payments and /or an increase in cohesiveness as a remedy for the tragedy of the commons)

*One-time payments can immediately increase the number of compliers. Likewise, an increase in the number of links between compliers increases local cohesiveness. Provided that the number of compliers and/or the increase in local cohesiveness resulting from such an action is high enough, the increased social pressure allows for the new number of compliers to be maintained, thus favoring the sustainable management of the resource.*¹²

For this argument to be plausible, one should bear in mind that the short-sighted behavior of defectors obstructs the emergence of cooperative behavior. The short-sightedness of defectors is the origin of the tragedy of the commons. However, at the same time it offers a solution. Such short-sightedness enables the number of compliers to be increased at relatively low costs. Since defectors abandon their strategy as soon as their utility is less or equal to the one of compliers, only a one-time payment is required. Further payments are not necessary if enough defectors change sides which, in turn,

¹² Nyborg, K. and M. Rege (2003). "On social norms: the evolution of considerate smoking behavior." Journal of Economic Behavior & Organization 52(3): 323-340. and Blanco, E., J. Lozano and J. Rey-Maqueieira (2009). "A dynamic approach to voluntary environmental contributions in tourism." Ecological Economics 69(1): 104-114., suggested an increase in the number of compliers such that an all-complier equilibrium can be achieved. However, their proposal does not consider network effects and determining the one-time payment.

increases the element of social punishment and eliminates the incentive to revert to a defection strategy. If defectors had a planning horizon longer than a year, the payment would have to be larger to compensate not only for the forgone extra benefits of the current period, but also for those of future periods. In the case of a one-year planning horizon a defector is willing to become a complier if their new utility is greater than or equal to before, i.e.

$$\pi^D - \omega_i(s, c_i, \tau_{c_i})(\pi^D - \pi^C) < \pi^C + v_i, \quad (12)$$

where v_i denotes the minimal one-time payment.

Alternatively, or in combination with a policy aimed at increasing the number of compliers, the community may employ the characteristics of the network to achieve a higher adherence to the social norm. In particular, it may aim to increase the number of links between compliers, for instance by particular actions such as organizing workshops or training courses for compliers. Newly created links between compliers, as a result of these actions, increases local cohesiveness which, in turn, increases social pressure. The choice of policy to be implemented will depend on the number of compliers and the strength of local cohesiveness required for the sustainable management of the resource. How to identify the missing number of compliers and how to determine the additional strength of cohesiveness that complies with Equation (12) is discussed in sub-section 7.4. If the community wants to comply with Equation (12) at minimal costs, it will need to identify the agents with the lowest costs and the neighborhoods with the lowest local cohesiveness. For this purpose, the experience gained from designing reverse auctions as payment schemes for environmental services could be used to target one-time payments (Alston et al. 2013, Schomers and Matzdorf 2013), along with undertaking surveys to target link-building activities

5.2 The economic value of the structural elements of social punishment

As discussed in Section 3, individual social pressure, ω_i , is often not equal to the social pressure, $\bar{\omega}_i$, needed to support network equilibrium. Missing or excessive social punishment could be substituted by a tax or a subsidy so that the sum of each defector's

social punishment and the amount of an individual tax/subsidy is equal to the social punishment equilibrium $\bar{\omega}_i(\cdot)(\pi^D - \pi^C)$.¹³ Mathematically, the tax/subsidy is given by

$$\omega_i(s, c_i, \tau_{c_i})(\pi^D - \pi^C) + \theta_i = \bar{\omega}_i(\cdot)(\pi^D - \pi^C). \quad (13)$$

Although it is difficult to imagine a community imposing this type of individual tax/subsidy, Equation (13) is very informative in other ways because it allows the economic values of a change in the share of compliers in the neighborhood of agent i , c_i , the strength of local cohesiveness among the compliers in the neighborhood of agent i , τ_{c_i} , and the stock to be determined. Based on a comparative static analysis, we obtain:

Observation 4: (The marginal economic value of social punishment)

An increase in the share of compliers or local cohesiveness will increase the economic value of social punishment, whereas an increase in stock will lead to a decrease in the economic value of social punishment.

The analysis shows that

$$\frac{\partial \theta_i}{\partial c_i} = -\frac{\partial \omega_i(\cdot)(\pi^D - \pi^C)}{\partial c_i} < 0, \quad \frac{\partial \theta_i}{\partial \tau_{c_i}} = -\frac{\partial \omega_i(\cdot)(\pi^D - \pi^C)}{\partial \tau_{c_i}} < 0. \quad (14)$$

Equation (14) indicates that, an increase in the number of compliers in the neighborhood of agent i reduces the tax/subsidy required to maintain the steady state equilibrium pressure. It also specifies that an increase in local cohesiveness between the compliers within the neighborhood of agent i leads to a decrease in the proposed tax/subsidy. Since the tax/subsidy is complementary to individual social punishment, a decrease amounts to an increase in the economic value of social punishment: $\omega_i(\cdot)(\pi^D - \pi^C)$. The comparative static shows further that

¹³ A subsidy would be required if the social pressure is too high so that even a defector that is not required to change would like to do so. Only a subsidy can compensate for strong social pressure and make the defector stick to their current strategy.

$$\frac{\partial \theta_i}{\partial s} = -\frac{\partial \omega_i(\cdot)(\pi^D - \pi^C)}{\partial s} = -\frac{\partial \omega_i(\pi^D - \pi^C)}{\partial s} - \omega_i \frac{\partial(\pi^D - \pi^C)}{\partial s} > 0. (15)$$

The sign of Equation (15) can be determined unambiguously because the signs of $\partial \omega_i / \partial s$ and $\partial(\pi^D - \pi^C) / \partial s < 0$ are both negative.¹⁴ Based on the complementarity of the tax/subsidy and social punishment, it follows that social punishment decreases with an increase in stock. Equations (14) and (15) present the marginal monetary values of social punishment with respect to an increase in the two intangible goods (the share of compliers and local cohesiveness) and in the tangible one (the stock).

6. The social network

The network itself is not randomly generated but has to meet certain properties. The criteria or characteristics considered are i) scale-free, ii) correlation by biological and socioeconomic attributes and iii) small world. Our analysis of cooperative behavior is built on a social network that takes into account all three characteristics. The building blocks for each of these three characteristics are presented in non-technical terms in Appendix A – The Structure of the Social Network. For a more technical description, in particular for the definition of their metrics, we refer the interested reader to Jackson (2010) or Newman (2010) .

The social network was set up in the programming language Python and evaluated with the network analysis igraph R package. Within this programming environment, we incorporated the strategy choice rules for the agents based on the evolutionary-game theoretic approach. Likewise, we incorporated resource demand functions so that the agents could evaluate the usefulness of the two available strategies. More details about the generation of the network, the programming tools and techniques, and the numerical solution procedure can be found in Appendix B - Methodological and Technical Aspects of the Implementation of the Social Network.

¹⁴ The negative sign of $\partial(\pi^D - \pi^C) / \partial s$ is based on the observation that the lower the stock, the higher the extraction costs for both strategies. Thus, the difference between the extraction profiles and corresponding net benefits decreases. This hypothesis is also confirmed by our empirical analysis – see Table B1, Figures D2a –D2d in the Appendix.

7. A numerical analysis based on the groundwater extraction case

The social-biophysical system defined by Equations(1) - (5), form the basis for the agents' strategy choice within the social network $N(A,L)$ which consists of 7500 agents. All the networks considered are scale-free and have an average degree of 15. The structure of the social network and its current state enters the system via the social pressure function ω , which depends on the depth of the water table, the share of compliers and the cohesiveness of the neighborhood of agent i . Given the complexity of this system, it is not possible to provide an analytical solution and therefore we offer a numerical analysis. For the numerical study, we focus on a case of groundwater extraction to irrigate agricultural land, more precisely the western La Mancha aquifer (Spain). The two resource demand functions were determined by a mathematical programming model that was programmed in GAMS (General Algebraic Modeling System). More details on this part of this model are provided in Appendix C - Numerical Analysis and Specification of the Functions Employed.

We start our analysis with the limiting cases where i) all agents are compliers or ii) all agents are defectors. Moreover, we assume that none of the agents change their strategies over time. In this case, there is no interaction between agents, i.e. there are no network effects. To analyze the evolution of the aquifer's water table, the social-biophysical system is based on Equations (1) - (5) with $\omega=0$. Figure 1 presents the drop in the water table assuming an initial water table depth of 0 m and 135 years as the hypothetical lifetime of the well.

Figure 1: Evolution of the water table for different strategies

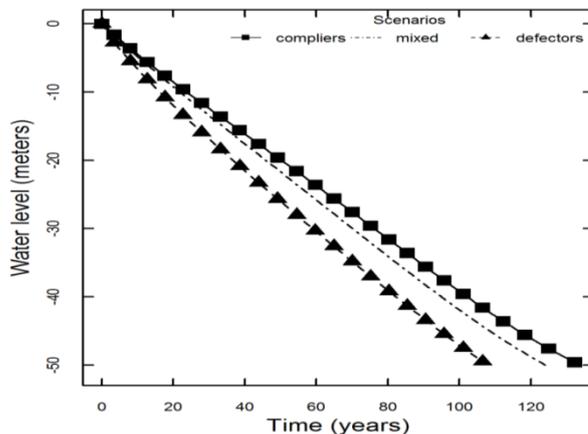


Figure 1 shows that the water table declines constantly and if all agents were compliers, (Case i), the aquifer would be depleted in 135 years. Conversely, if all agents were defectors, (Case ii), the extraction rate would be higher and the aquifer would be depleted within 106 years. Finally, if the population of agents consists of compliers and defectors (mixed case) for at least some period of time, the aquifer would be depleted sometime between 106 and 135 years. Furthermore, our calculations indicate that an identical qualitative pattern of extraction (not presented in Figure 1) is obtained if the initial depth of the well were lower and the economic lifetime were 25 years. In both cases, it is always optimal to decrease the water table constantly until (whichever comes first) the bottom of the well is reached or the economic lifetime of the well concludes.

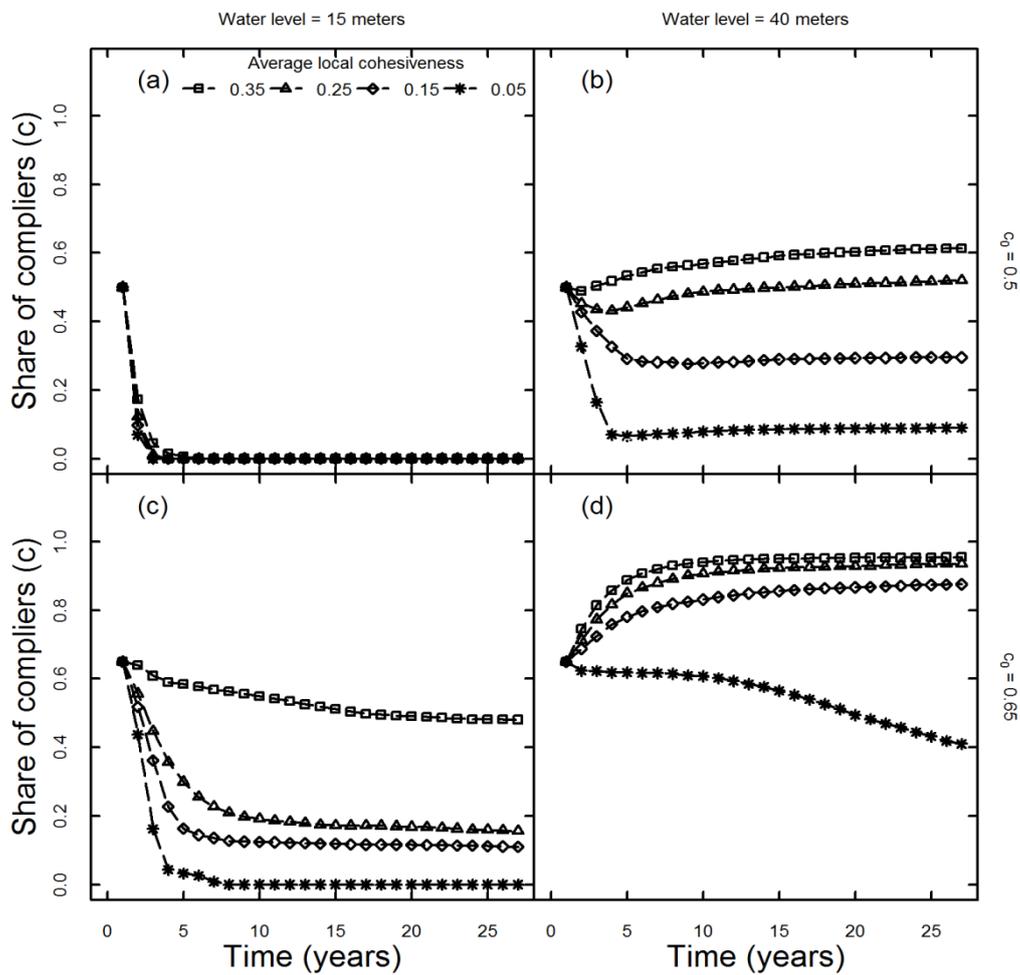
The estimated marginal benefits and the calculated extraction cost (Appendix C) explain why both types of agents extract down to the full depth of the well. Once the bottom of the well has been reached, the current social norm cannot be maintained since natural recharge is not sufficient to satisfy the demand of the agents, even if they were all compliers.¹⁵ Thus, the members of the social network need to agree on a shift in the regime and stipulate a new social norm that allows supply and demand to be met once the aquifer has been depleted. Alternatively, the members could have defined a more stringent social norm right from the beginning that would have guaranteed a sustainable level of extraction at an earlier point in time, i.e. when the level of water table was higher than the depth of the well. For our analysis, however, these considerations are not of real importance since we are studying social punishment and the factors that influence an agent's decision to comply or not with the social norm. The factors we consider are related to the structure and state of the social network, and to an agent's strategy, but not to the formulation of the underlying social norm. In this respect, the results of our study are also valid if the social norm were redefined.

7.1 Cooperation vs. non-cooperation

¹⁵ The water table constantly decreases over the entire planning horizon, even if all agents were compliers. This implies that the natural recharge is always less than the agents' demand. In other words Equation (8) in general terms or Equation (18) from Appendix C cannot be met for the case of the aquifer.

Given the specification of the social-biophysical system (Equations (1) - (5)), Figures 2a - 2d show the evolution of the share of compliers c and defectors over time for different initial values of the share of compliers \hat{c} , the initial depth of the water table $s(0)$, and different degree of the average local cohesiveness of the entire social network τ (macro perspective).

Figures 2a – 2d: Evolution of the share of compliers in the neighborhood of agent i for different degrees of average local cohesiveness with $\tau = 0.05, 0.15, 0.25$ and 0.35 . Figure 2a: $\hat{c} = 0.5, s(0) = 15$, Figure 2b: $\hat{c} = 0.5, s(0) = 40$, Figure 2c: $\hat{c} = 0.65, s(0) = 15$ and Figure 2d: $\hat{c} = 0.65, s(0) = 40$.



With an initial value $c = 0.5$ for the share of compliers, Figure 2a shows that even higher values of average local cohesiveness cannot delay the decrease in the share of compliers in the network if the initial water depth is 15 m. The relatively small scarcity

of groundwater leads to ineffective social punishment of defectors and so compliers abandon their current strategy and become defectors within 5 years. If the initial water table is only 40 m, higher values of average local cohesiveness allow the values of compliers in the network to be maintained ($\tau = 0.25$) or increased ($\tau = 0.35$) (see Figure 2b). In other words, provided that groundwater is sufficiently scarce, average local cohesiveness (network effect) allows for sufficient social pressure to build up so that compliers maintain their current strategy. If the initial value of the share of compliers is 0.65 (Figure 2c), most compliers are likely to abandon their current strategy (as in Figure 2a), however, to a lesser degree. Only when the average local cohesiveness is 0.35, are some compliers likely to change from compliance to non-compliance. A reversed result is obtained in Figure 2d, where scarcity of groundwater and values of local cohesiveness above 0.05 lead to sufficiently high social pressure that the number of compliers increases over time. Only very weak average local cohesiveness, $\tau = 0.05$, is not sufficient to accumulate the social pressure required to maintain and expand the initial number of compliers. Figure 2d also reveals that even though the share of compliers increases, it does not reach one. There is always a certain (albeit small) number of defectors that receive no or very little social pressure. In the case where the defectors' neighborhood consists mainly or exclusively of other defectors, social pressure is very weak or does not even exist. In other words, defectors can survive if they live in a fairly isolated community where compliers are absent. Figures D1a - D1d in Appendix D (Evolution of Social Pressure) illustrate this phenomenon. This observation is analogous to a finding in the non-cooperative game literature where (Bramoullé 2007) observed that agents have an incentive to anti-coordinate if they are embedded in a bipartite network. Although these findings are obtained in very distinct frameworks, the underlying force in both cases is the social network heterogeneity that leads to segregation. Figures 2a – 2d show that, overall, sufficiently strong network effects and the state of the resource can modify or even reverse the effect of the share of compliers. The results can be summarized in the following observation:

Observation 5: (Critical mass of compliers and limited substitutability between the share of compliers and local cohesiveness on the macro level)

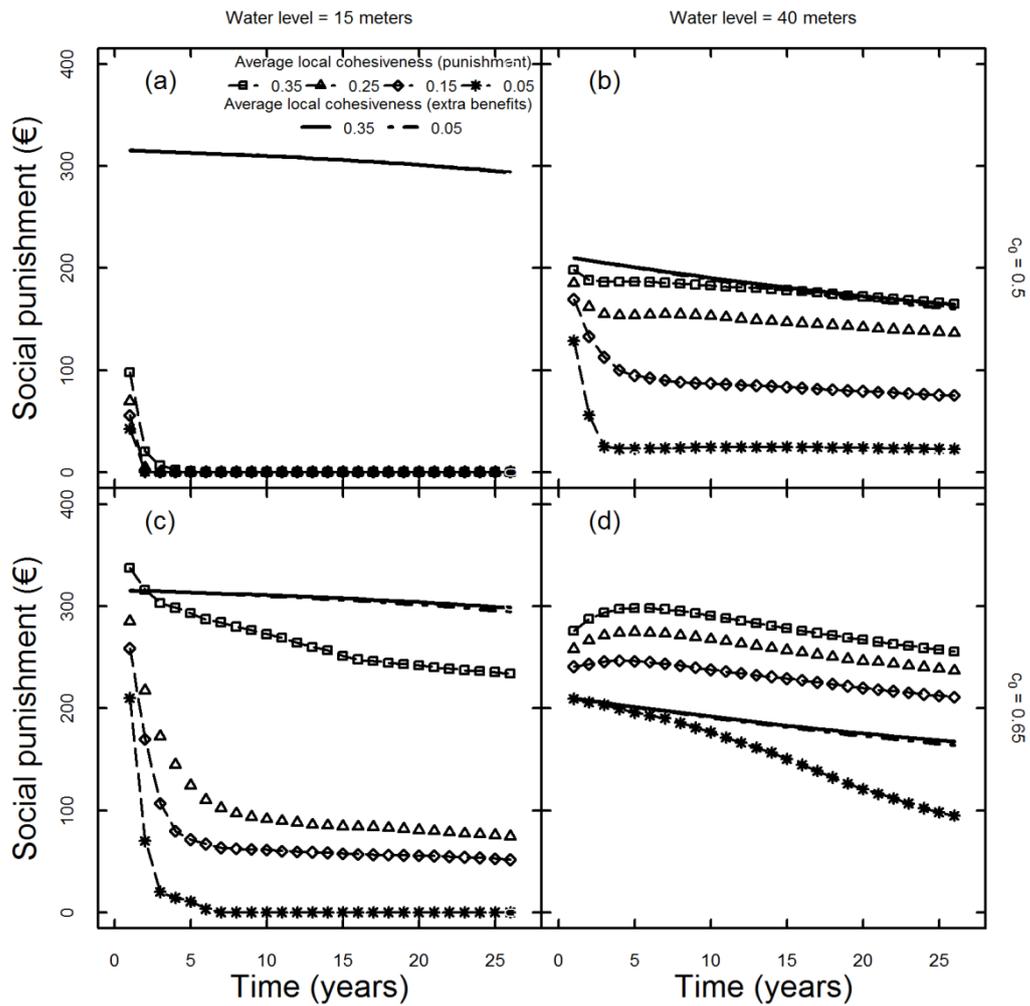
Figures 2a -2d show that the resource can only be managed in a sustainable way if the initial number of compliers in the network exceeds a “critical mass”. The value of this

“critical mass” depends on the strength of the average local cohesiveness of the network and the depth of the water table. The share of compliers, network effects and the state of the resource are substitutes within certain limits. Thus, for a given share of compliers, average local cohesiveness and the state of the resource can be decisive for the agents’ strategy choice. An all-complier equilibrium does not emerge if an isolated group of defectors, who are hardly exposed to any social pressure, evolves.

A fundamental element for establishing cooperation is putting social pressure on defectors. Figure 3a – 3d show the evolution of social punishment $\omega(\cdot)(\pi^D - \pi^C)$ for different initial values of the share of compliers \hat{c} , the initial depth of the water table $s(0)$, and the different degrees of average local cohesiveness of the social network τ_c . Likewise, they show the evolution of the defector’s extra benefits $(\pi^D - \pi^C)$ for an average local cohesiveness of 0.35 and 0.05.¹⁶ As long as the defector’s extra benefits are greater than social punishment, the agent will likely maintain their strategy. Once this relationship is reversed, however, the agent will likely become a complier. Thus, the evolution of the difference between the defector’s extra benefits and social punishment explains the evolution of the share of compliers observed in Figures 21 – 2d.

Figures 3a – 3d: Evolution of social punishment for differing degrees of local cohesiveness with $\tau = 0.05, 0.15, 0.25$ and 0.35 . Figure 3a: $\hat{c} = 0.5, s(0) = 15$, Figure 3b: $\hat{c} = 0.5, s(0) = 40$, Figure 3c: $\hat{c} = 0.65, s(0) = 15$ and Figure 3d: $\hat{c} = 0.65, s(0) = 40$.

¹⁶ Average local cohesiveness does not affect $\pi^D - \pi^C$ directly but it does indirectly through its effect on the evolution of the depth of the water table which, in turn, affects net benefits.



Moreover, Figures 3a - 3d provide information about the tangible monetary value of social pressure on the scale of the network - as mentioned in **Observation 4**. Figure 3a, for instance, shows that an increase in local cohesiveness has virtually no monetary value since the four lines are nearly identical three years later. Comparing the level of social punishment between Figures 3a and 3b, the same degree of average local cohesiveness offers information about the monetary value of a decrease (15 m down to 40 m) in the water table. It shows, for example, that in Year 10, and given an average local cohesiveness of 0.05, the decrease in the water table elicits a social punishment equivalent to €24.54. Similarly, an increase in average local cohesiveness by 0.1 in Year 10 intensifies this social punishment to €87.05. Thus, the comparison between Figures 3a and 3b and between 3c and 3d allows for the monetary value of social punishment attributable to the change in the water table to be determined. Likewise, the distance

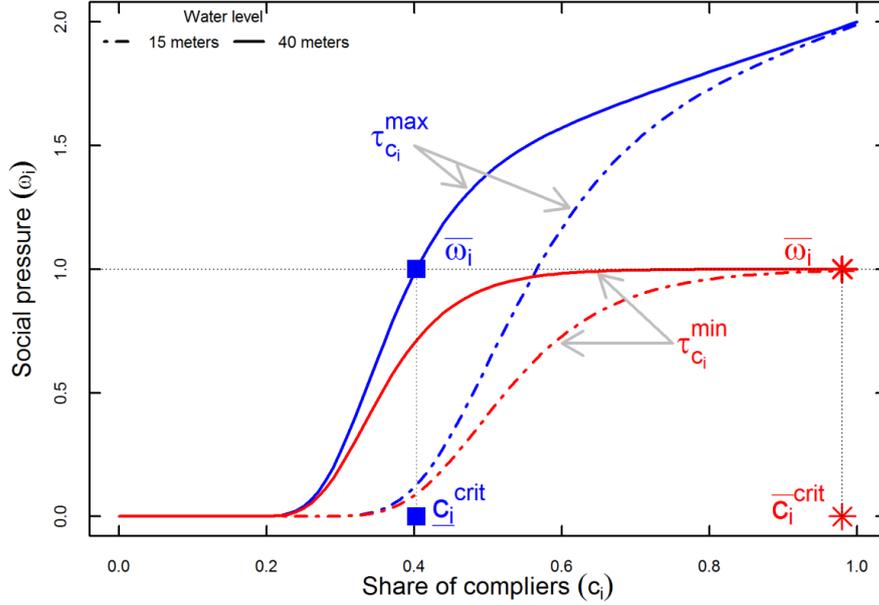
between the different trajectories of the social punishment in each of the four figures allows for the monetary value of the social punishment attributable to a change in the degree of average local cohesiveness to be established.

7.2 The share of compliers as a catalyst for sustainable management

Figures 2a – 3d have highlighted the importance of the depth of the water table, local cohesiveness and the share of compliers for a sustainable and socially efficient management of the resource. For the choice of the values of local cohesiveness, however, one has to take into account that the share of compliers conditions the maximal magnitude of local cohesiveness of compliers. By definition, the fewer compliers in the neighborhood there are, the lower the maximum value of local cohesiveness of compliers τ_c^{\max} is, since the set of compliers in the neighborhood is a subset of the set of neighbors – see Appendix B (Methodological and Technical Aspects of the Implementation of the Social Network) for more details. For this reason, there is a functional relationship between the share of compliers in the neighborhood and the maximum local cohesiveness of compliers that can be achieved. It can be approximated by $c_i^2 \approx \tau_c^{\max}$.

Figures 2a – 3d show, in particular, that initial values of the share of compliers, the state of the resource and local cohesiveness are driving factors behind the agents' decision to adhere to the social norm. This echoes the idea that these factors shape the individual's incentives to become a complier. One of the critical factors for the evolution of the resource is the share of compliers. For the values considered for the state of the resource and local cohesiveness, Figures 2a - 3d seem to suggest that the critical mass of the share of compliers is situated somehow between 0.5 and 0.65. These critical mass values can also be read in the more general form of the social pressure function (as defined in Equation (20) in Appendix C - Numerical Analysis and Specification of the Functions Employed). For the sake of brevity, we have employed only a graphical presentation of the social pressure function in the main text and have left the mathematical details for Appendix C.

Figure 4: Social pressure as a function of the share of compliers c_i given water table depths of 15 m (dashed line) and 40 m (continuous line) given the minimal ($\tau_{c_i}^{\min} = 0$) and maximal local cohesiveness, ($\tau_{c_i}^{\max}$).



If social pressure is equal to 1 ($\bar{\omega}_i$), we see that agents have no incentive to change their strategy, whereas if the social pressure is below 1, the defector's utility is positive and consequently compliers are likely to change their strategy to non-compliance. If the social pressure is above 1, defectors are likely to change their strategy to compliance. The more the social pressure differs from 1, the more likely the agent is to switch from their current strategy to the alternative one. Thus, a social pressure of 1 allows the critical mass c_i^{crit} of the share of compliers to be determined. The minimal required share of compliers leading to a positive evolution is given by the intersection of the social pressure function, evaluated at the highest value of the stock ($s = 40$ in Figure 4), and the maximum value of local cohesiveness ($\tau_{c_i}^{\max}$), where the straight line depicts the social pressure of 1. The minimal share of compliers required is denoted in Figure 4 by point \underline{c}_i^{crit} . Likewise, the maximal share of required compliers that guarantees positive evolution, is given by the intersection of the social pressure function, evaluated at the lowest value of the stock ($s = 15$ in Figure 4) and the lowest value of local cohesiveness,

where the straight line indicates the social pressure of 1. The maximal required share of compliers is indicated by the point \bar{c}_i^{crit} in Figure 4. Hence, we can conclude that the evolution of the share of compliers is always negative if the initial number of compliers is smaller or equal to \underline{c}_i^{crit} , and will always be positive if the initial number of compliers is larger than \bar{c}_i^{crit} . The two values, \underline{c}_i^{crit} and \bar{c}_i^{crit} , are the limiting values of the critical mass, i.e. $c_i^{crit} \in [\underline{c}_i^{crit}, \bar{c}_i^{crit}]$. Thus, if we initially consider the least favorable conditions for social pressure (resource is in a good state and no local cohesiveness) the critical mass for a positive evolution of the number of compliers is equal to \bar{c}_i^{crit} . However, as the resource deteriorates and/or local cohesiveness increases, the critical mass c_i^{crit} decreases and moves to the left in Figure 4 and will be equal to \underline{c}_i^{crit} once the most favorable conditions for social pressure are reached. If the initial depth of the water table were known and immutable ($s = 40$ or $s = 15$) the interval $[\underline{c}_i^{crit}, \bar{c}_i^{crit}]$ would be given by the vertical distance between the two continuous or two dashed lines evaluated at $\omega = 1$. This reflects the influence the strength of local cohesiveness (network effect) has on the evolution of the critical mass of compliers. Likewise, the vertical distance between the continuous and dashed line, given the local cohesiveness $\tau_{c_i} = 0$ or $\tau_{c_i}^{max}$, indicates the influence the depth of the water table exerts on the interval $[\underline{c}_i^{crit}, \bar{c}_i^{crit}]$. The possible (wide) range of $[\underline{c}_i^{crit}, \bar{c}_i^{crit}]$ also indicates that the share of compliers alone is an inaccurate indicator for cooperativeness and needs to be accompanied by other characteristics of the social network, for instance local cohesiveness, to be correctly interpreted.

The results have so far been framed in terms of the neighborhood of agent i . As far as the neighborhood of agent i is representative of the network, the results can be generalized. For the case where this condition does not hold, the results cannot be carried over directly. In this case, the specific values of the points \underline{c}_i^{crit} and \bar{c}_i^{crit} are likely to be different, but the elements and principal conclusions of the analysis will not be affected.

Figure 4 shows that a critical mass of compliers is necessary for the sustainable and efficient management of the resource, however, this is not actually sufficient to ensure this is so. The population dynamics themselves are important but need to be accompanied by the dynamics of the network and the state of the resource. Figure 4 highlights these dependencies. In the absence of local cohesiveness and scarcity of the resource, even an extremely high share of compliers is not sufficient to prevent the degradation of the resource and the proliferation of defectors over time. These results are summarized in the following observation:

Observation 6: (Critical mass of compliers, state of the resource and network effects)

Figure 4 shows that a sufficiently high share of compliers is necessary, but is not sufficient for the sustainable management of the resource. The necessary share of compliers depends on the state of the resource and the strength of local cohesiveness.

7.3 Social pressure and the density and size of the network

The influence of local cohesiveness and the state of the resource on the critical mass of compliers c_i^{crit} is presented more explicitly in Figure 5a, where the value of the critical mass is high if the strength of local cohesiveness is low. The critical values decrease as the network effect increases or as the depth of the water table declines. The values indicated for the critical mass in Figure 4, $c_i^{crit} \in [\underline{c}_i^{crit}, \bar{c}_i^{crit}]$, are shown as well in Figure 5a to facilitate the interpretation of the graph. The graphs are bounded to the right because local cohesiveness is limited by the number of compliers; more precisely by $\tau_{c_i}^{max} \approx c_i^2$. Figure 5a is linked to Figure 5b through the strength of local cohesiveness τ_{c_i} . Moreover, Figure 5b shows the number of links between the neighbors (compliers and defectors) of agent i , denoted by τ_i . An increase in the number of links (increase in density) between the neighbors can be allocated randomly or directionally. In the latter case, new links are only formed between the neighbors who are compliers. Directional formation of new links leads to a one-to-one increase in local cohesiveness. Hence, the slope of this directional line is 1, along which it holds that $\tau_i = \tau_{c_i}$. The term τ_{c_i} increases until $\tau_{c_i}^{max}$ is reached. From there on, additional links between neighbors do not strengthen local cohesiveness any further because the value of local cohesiveness is

limited by $\tau_{c_i}^{\max}$. For the graph in Figure 5b, we considered a share of compliers of 0.6 (0.4) so that $\tau_{c_i}^{\max}$ is approximately given by 0.36 (0.16). A random allocation of new links between the neighbors of agent i also leads to an increase in local cohesiveness, but requires far more new links for the same increase in local cohesiveness. Only if nearly all the neighbors are randomly connected, is the value of $\tau_{c_i}^{\max}$ reached. Thus, any value located in the blue area is characterized by links between defectors and between compliers and defectors that are inefficient with respect to local cohesiveness. The degree of efficiency η of the combinations of density and local cohesiveness can be read off Figure 5b directly. The vertical difference between the value in the blue area and the directional line denotes the degree of efficiency. For $0 < \tau_{c_i} \leq \tau_i \leq c_i^2$, the degree of efficiency η is given by $\eta = \tau_{c_i} / \tau_i$ with $0 < \eta \leq 1$. Any value in the red area indicates that links are redundant. For $\tau_i > c_i^2$, the degree of redundancy rd can be measured by $rd = \tau_i - c_i^2$ with $0 \leq rd \leq 1 - c_i^2$. The share of compliers of 0.6 (0.4) is used as an example. For different values of the share of compliers, $\tau_{c_i}^{\max}$ would change, but the pattern of the two graphs would remain the same. As such, the results are independent of the value considered for the share of compliers.

The fact that links are redundant sheds new light on the findings in the previous literature (Coleman 1988, Karlan et al. 2009), where an increase in τ_i (denser networks) favors the compliance to a social norm. Figure 5b shows that an increase in links only favors compliance to the social norm up to the point where τ_i is equal to the value of the maximal local cohesiveness, $\tau_{c_i}^{\max}$. Beyond this point an increase in density does not contribute to higher social pressure.

Many authors have highlighted the importance the share of compliers (Sethi and Somanathan 1996, Osés-Eraso and Viladrich-Grau 2007, Tavoni et al. 2012) has for the socially efficient management of the resource. However, the share of compliers is independent of the size of the community, which questions the widespread hypothesis (Ostrom et al. 1999) that a small community exercises more social pressure than a large community does. Figure 5b offers an explanation for this apparent contradiction. For

this purpose, we compare a small and large community where the share of compliers is identical.

In a small community, it is often the case that agents know each other well and so the density or local cohesiveness of all neighbors τ_i is high. For example, consider a complete network where by definition $\tau = \tau_i = 1$. This equation holds simply because all agents are connected with each other so that all the agents have the same neighborhood. Thus, given a share of compliers, for example 0.6, a small community presented by a complete network is always located in Figure 5b at the point $(\tau_{c_i}^{\max}, 1)$.

In more general terms, with respect to the network structure, recent research (Barabási and Albert 1999, Clauset et al. 2009) has shown that agents can only maintain a limited number of links ($k \ll n$), which results in a sparse (low density), scale-free social network as the number of agents n of the network increases. As the network grows, the total number of links increases as a linear function of the number of agents and given by

$|L| = \sum_{i=1}^n k_i$. However, the possible number of links increases with the square of the network size given by $L^{\max} = \frac{n(n-1)}{2}$. Thus, the network density, $d = \frac{2|L|}{n(n-1)} < 1$,

decreases with the network size.¹⁷ As the density of the network is reduced, the probability of transitive relationships between agents is severely constrained. Moreover, for scale-free networks Dorogovtsev et al. (2002) and Szabó et al. (2003) found that the local cohesiveness of all neighbors decreases with the degree of agents by approximately $\tau_i \approx k_i^{-1}$, which means that high-degree agents tend to have a low cohesiveness coefficient. These findings suggest that the probability of having $\tau_i \geq \tau_{c_i}^{\max}$ decreases rapidly with the network size and degree of the agents. Figure 5b shows that large networks, characterized by the fact that the density of higher-degree agents is

¹⁷ Although the following example is not based on a scale-free network it illustrates the relationship between density and degree. Assume that every agent knows exactly 100 other agents. Thus, if the network consists of 100 agents we have a complete network with degree 100. However, if the network would consist of 1000 agents the agents only knows 10% of all agents and the density of the network would decrease while the degree remains 100.

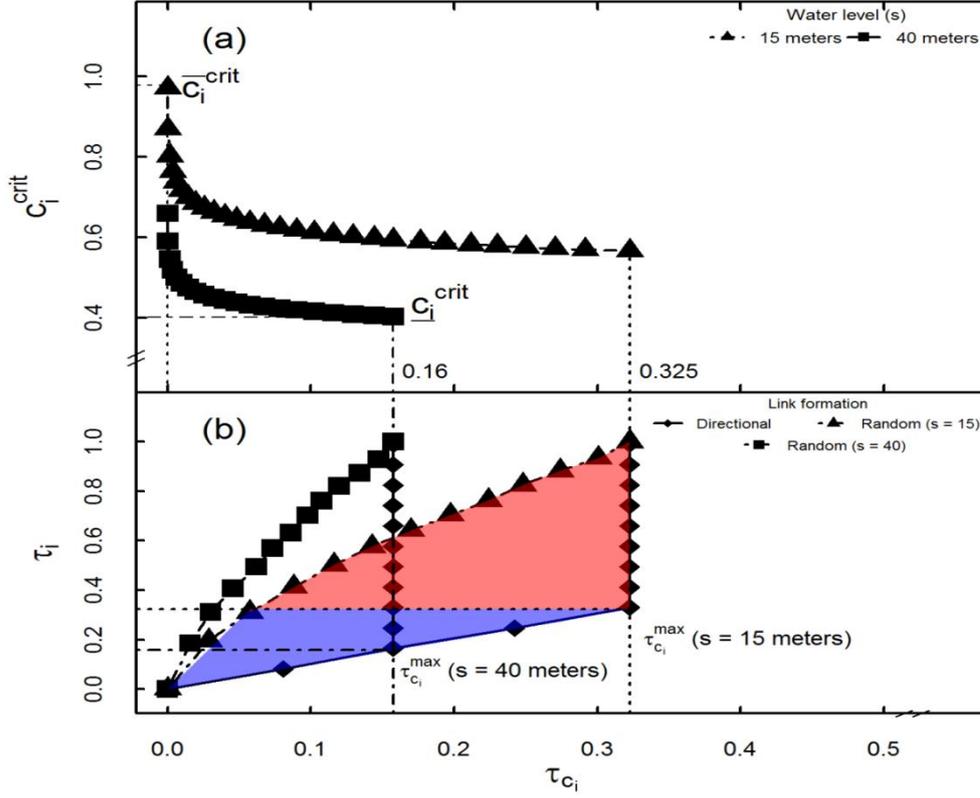
significantly lower than $\tau_{c_i}^{max}$, cannot build up sufficient local cohesiveness between compliers to attain the value of $\tau_{c_i}^{max}$. In a particular neighborhood, $\tau_{c_i}^{max}$ may be achieved, especially for agents with small degrees, but not the maximal average local cohesiveness on the scale of the network.

Observation 8: (Social pressure in relation to the size and degree of the network)

Given a network same size, denser networks favor compliance to the social norm, but only up to the point where the maximal strength of local cohesiveness is reached. Beyond this point higher density is redundant. The density of a network is an imprecise indicator for cooperativeness because it considers not only links that help to tighten local cohesiveness but also redundant links. Given the same share of compliers and same degree, smaller networks with high densities facilitate attaining the maximal local cohesiveness, whereas larger networks with low densities and scale-free structure cannot reach the maximal local cohesiveness.

Observation 8 provides a conceptual interpretation of the oft-cited finding that closely knit networks favor social norm compliance more than loosely knit networks do. Yet, this finding has to be considered with caution since it is the type of knit, more than the tightness of the knit, that is important. Likewise, this explains why, given a degree, smaller networks comply to the social norm more than larger networks do. Thus, while the share of compliers is important, so too is the size and density of the network as these two factors exercise a very significant influence on the strength of social pressure.

Figures 5a -5b: Figure 5a: The critical share of compliers as a function of local cohesiveness (level curves) with $\tau_{c_i}^{max} = 0.6$ and $\tau_{c_i}^{max} = 0.4$. Figure 5b: The relationship between density and local cohesiveness with $\tau_{c_i}^{max} = 0.6$ and $\tau_{c_i}^{max} = 0.4$



7.4 Social punishment and the social network characteristics on the micro level

Our previous analysis focused on the overall structure of the network (i.e. a macro perspective). For the remainder of the analysis, we concentrate on the structure of agent i 's neighborhood (i.e. a micro perspective). Figures 3a – 3d allowed the monetary value as a function of time, the average local cohesiveness of compliers and of the depth of the water table at the macro level to be determined. Figure 6 provides information about the economic value of the share of compliers and local cohesiveness in the neighborhood of agent i (i.e. at the micro level). As explained above, to interpret Figure 5 one should keep in mind that the value of the share of compliers introduces an upper limit of local cohesiveness of compliers. For this reason, the part of the c_i, τ_{c_i} plane that is not admissible has been left blank.

Based on Equation (12), we determine the one-time payment v_i as the difference between the defector's and complier's utility. Thus, if the community were to offer this one-time payment to a defector, they would abandon their current strategy and would become a complier. This one-time payment is determined by the solution of the following equation:

$$v_i = U_i^D - U^C = \pi^D - \omega_i(s, c_i, \tau_{c_i})(\pi^D - \pi^C) - \pi^C = (1 - \bar{\omega}_i)(\pi^D - \pi^C) \quad (16)$$

with respect to the three unknown s, c_i, τ_{c_i} . The three-dimensional plane in Figure 6 shows the level curves of social punishment for different values of the share of compliers, of the local cohesiveness of the compliers at time 0 and given a water table depth of 15 m. The defector's extra benefits, $\pi^D - \pi^C$, amount to €316.36 and are presented by the line in bold. These extra benefits are marked by a straight line because, for a given moment in time, they depend only on s , and not on c_i or τ_{c_i} . If social punishment is below the line in bold ($\omega_i < 1$), the defector's extra benefit $\pi^D - \pi^C$, is greater than social punishment. In this case, a one-time payment of $(1 - \omega_i)(\pi^D - \pi^C)$ is needed to offer the agent an incentive to abandon their current strategy and to adhere to the complier's strategy. The difference between the defector's extra benefits $\pi^D - \pi^C$ and the three-dimensional plane for the monetary value of social punishment determines the amount required for the one-time payment.

Figure 6 also shows the level-curves of social punishment. The distance between the level curves indicates an €80 decrease or increase in social punishment. To keep Figure 5 simple, we have only marked the level curve whose value is equal to the defectors' extra benefits of €316. The form of the level curves indicates that the substitution elasticity between the share of compliers and the local cohesiveness of compliers is relatively close to 0. Only within a small range of the values of the share of compliers and of local cohesiveness of compliers can both arguments for social punishment substitute each other. The level curves are not evenly spaced, indicating that the greater the distance between the level curves, the lower the effect an increase in the share of compliers or local cohesiveness of compliers has on the social punishment. We also solved Equation (16) for $s = 40m$. Since the qualitative interpretation of the graph is very similar to the one presented in Figure 6 we have not presented it here.

Figures 6: Social punishment as a function of the share of compliers c_i and local cohesiveness of compliers τ_{c_i} with $s(0) = 15$.

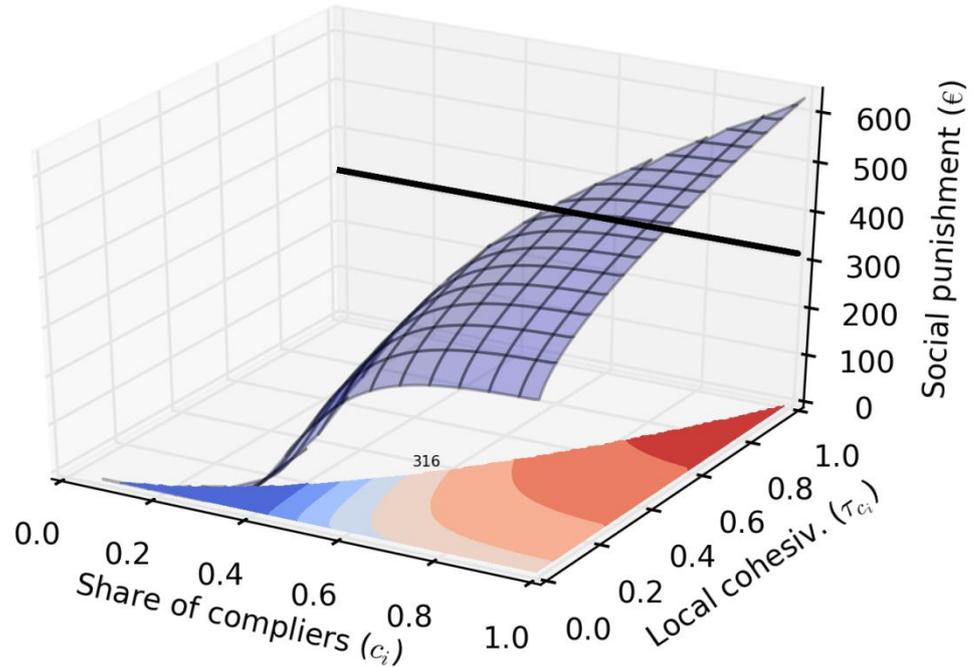


Figure 6 is the result of a snapshot at time 0 and, as such, it does not provide any information about the evolution of the social punishment over time. Figures 2a – 3d show the evolution of compliers and of social punishment over time. Thus, the only missing information to determine the social punishment over time is the evolution of the defector’s extra benefits. This information is presented in Figures D2a – D2d in Appendix D (Evolution of Social Pressure). The results of this discussion can be summarized by the following observation:

7. Conclusions

This study defines a social norm based on the socially-optimal management of a renewable natural resource owned by a community. In contrast, the non-compliance of the social norm is linked to short-sighted behavior where agents maximize the net benefits of the current time period. Based on these two extraction strategies, we define compliers (in compliance with the social norm) and defectors (non-compliance with the social norm). Agents can revise their strategy within an evolutionary game-theoretic approach, i.e. the probability of changing from their current strategy to the alternative one increases the higher the perspective gains become. Although agents are free to choose their preferred strategy, we consider the case where compliers exercise a social

punishment that reduces the defector's utility. Social punishment depends on the remaining level of the natural resource, the number of compliers and their local cohesiveness in the neighborhood of agent i . This formulation aims to answer the question as to what extent network effects (share of compliers, local cohesiveness, size and density) and stock effects (resource) provide incentives for individual agents to comply with a social norm, to what extent compliance with a social norm is a self-enforcing process and what exactly are the social and physical conditions required to either initiate this process or choke it off.

If all equilibrium conditions hold, an overall equilibrium (with respect to the dynamics of the resource, the network and the resource demand) may emerge. However, given the asymmetry and complexity of the network, no analytical solution can be provided. In contrast with the previous literature, the emergence of an all-complier-network equilibrium is extremely unlikely since isolated communities of defectors immune to social punishment may emerge. Nevertheless, the study provides a measurement of the distance required for the current state of the network to reach network equilibrium.

Given the limitation of an analytical solution, the study analyzes the case of the western La Mancha aquifer in Spain. There, the social network consists of approximately 7500 farmers. Given the economic conditions and the limited maximal depth of the aquifer, an economic equilibrium does not exist. The results show that, while a sufficiently high share of compliers is required for the efficient management of the resource this is not sufficient in itself. The magnitude of the critical mass of compliers depends on the dynamics of the resource, the density, the size and local cohesiveness of network. The critical mass of the initial share of compliers ranges between 0.4 and 0.96, where the lower bound corresponds to the most favorable conditions and the upper bound to the least favorable conditions. The wide range of the critical mass highlights the fact that the share of compliers alone is not a precise indicator for evaluating cooperativeness. Additional information about the characteristics of the social network and the state of the resource is indispensable. A similar result is obtained for the density of the social network. A higher density is likely to favor cooperativeness but on its own it is an imprecise indicator for cooperativeness since it does not distinguish between links that tighten the local cohesiveness or those that are redundant. The results also show that, given the same share of compliers and average degree, smaller networks better support cooperativeness than larger networks do.

Moreover, the analysis allows for practices favoring the sustainable management of natural resources to be identified and targeted. An example of such a practice would be the one-time payment to defectors based on the condition that they adopt the complier's strategy. As a result of the increase in social pressure, one would expect defectors not to revert to their former behavior. The critical mass of the initial share of compliers indicates how many compliers are needed to implement such a policy. Finally, the study provides a monetary valuation of the intangible good – social pressure – in the case of the western La Mancha aquifer.

There seem to be two promising directions in which the analysis of the paper could be extended. First, the current work can be considered as a building block to developing a metric for the cooperativeness of a social network. This implies analyzing and extending the relationships between the metrics employed for the different characteristics of the network. The second line of research is related to changes in the underlying economic forces. The assumption that social pressure is costless for the compliers or the defector's extra benefits are independent of the state of the social network could be revised. A change in the later assumption, for instance, may lead to an anti-coordination behavior if the defectors' extra benefits were to increase as the number of compliers increases.

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Appendix A

The Structure of the Social Networks

The three important building blocks of a social network are labeled as i) scale free, ii) correlation by biological and socioeconomic attributes and iii) small world.

i) Scale-free

An agent j linked to an agent i is called i 's neighbor. The degree $k_N(i) = k_i = \sum_j l_{ij}$ of an agent i is the number of links at i , i.e. the number of neighbors i has. Denote by $P(K = k) = p_k$ the degree distribution of N , that is the probability that an agent i in N chosen uniformly at random has exactly k neighbors. If the links of all the agents were formed assuming the same probability p , we would obtain a random network whose degree distribution approximately follows a Poisson distribution. However, empirical studies (Jeong et al. 2000, Liljeros et al. 2001) have shown that the degree distribution of large social networks does not follow a Poisson distribution and therefore recent research (Clauset et al. 2009), (Barabási and Albert 1999) has focused on scale-free topology. These networks are characterized by a degree distribution that follows the power-law $p_k = k^{-\gamma}$ with $2 < \gamma < 3$ (Nguyen and Tran 2012). Scale-free networks have more weight in the tails than random networks do and thus offer a better match with the social networks observed (Jackson 2010). Moreover, scale-free networks, in comparison to random networks, where there are few central agents of high degree, and many other agents of small degree, allow for some organizing principles to be considered (Rèka and Barabasi 2002). In a social system, central agents are likely to have more influence, more prestige and/or better access to information in terms of quantity and quality. However, other organizing principles are also possible when centrality is not based on the degree, but rather on the importance the link has for the social network. Depending on the question being analyzed, an adequate concept of centrality has to be employed. (Ballester et al. 2006, Bramoullé et al. 2014).

ii) Relationship between agents

Every agent i has individual attributes or characteristics so that many agents differ from each other and form a heterogeneous population. These attributes consist of biological

and socioeconomic factors like sex, gender, age, race, nationality, education, profession, social status, wealth, income, size of the neighborhood (degree) etc. The S attributes of each individual, denoted by Φ_i , can be expressed as a numerical value falling within the interval $(0, \infty]$. Empirical studies have shown that attributes are an important factor in forming links between individuals (Jackson 2004). For instance, a known tendency of agents is to connect to other agents with similar attributes. This tendency, colloquially expressed as “birds of feather”, is considered in the setup of a network (McPherson et al. 2001). More precisely, the closer the attributes Φ_i, Φ_j of the individuals i and j are, the greater the probability of these two agents being connected. Thus, similarity attachment (often referred to as homophily) is implemented by assuming that the probability of connecting individual i and j is proportional to the similarity of their attributes.

Alternatively, individuals might be attracted by certain elements of the attributes an agent has, for example language, wealth or social status. In the case where very few elements, or even a single element of the attributes, are decisive in forming connections between agents, the network is then constructed on the base of those preferential attachments. This is based on the attractiveness of an agent, which is measured by the strength of expression of the dominant attributes. In this case, the probability that agent i is connected to agent j is proportional to the “attractiveness” of agent j , i.e. the magnitude of the dominant attributes in comparison with other agents (Barabási and Albert 1999, Kadushin 2012).¹⁸

Since the measurement of preferential or similarity attachments is based on correlation, its value lies between -1 and 1, where a value of -1 expresses strong preferential attachment, and a value of 1 strong similarity attachment.

The above-mentioned concept of centrality (Jackson 2010, Bramoullé et al. 2014) or the concept of modularity¹⁹ (Newman and Girvan 2004) are other topological properties of social networks that are also helpful when describing characteristics that influence a

¹⁸ In the case where the vector of attributes is formed exclusively by the degree k , the correlation between the agents’ degree is defined as assortativity with values between 0 and 1.

¹⁹ Modularity measures the degree of cohesiveness and the strength of the division of a network into modules (subgroups).

relationship between agents. However, while centrality focuses on the macro-level and modularity on the meso-level of a social network, our approach is on a micro level, i.e. agents take decisions based on the structure and state of their neighborhood. For this reason, centrality and modularity are not considered here.

iii) Small world

The small-world effect has been observed and studied in a large number of different real networks (Currarini et al. 2015) and can be characterized by two salient properties. Firstly, in most social networks agent i is directly connected to agent j , i.e. the path between them is short and does not normally require the intermediation of other agents. Secondly, social networks are highly clustered, i.e. agents form close-knit communities that are only loosely connected to other communities. This property, known as clustering or local cohesiveness, measures to what extent the neighborhood of agent i , $N(i)$, forms a complete network. Local clustering is denoted by the term τ_i with $0 \leq \tau_i \leq 1$. For instance, the extent to which agent i 's friends are friends with one another is one interpretation of cohesiveness. Thus, if $\tau_i = 1$, all neighbors of agent i are connected to each other. As mentioned in the main text we define the degree of local cohesiveness of all compliers in the neighborhood of agent i by τ_{c_i} with $0 \leq \tau_{c_i} \leq 1$. This measure to what extent compliers making up part of $N_c(i)$ are connected amongst each other. Alternatively, as mentioned the measurement of cohesiveness for nodes or agents can also be measured on a network level. On this scale, we define transitivity or average local cohesiveness, as the average value of local

cohesiveness, i.e. $\tau = \frac{1}{n} \sum_i^n \tau_i$.

Agents that belong to one community but also connect to another one, may act as a bridge between the two communities. If the different communities are only loosely connected the flow of information might be slow or the capacity to reach consensus might be limited. To this purpose, (Newman and Girvan 2004) defined modularity as a measure for detecting community structure in networks. A network with high modularity consists of several internally close-knit communities that are loosely connected to each other.

Our analysis of cooperative behavior is built on a social network that takes into account the topological properties presented above. The social network was set up in the programming language Python and evaluated with the network analysis `igraph` R package. Within this programming environment, we incorporated the strategy choice rules for the agents based on the evolutionary-game theoretic approach. Likewise, we incorporated resource demand functions so that the agents could evaluate the usefulness of the two available strategies. More details about the generation of the network, the programming tools and techniques, and the numerical solution procedure can be found in Appendix B - Methodological and Technical Aspects of the Implementation of the Social Network.

Appendix B

Methodological and Technical Aspects of the Implementation of the Social Network

As described in Section “The social network” the S attributes (characteristics, attractiveness, fitness) of each individual present socioeconomic and biological factors and are denoted by Φ_i . They can be expressed as a numerical value within $(0, \infty]$. We assume that these factors are independent of each other and contribute multiplicatively to the value of Φ_i . Under these conditions, Φ_i will be lognormally distributed, irrespective of the distribution of each single factor. The individual type can be written as $\Phi_i = \prod_{s=1}^S \phi_s, \forall i \in n$ and $\phi_s \in \mathbf{R}_{>0}$. Network generation is governed by the individual characteristics of the agents. Agents may prefer to establish links with other agents that are either very attractive (preferential attachment) or have similar characteristics (similar attachment).

The network is generated link by link and the formation of a new link is decided by a stochastic decision rule. We distinguish between a resident, i.e. an agent that forms part of the existing network, and a newcomer. The higher the characteristics (attractiveness) of a resident are, the greater the probability is of that being resident selected by the newcomer. In contrast to other methods, this network generation process has the advantage that it is endogenous, i.e. it depends on the underlying distribution of the agents’ characteristics. With this procedure, it is also unlikely that the initially selected

agents will accumulate more links compared to the agents selected later on. Thus, the positive correlation between the agent's degree and the time they have resided in the network is reduced. Finally, the attribute-based generation process is not based on a macro-level structure of the network like the degree is. As such, this does not hamper the design of the micro-level structure of the network and, in fact, provides sufficient freedom for variations of the structure on a micro-level; as sought by this study.

The network generation process based on preferential attachment is implemented using the following five steps:

1.

Let N_0 be the initial network, which can be any network, where the initial number of agents is very small and given by $|A_0| = n_0$.

2.

Define as $m \leq n_0$, the number of agents to whom a newcomer j may connect to when it joins the network, and let $k_j = 0$ be the initial degree of a newcomer j .

3.

At each step t of generation, $0 \leq t \leq n - n_0$, an agent i already present in the network is selected with a uniform probability $P_i = \frac{1}{n_0 + t}$ that is independent of agent i 's characteristics Φ_i . If the newcomer j is already linked to agent i , repeat Step 3.

4.

With probability $P_i = \frac{\Phi_i}{\Phi_{max}}$, the newcomer j connects to agent i , where

$\Phi_{max} = \max\{\Phi_i\}_{i=1}^{n_0+t}$ denotes the maximal value of the characteristics of all the agents in the network ($t < n$). Let us assign the value 1 to the decision to connect the newcomer to the existing network and 0 otherwise. For all randomly generated probabilities that are less than P_i , the newcomer should be connected and otherwise not. To transform this decision rule into an operation rule we define the Bernoulli random variable X that results from

$$X = \begin{cases} 1 & \text{if } u \leq P_i \\ 0 & \text{if } u > P_i \end{cases},$$

where u is a number randomly drawn from the uniform distribution $Uni(0 < P_i \leq 1)$.

In case of rejection ($X = 0$), Steps 3 and 4 are repeated. Likewise, Steps 3 and 4 are repeated in case of acceptance to establish as many links as defined by m until $k_j = m$

5.

Selection stops when $t = n - n_0$.

Let us assume that Φ_i is lognormally distributed within the network. It is denoted by

$$\rho(\Phi) = \text{Logn}(\mu, \sigma) \text{ and its density function is given by } f(x) = \frac{1}{\sqrt{2\pi}\sigma x} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}}.$$

We further assume that $\mu = 0$, and thus attribute distribution is characterized completely by the parameter σ . If σ is chosen such that it falls within the range of $1 < \sigma < 4$, then degree distribution follows a power-law distribution $P(k) \propto k^{-\gamma}$ where γ satisfies the inequality $2 < \gamma < 3$. If $\sigma = 0$, the network generation process leads to a random network. If $0 < \sigma < 1$, the degree sequences of the generated networks are close to the exponential distribution. If $\sigma > 4$ holds, the generated networks are monopolistic. These types of networks are also called ‘winner-takes-all’ networks. Within the admissible spectrum for power-law networks, i.e. $1 < \sigma < 4$, we specified the distribution function of the characteristics as $\text{Logn}(0, 1.5)$. Moreover, the choice of the parameter m allows the network density, d , and the average degree of network, $\langle k \rangle$ to be defined as both properties depend on m . More precisely, these properties are

$$\text{defined by } d = \frac{2(l_0 + m(n - n_0))}{n(n-1)} \text{ and } \langle k \rangle = \frac{2(l_0 + (n - n_0)m)}{n}, \text{ where } l_0 \text{ corresponds to}$$

the initial set of links at $t = 0$. If the initial network is complete, $l_0 = \frac{n_0(n_0 - 1)}{2}$ holds.

As we are assuming all agents add links at a constant rate m , $d = \frac{2m}{n-1}$ and $\langle k \rangle = 2m$

holds. Each newcomer starts in the network with the degree of k_j . However, as the network grows new links may be added so that the initial degree will be modified.²⁰

Although the generated networks are quite realistic, some important features of real-world networks are left out, for example, aspects of directed network topology, agents exiting the network and/or links being newly formed or cut. Despite these simplifications, the generating process allows us to create null networks that preserve the original density and degree distribution, while properties such as assortativity (correlation with respect to the agent's degree), local cohesiveness, modularity (strength of division into subgroups) and hierarchical clustering are maintained. For the economic analysis, null networks are important because they allow us to isolate the effects of specific meso- and micro-level topological characteristics on the agents' behavior.

Once the social network has been generated, directional rewiring (reorientation of existing links) is applied to modify the generated micro-level characteristics to the different levels required for the economic analysis. Directional rewiring is based on a probabilistic rule: the more similar the pair (Φ_i, Φ_j) , the greater the probability agents i and j have to being connected. The rule consists of two of the following three steps:

- 1.

²⁰ The network generation process based on LogNormal Fitness Attachment (LNFA) was originally suggested by Nguyen, K. and D. Tran (2012). Fitness-Based Generative Models for Power-Law Networks. Handbook of Optimization in Complex Networks. M. Thai and P. Pardalos. New York Springer: 39 - 55., and Ghadge, S., T. Killingback, B. Sundaram and D. Tran (2010). "A statistical construction of power-law networks." International Journal of Parallel, Emergent and Distributed Systems **25**(3): 223 - 235. Lipowski, A. and D. Lipowska (2012). "Roulette-wheel selection via stochastic acceptance." Physica A: Statistical Mechanics and its Applications **391**(6): 2193-2196., modified this approach by reformulating the fitness-proportionate selection method. It allows better computational performance to be obtained while maintaining the qualitative properties of the previous approach.

Two links in the network connecting four different agents are selected with uniform probability $\frac{1}{|L|=l}$ at each step of rewiring.

2.

The four agents associated to these two links are ordered according to their complete characteristics. The proposed rewiring process is a modification of the approach proposed by (Xulvi-Brunet and Sokolov 2005) since it is based on the agents' characteristics and not on the agents' degree. With probability P_q , the links are rewired in such a way that the new links connect the two agents who have the lowest characteristics and the two who have the highest. Figure A1 demonstrates the three possible configurations for $q=1,2,3$ for rewiring. Let us define the set of the three possible links by $C_q = \{(i_q, j_q) : i_q < j_q\}$. As the criteria for the choice of the new link, we define the characteristics of the new link as a heuristic distance between the characteristics of the new pair of agents. This is given by $\exp\left(-\sqrt{|\Phi_{i_q} - \Phi_{j_q}|}\right)\Big|_{(i_q, j_q) \in C_q}$

and the probability of establishing the new link is given by

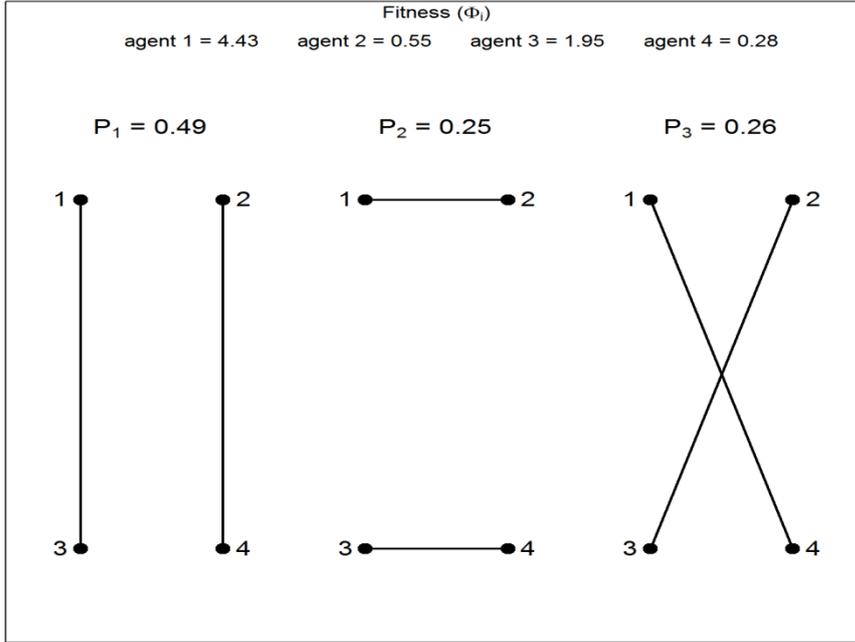
$$P_q = \frac{\sum_{i_q, j_q} \exp\left(-\sqrt{|\Phi_{i_q} - \Phi_{j_q}|}\right)\Big|_{(i_q, j_q) \in C_q}}{\sum_{i < j} \exp\left(-\sqrt{|\Phi_i - \Phi_j|}\right)}. \text{ Since the objective of rewiring is connecting}$$

agents with similar characteristics, the $\max\{P_1, P_2, P_3\}$ is chosen. This process results in connecting the two agents with the highest characteristics and the two the lowest characteristics. In the case that one or both new links already exist in the network, Step 2 is discarded and Step 1 is repeated. Based on the selection of $\max P_q$, the rewiring step is carried out.

3.

Rewiring stops if the desired micro-level structure local cohesiveness has been reached.

Figure B1. Rewiring of links that reduce preferential attachment and increase similar attachment.



To compute the assortativity of a network we use the Pearson correlation coefficient between the degrees of agents joined by a link (Newman 2010):

$$r = \frac{l^{-1} \sum_i j_i k_i - \left[l^{-1} \sum_i \frac{1}{2} (j_i + k_i) \right]^2}{l^{-1} \sum_i \frac{1}{2} (j_i^2 + k_i^2) - \left[l^{-1} \sum_i \frac{1}{2} (j_i + k_i) \right]^2},$$

where $|L|=l$ is the number of links in the network, and j_i and k_i denote the two agents' degree connected by the i^{th} link. The measure lies within the range of $-1 \leq r \leq 1$, where 1 indicates maximal assortativity. For random networks, since agents are placed at random it follows that $r=0$ when the generated networks are sufficiently large ($n \rightarrow \infty$).

The transitivity or average local cohesiveness (average local clustering) coefficient τ_i measures how close the neighborhood $N(i)$ of agent i is to a complete network. If agent i has k_i neighbors, there can be, at most, $\binom{k_i}{2} = \frac{k_i(k_i-1)}{2}$ links connecting agent i 's neighbors. If we define a transitive relation in the neighborhood of i as $\forall i \in A$,

$\forall u, v \in N(i) : (uRi \wedge iRu) \Rightarrow uRv$, where $N(i) = \{a_u : l_{iu} \in L \vee l_{ui} \in L\}$, the local clustering can be quantified as:

$$\tau_i = \frac{2|\{l_{uv} : a_u, a_v \in N(i), l_{uv} \in L\}|}{k_i(k_i - 1)}. \quad (17)$$

Transitivity lies within the range $\tau_i \in [0, 1]$. Likewise, the local cohesiveness of compliers coefficient τ_{c_i} measures how close the set of compliers in agent i 's neighborhood, $N_c(i)$, is to a complete network. Its definition is given by

$$\tau_{c_i} = \frac{2|\{l_{uv} : a_u, a_v \in N_c(i), l_{uv} \in L\}|}{k_i(k_i - 1)}.$$

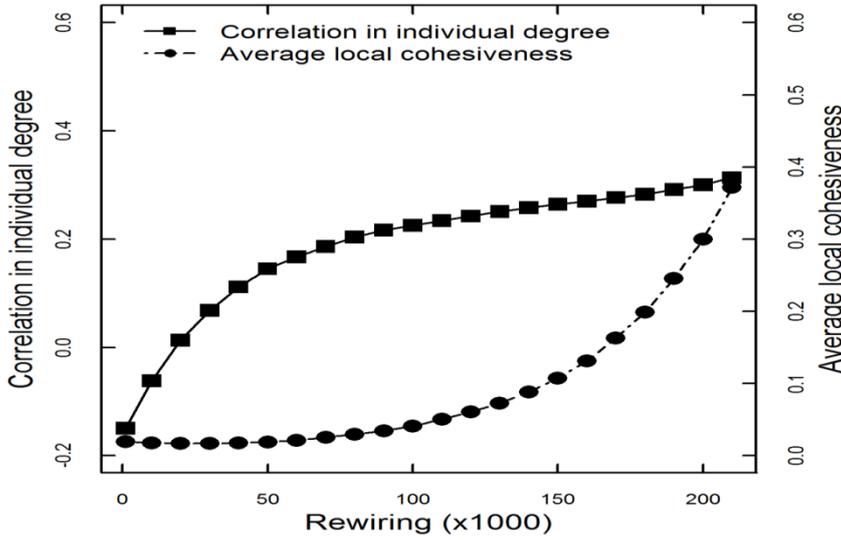
The upper value of local cohesiveness $\tau_{c_i}^{\max}$ can be approximated by

$$\tau_{c_i}^{\max} = \frac{c_i k_i (c_i k_i - 1)}{k_i (k_i - 1)} = \frac{c_i (c_i k_i - 1)}{(k_i - 1)} \approx \frac{c_i^2 k_i}{k_i} \approx c_i^2.$$

Since for its measurement only the share of compliers in the neighborhood is needed, the value of $\tau_{c_i}^{\max}$ is independent of the network structure, i.e. the agent's number of links, k_i , do not need to be considered. Thus, if there are only a few compliers, local cohesiveness of compliers cannot be large and if all neighbors are compliers, local cohesiveness of compliers can be one at the maximum. For a share of compliers of 0.25 (0.3, 0.5, 0.75), the upper bound of local cohesiveness of compliers is given by 0.0625 (0.09, 0.25, 0.562).

Figure B2 shows how average cohesiveness and the type of attachment (from preferential to similar) changes as more and more agents are disconnected and reconnected (rewiring) such that the new connection increases the average local cohesiveness. This allows us to identify the interrelation between the different topological properties of the network. Figure B2 illustrates that directional rewiring leads to a positive relation between correlation in individual degree and average local cohesiveness. However, it is important to observe that an increase in degrees is negatively related with local cohesiveness since the more links there are, the more difficult it is that the neighborhood formed by compliers constitutes a complete network.

Figure B2. Rewiring of links and subsequent effect on correlation in degree and average local cohesiveness.



So far, we have described generating the social network but not its initialization in terms of compliers and defectors. We randomly assigned the desired number of compliers and defectors within the network, simulated the evolution of the network and calculated the social pressure function after one year. Let us denote that this results in $\hat{\omega}$. However, depending on the initial distribution of compliers and defectors within the network, the value of $\hat{\omega}$ may vary greatly. To evaluate the magnitude of this bias, we used the Monte Carlo method and repeated the calculations for $\hat{\omega}$ n -times. The variance of the n -times repeated calculations, $\sigma_{\hat{\omega}}^n$, is employed to determine the magnitude of the bias. Following (Vose 2012), we determined the required number of repetition n that guarantees that $\sigma_{\hat{\omega}}^n$ is less than an acceptable error ϕ given a confidence interval $(1-\alpha)$.^{21,22} For a confidence interval of 95% and an acceptable error of 0.004, the required number of repetitions is 96.04. For this reason, we repeated all our calculations

²¹ It would have been possible to evaluate the social pressure function in later years. However, the effect of the initial assignment is diluted over the years, thus, limiting the error term of the first year depicts the stringent test.

²² The formula for the calculation of the necessary simple size is given by $n = \frac{(1.96 \sigma_{\hat{\omega}}^n)^2}{\phi^2}$.

presented in this study with 100 different initial assignments. The results presented throughout the article are the average values over those 100 repetitions.

One may think that the required number of repetitions is low. However, this can be explained by the large number of agents (7500) that diminish the effect of the initial assignment to the final value of $\hat{\omega}$.

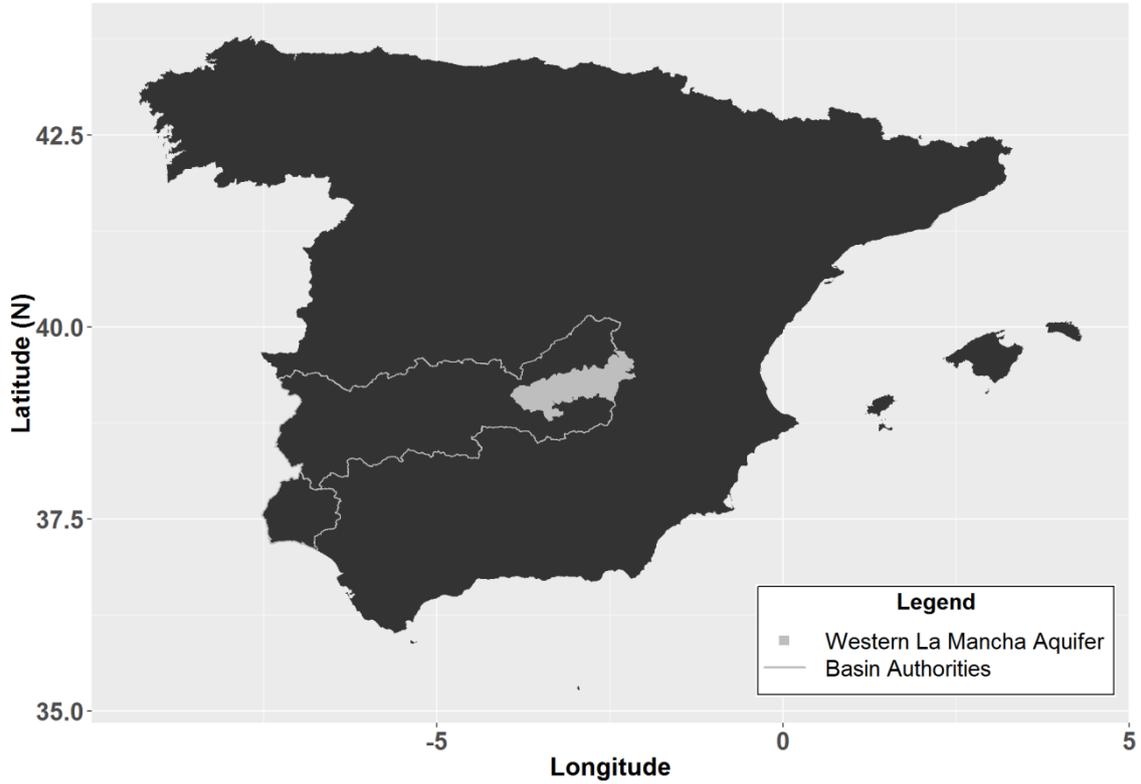
The differential equation $\dot{s} = g(s) - \sum_i^{cn} w_i^C - \sum_{cn+1}^n w_i^D$, was solved analytically for the case of pure strategies: all agents are compliers or all agents are defectors. However, for the case of mixed strategies, an analytical solution cannot be provided because the share of compliers c changes over time. Hence, the value of $s(t)$ was determined numerically by the Euler method at each moment of time.

Appendix C

Numerical Analysis and Specification of the Functions Employed

As an example of high policy relevance, we focus on the western La Mancha aquifer situated within the upper Guadiana basin (inland region of Castilla La Mancha, Spain) and extending over 5000km² (see Figure C1). The constant overdraft of this aquifer has led to a variety of policy measures designed to curb its deterioration and comply with the European Union Water Framework Directive (European Commission 2000, Blanco-Gutiérrez et al. 2011).

Figure C1: Geographical location of the western La Mancha aquifer



Hydrological model

We start out with the specification of the dynamics of the aquifer,

$\dot{s}(\xi) = g(s(\xi)) - \sum_i^{cn} w_i^C(\xi) - \sum_{cn+1}^n w_i^D$, $s(\xi) = s_t$. In the case of an aquifer, natural

replenishment is independent of the stock and thus the term $g(s(\xi))$ is equal to R which denotes natural replenishment. The stock $s(t)$ indicates the depth of the water table in meters, and $w_i^C(t)$ and $w_i^D(t)$ indicate the water extracted in m^3/ha . Since the extraction is measured in m^3 and the depth of the water table in m, we introduce the conversion factor φ that expresses the change in the depth of the water table as a result of the water extraction. Moreover, a part of the water extracted for irrigation percolates back into the aquifer. Following Esteban and Albiac (2010, 2011), we set this return rate, denoted by ψ , equal to 20%. Thus, the dynamics of the natural resource are now given by

$$\dot{s}(t) = \varphi \left(R - \psi \left(\sum_i^c w_i^C(t) + \sum_{c+1}^n w_i^D(t) \right) \right). \quad (18)$$

Esteban and Albiac (2011) report that in 2007 the land cultivated for agricultural production comprised 191,400 ha. Esteban and Albiac (2010, 2011) calculated that the irrigation practices lead to a gross extraction of 1km^3 of water from the aquifer and extended the irrigated area by 62,000 ha. Consequently, the water table dropped by 32 meters, i.e. a decrease of 2.6666 m per year. The gross extraction per m^3 of water per ha is given by $1,000,000.000\text{m}^3/253400\text{ha}= 39,463,299,131.807 \text{ m}^3/\text{ha}$. To keep the model more manageable, but without losing any important characteristic related to the hydrological processes, we scaled the aquifer down to 7500 ha which implies that all agents own exactly one hectare. Hence a drop of 2.6666 m per year is caused by a total extraction of $39,463,299,131.807 \text{ m}^3/\text{ha}$ times 7500ha. In other words, a decrease in the water table in meters per m^3 of extraction is given by the conversion factor $2,6666\text{m}/29597474,34885525\text{m}^3 = 0.0000009009778\text{m}/ \text{m}^3$. Although we downscaled the aquifer, we kept the number of agents approximately identical. However, we had to adjust the number of stakeholders and so we assume that every agent owns exactly one hectare.

According to Esteban and Albiac (2011), the overall recharge is 0.36 km^3 . Hence, per cultivated ha we obtain a recharge of $360.000.000/253400=1420,678768\text{m}^3$. This number links well with the reported rainfall of 415 mm/ha (Martínez-Santos et al. 2008). In term of cubic meters, it results in $10,000\text{m}^2$ times $0.415 \text{ m} = 4150 \text{ m}^3/\text{ha}$.

Water extraction costs

We calculated the extraction costs as a function of the overall depth of the well (annualized construction and maintenance costs) and of the lifting costs (Tecnoma and Universidad de Cordoba 2004). They are denoted by $c(w,s)$. Based on average values for the area of the western La Mancha aquifer, the cost of wells with a lifetime of 25 years and a depth of 46.83m are €371 per ha. is €7.94 per lineal meter of the constructed well depth. Assuming an average price rise of 4% p.a. over 10 years (2013 onwards), the nominal costs per lineal meter for 2014 are €11.75 per lineal meter. As reported by Llamas and Garrido (2007), it takes 0.004 kWh to draw 1 m^3 of water per meter. At €0.12 per kWh, water drawing costs per m^3 are € 0.00048 per lineal meter.

Net benefits of agricultural production and water demand

Varela-Ortega et al. (Varela-Ortega et al. 2011), developed a mathematical programming model for four different types of farm characterizing the variety of production systems and farm types found around the western La Mancha aquifer. Using economic, agronomic and policy constraints, the authors calculated the net income for a farm under different water allocation schemes. In other words, they calculated the best response the farmer would make to changes in the amount of water allocated per ha. for the upcoming agricultural campaign, i.e. the changes in inputs other than water or changes in the type of crop to be planted (to adjust to allocated water changes) to maximize the farm's net income. The reported results by Varela-Ortega et al., allow us to relate the maximal net income for a farm, with respect to composite input, as a function of the water assigned per ha, i.e. $\pi(x^*(w))$. Optimal farm income and the water assigned to it are reported in Table 3 of their work (Varela-Ortega et al. 2011). For the empirical estimation of this relationship, we calculated the weighted average of a farm's net income and water consumption for the four different types of farm. Unfortunately, the data that was collected and presented only reflects the upward sloping section of the farm-net-benefit function. Yet, the same authors report that prior to water restrictions being implemented at the beginning of the 21st century, the economic optimum corresponded to extracting 4300 m³ of water per ha per year. By adding this information as a decrease when consumption surpassed 4300 m³ in the farm-net-benefit function, we were able to estimate the net benefits of the farm as a function of water consumption. Additionally, we incorporated water extraction costs. The function that best fitted the data was a quadratic function with an R² adjusted of 0.94. This is given by

$$\pi(x^*(w, s)) = 70,3547448 + 0,5061w - 0,0000601w^2 - 7.94s - 11,75s - 0,00048ws. \quad (19)$$

In the next step, we need to obtain the solution of the dynamic optimization problem (detailed in Equations (1) and (2)). For this purpose, we substitute the general resource dynamics \dot{s} and the term $\pi(x^*(w, s))$ in Equations (1) and (2) by their specifications given in Equations (18) and (19), respectively. Thereafter, the dynamic solution problem is solved numerically in GAMS. The compliers' and defectors' strategies differ by the length of their planning horizon. Compliers adhere to the social norm by having a farsighted perspective, whereas defectors deviate from it as they focus on a planning horizon of merely one year. The choice of a planning horizon of 25 years is obviously

debatable, but this period of time coincides with the current farming generation leaving the farm to the next and with the economic lifetime of the investment itself.²³

The data obtained from the solution the dynamic optimization model provided for different initial values of s_0 , allowed us to estimate the water demanded by the compliers and defectors to maximize their net benefits, $w_i^C(t, T, s(t))$ and $w_i^D(t, 1, s(t))$, as a function of the depth of the water table. Likewise, the optimal water demand for each strategy for different initial values of s_0 allowed us to calculate the farms' optimal net benefits, $\pi^C(x_i^*(w_i^C(\cdot), s(t)), w_i^C(\cdot), s(t))$ and $\pi^D(x_i^*(w_i^D(\cdot), s(t)), w_i^D(\cdot), s(t))$ as a function of the depth of the water table.²⁴ The results from both estimations are presented in Table C1.

	Defector	Complier
Water demand	4004,032258 - 3,870967742 s(t)	3910,124356 - 18,28383925 s(t) + 0,855521467 s(t) ² - 0,012022391 s(t) ³
Farm net benefits	924,2879956 - 13,86127128 s(t)	529,5613916 - 0,989226044 s(t) - 0,81859727 s(t) ² + 0,023769413 s(t) ³ - 0,000212445 s(t) ⁴

²³ Alternatively, we could have distinguished the behavior of compliers and defectors by the choice of different time preferences and their corresponding discounted rates. Yet, the choice of different discount rates would have been more difficult since there is no natural orientation for its specification, unlike generational succession or the economic lifetime of the investment.

²⁴ For the case of the compliers, we used the average water demand and the farm's average discounted net benefits over 25 years. In this way, the compliers' water demand can be considered as the expected annual water demand. Moreover, taking the average value moderates the end-value problem toward the end of the planning horizon.

Table C1: Water demand and optimal farm net benefits as a function of the depth of the water table.

Although the compliers maximize their net benefits over 25 years, both compliers and defectors may change their strategy at each moment of time. For this purpose, every agent compares the usefulness of their current of strategy with the effectiveness of the alternative strategy. The probability of a change in strategies is given by Equations (6) and (7) and takes into account, among other elements, a farm's optimal net benefits π^C and π^D .

Cooperative behavior and groundwater management

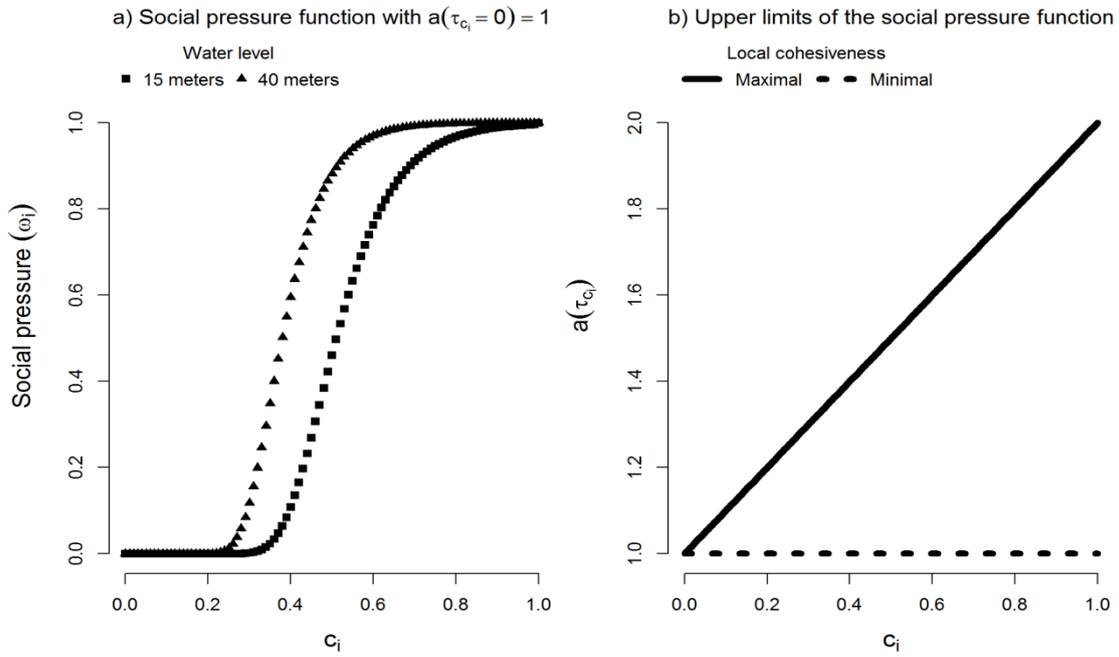
As mentioned above, the social pressure exercised by the compliers is an informal mechanism to enforce the social norm. It allows compliers to retaliate for the defectors' higher extraction rates of the groundwater which cause a faster decrease in the water table level, higher pumping costs and scarcity for all agents.

After having specified the optimal net benefits per farm for each strategy, π^C and π^D , we specify social pressure as a function of the depth of the water table, the number of compliers and the cohesiveness of the neighborhood $N(i)$ of agent i . Following (Tavoni et al. 2012), we model social pressure, ω , using a Gompertz growth function. This asymmetric sigmoid function is given by $\tilde{\omega}(c_i) = ae^{-de^{-gc_i}}$. The shape of $\tilde{\omega}$ is determined by the three positive constants: a, d and g which correspond to the upper asymptote, the displacement along the origin and the growth rate of the function, respectively. We modified the original formulation of the function so that it takes account of the relevant arguments of social pressure. For this purpose, we substitute the parameters a and g with the functions $a(\tau_{c_i})$ and $g(s)$, respectively. Hence, the modified Gompertz function depends on the characteristics of the neighborhood with respect to its share of compliers, its cohesiveness and the depth of the water table, and is given by

$$\omega(s, c_i, \tau_{c_i}) = a(\tau_{c_i}) e^{-de^{-g(s)c_i}}. (20)$$

Figure C1a shows its form as a function of the share of compliers for a given depth of the water table (15 m and 40 m) and $a(\tau_{c_i}=0)=1$. Figure C1b) illustrates the scaling factor that determines the upper limit of the social pressure function. While higher values of local cohesiveness lead to higher values of the upper limit (asymptote), the shape of the social pressure function remains unchanged. The specification of the functions and parameters is explained in detail below.

Figure C1 a – b: a) Social pressure as a function of the share of compliers for a given depth of the water table (15 m and 40 m) and minimal local cohesiveness $\tau_{c_i} = 0$, b) Upper limits of social pressure as a function of the share of compliers c_i



Social pressure is then characterized as incremental sanctioning driven by the four parameters: the share of compliers in agent i 's neighborhood (c_i), the stock levels (s), the effectiveness of sanctioning (d) and the number of compliers in the agent's neighborhood who are connected (τ_{c_i}).

Compliers are well aware of the evolution of the stock and increase their pressure on defectors as s falls. The function $g(s)$ induces ω to grow faster as the water table s

approaches the maximal depth of the well, s_{\max} , in particular if $s > \frac{s_{\max}}{2}$. The precise formulation of g is given by

$$g(s) = A + (B - A) \left(\frac{s}{s_{\max}} \right)^n$$

and is bounded between $A < g(s) < B$. We set the parameter $A = 10, B = 20$ and $n = 3$ so that $10 < g(s) < 20$. Higher values of the parameter d displace the social pressure function to the right so that higher values of c_i are needed to exert the same pressure as before on defectors. Thus, the parameter d describes the ability to exercise social pressure, i.e. the ability to sanction defectors (Tavoni et al. 2012). In the model, we set $d = 150$ in accordance with the study of (Tavoni et al. 2012).

Since the function $a(\tau_{c_i})$ defines the upper asymptote, it reflects the maximal social pressure that compliers can exercise. Provided that agent i is a defector, the social pressure agent i experiences increases if the compliers in the neighborhood of agent i coordinate their action against agent i . Thus, the cohesiveness of the compliers in the neighborhood of agent i is a precondition to their cooperation and is liable to increase the social pressure placed on defectors. For this reason, we introduced the function $a(\tau_{c_i})$ which measures to what extent compliers in the neighborhood of agent i are connected to each other. The specification of the cohesiveness function $a(\tau_{c_i})$ is given by

$$a = 1 + \left(\frac{\tau_{c_i}}{\tau_{\max}} \right)^\alpha = 1 + \sqrt{\tau_{c_i}}. \quad (21)$$

If all neighbors of agent i were compliers $c_i = 1$ and connected to each other, we would have $\tau_{c_i} = \tau_{\max} = 1$. However, if not all neighbors are compliers, it holds that $0 < \tau_{c_i} < \tau_{\max} = 1$ and consequently the function a is bounded by $1 \leq a \leq 2$. Moreover, we stipulate to set $\alpha = 0.5$. This choice affects only the behavior of the function within its boundaries but not the boundaries itself. Given that the term $e^{-de^{-g(s)c_i}}$ of the social pressure function is bounded by $0 < e^{-de^{-g(s)c_i}} \leq 1$, we know that the social pressure function is limited as well, more precisely by $0 < \omega \leq 2$.

The defined boundary of the social pressure function is of outmost importance since it limits social punishment to be at most twice the difference between the benefits of defectors and compliers, i.e. $\omega \leq 2(\pi^D - \pi^C)$.

Obviously, the choice of the parameters and the specification of the social pressure function ω is debatable and we cannot defend its choice on the grounds of the literature or experiments previously conducted. However, the choice of limiting ω to be smaller or equal to two seems rational in terms of economic reasoning. The main objective of social punishment is to deter agents from defecting from the social norm. Once social punishment outweighs the non-compliance benefits it would be best for rational agents to adhere to the social norm. However, since social punishment of agent i depends on the structure and state of the network, we allowed $0 < \omega \leq 2$ so that effective social punishment, $\omega > 1$, occurs regardless if all the neighbors of agent i are compliers and perfectly connected to each other.

The definition of the social pressure function, however, is not only motivated by economic reasoning but also allows the structure and state of the network to be linked to the decisions taken by each agent. Finally, the choice of boundaries for ω are also decisive for limiting the probability of a change from the agent's current strategy to an alternative strategy. Denote the utility of the agent's current strategy by U_i and their alternative strategy by U_i' . Thus, based on Equations (4) - (7), we observe that the probability of a change in the agent's current strategy to the agent's alternative strategy is given by

$$p_i(t) = \frac{U_i'(t) - U_i(t)}{\max\{U^D(t) - U^C(t)\}} = 1 - \omega. (22)$$

If $U_i'(t) - U_i(t) \geq 0$, we have $0 \leq p_i(t) < 1$ and if $U_i'(t) - U_i(t) \leq 0$, we have $0 \geq p_i(t) \geq -1$. Thus, Equation (22) shows that the probability is limited by $-1 \leq p_i(t) < 1$ and links to the mathematical conception of probability. In Equations (6) and (7) we set the probability of a change in strategies equal to zero if it leads to an economic loss, i.e. if $U_i'(t) - U_i(t) \leq 0$. Consequently, it will not be realized. Despite

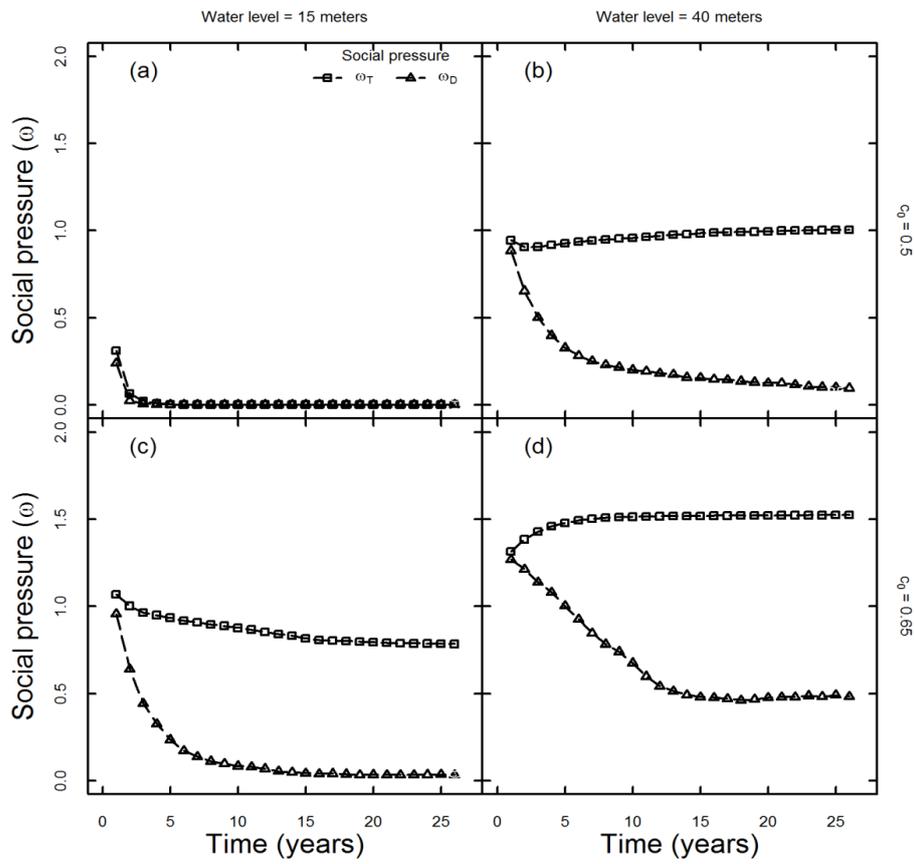
this modification, Equation (22) shows the importance of the boundary choice of ω for linking the behavioral model to the mathematical concept of probability.

Appendix D

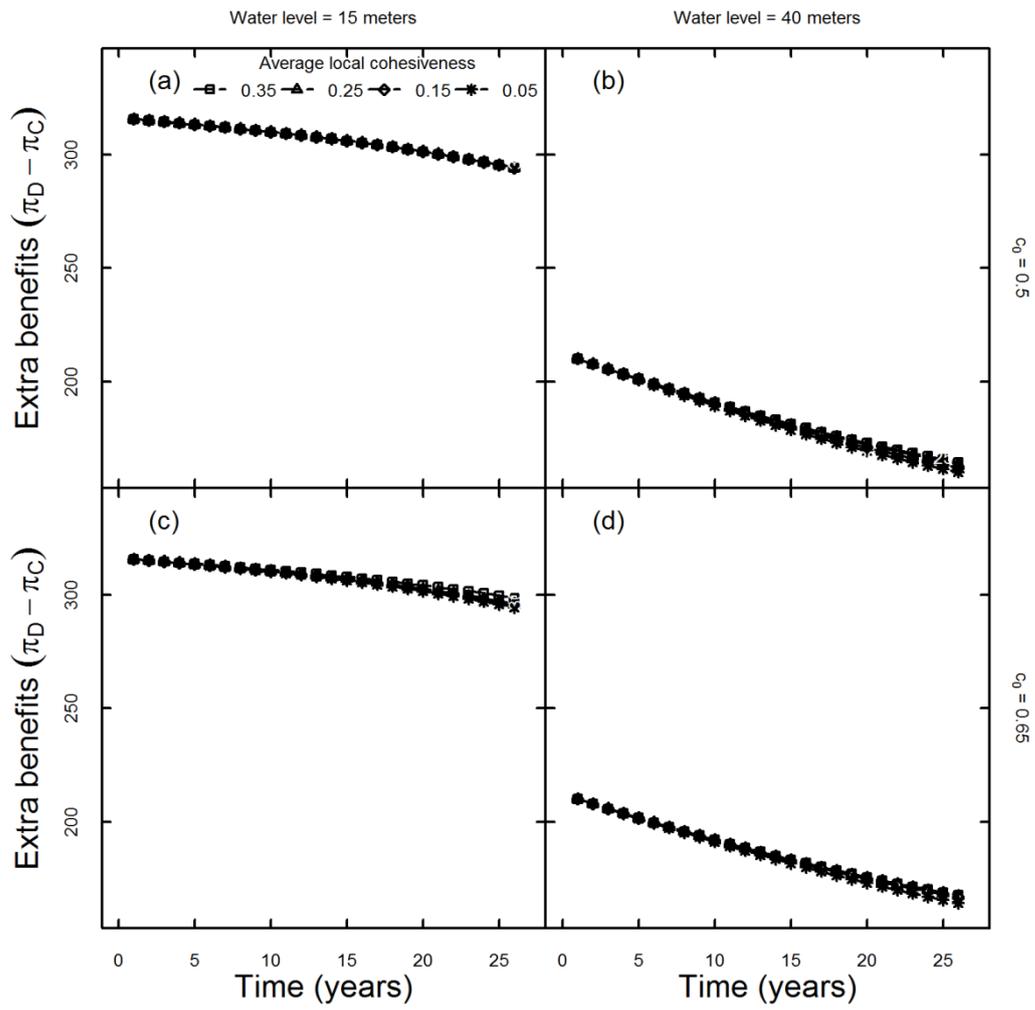
Evolution of Social Pressure

Figures D1a – D1d show the evolution of the average social pressure within the network, ω_t . This consists of the social pressure received by all agents, i.e. the social pressure experienced by defectors and the potential social pressure that compliers would receive if they decided to abandon their current strategy. Alternatively, we calculate the average social pressure that only defectors would receive and denote it by ω_D . The graphs show that ω_D always decreases over time, suggesting that neighborhoods are formed where the share of defectors increases.

Figures D1a – D1d: Evolution of social pressure ω . Figure D1a: $c_i = 0.5, s(0) = 15$, Figure D1b: $c_i = 0.5, s(0) = 40$, Figure D1c: $c_i = 0.65, s(0) = 15$ and Figure D1d: $c_i = 0.65, s(0) = 40$.



Figures D2a – D2d: Evolution of the defector’s extra benefits for different degrees of average local cohesiveness with $\tau = 0.05, 0.15, 0.25$ and 0.35 . Figure D2a: $c_i = 0.5, s(0) = 15$, Figure D2b: $c_i = 0.5, s(0) = 40$, Figure D2c: $c_i = 0.65, s(0) = 15$ and Figure D2d: $c_i = 0.65, s(0) = 40$.



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