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

Jorge Marco
University of Girona

Renan Goetz
University of Girona

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Abstract

This study revisits the problem of the tragedy of the commons. Extracting agents participate in an evolutionary game on a complex social network and are subject to social pressure if they do not comply with the social norm. Social pressure depends on the dynamics of the resource, the network and the population of compliers. We analyze the influence of the network structure 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 not sufficient. The study suggests that the origin of the problem – shortsighted behavior - is at the same time the starting point for a solution in form of a one-time payment. A numerical analysis with a social network formed by 7500 agents and a realistic topological structure is accomplished with empirical data of the Western La Mancha Aquifer in Spain.

Keywords: Tragedy of the commons; cooperation; evolutionary game; social network; social punishment

JEL Classification: C71; D 85; Q25

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Corresponding author:
Renan Goetz
Department of Economics
University of Girona, Spain

1. Introduction

Traditionally economists considered agents as rational individuals whose decisions are not influenced by the type and pattern of interaction with other individuals. While this approach seems legitimate for studying many social and economic phenomena it falls short for explaining the emergence of trust, cooperativeness or the compliance of social norms. Since they are a foundation of social relationships individual decisions are influenced by the choices of other individuals, and are governed by the type and pattern of connections between agents. Like prices are the principal vehicle to coordinated individual actions in market, trust, cooperativeness and social norms are the principle vehicle to coordinate social actions. The sustainable management of common property resources is an evident example that requires the coordination of the agents' behavior, for example by compliance of a social norm. The determination and analysis of the factors that favor the disposition to comply with social norms has been studied intensively in economics and other social sciences (Wenegrat et al. 1996, Ostrom et al. 2002, Hanaki et al. 2007). The results of these studies show that individual decisions are not guided completely by complex self-interested calculation but under certain conditions also by the collective interests – for example the presence of a community that is based on a small and stable population with a thick social network and social norms promoting the collective interests (Ostrom et al 2002).

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 evolutionary game-theoretic approach was based on the premise that every agent can randomly meet any other agent, i.e. all agents are linked directly with 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 for the emergence and preservation of cooperation it does not take full account of the complexity, vicinity and segregation pattern in interaction between agents 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 allowed to demonstrate that cooperation is evolutionary 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) that shows that agents are grounded in strongly heterogeneous networks with a strong diversity among the agents' 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 strongly 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 to that behavior exceeds the average payoff in the population, and decreases when the reverse is true. Hence behavior that does badly from the point of view of the individual gets weeded out, while behavior that does well is imitated (Sethi and Somanathan 1996, Osés-Eraso and Viladrich-Grau 2007). Within the evolutionary-game-theoretic framework the determination of the payoffs has so far received little attention. It could be based on a short-term or long-term perspective depending on the degree of individual commitment with the collective interests. A short-term perspective presents the predominance of individual interests while a long-term perspective reflects collective interests. In the latter case the payoff can be calculated as the outcome of a differential game. Finally, the determination of the optimal strategic response to let‘s say thousands of other agents each of them in a unique position in the social network might stretch the assumption of rationality beyond its limits due to the complexity of the strategic decision problem. Therefore, the assumption of limited rationality seems reasonable to us if the social network is large and topologically complex.

Alternatively, economists studied the behavior of agents that form 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 prisoner dilemmas at a bilateral or multilateral level. While the results of these studies are interesting their applicability to real life situation is limited because equilibriums are only found on the basis of the above described grim trigger strategies within the set-up 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 trigger strategies. Repeated games are the repetition of static games and as such they do not consider the evolution of a stock variable. Consequently, they do not allow analyzing the tragedy of the commons where the evolution of the natural resource is a fundamental element of the problem.

In view of these considerations we suggest a new framework that combines the distinctive aspects of the three strands of the literature – an evolutionary game-theoretic approach based on the solutions of differential games which are employed within a social network that gives account of the complexity of the agents' interaction.

With respect to the social network we describe the structure of connections and analyze to what extent macro and micro characteristics of social interaction support social norms in order to conserve natural resources (Jackson et al. 2017). We focus on a common property resource, and ask the question whether network effects are able to sustain the socially optimal use of the resource or at least to moderate or avoid the tragedy of the commons, i.e., the overuse or depletion of the natural resource. The decision to comply with the social norm is voluntary since the members of the community have open access to the natural resource. The community owns the natural resource but it has no legal power to enforce the social norm or it is too costly to rely on formal contracting. However, the compliers may exercise social pressure (social shunning, social rejection) on members of the community that do not adhere to the social norm (Ali and Miller 2016). Social pressure is undertaken by the compliers themselves, without the presence of the authorities, and depends heavily on their structure and pattern of interactions.

The realized study does not only aim to contribute to the analysis of cooperative behavior but also to the valuation approaches of intangible goods. Environmental economics contributed to the general economics with the foundation and formalization of methods to measure the value of intangible goods and services, for example, the scenic value or the existence value. This study aims to extend the literature by analyzing the effects of social shunning within a social network in monetary terms. Moreover, we formulate and evaluate the conditions under which social shunning or rejection is a relevant mechanism for supporting cooperation.

The study proceeds as follows. In section 2 we present the economic model based on an integrated social-biophysical system. In section 3 we define an equilibrium concept and analyze possible equilibria. In following section we analyze policy options for overcoming the tragedy of the commons and we determine the economic value of the different elements of social pressure. In section 5 we present in more detail the employed structural elements of the social network that are utilized in a numerical analysis for the case of groundwater presented in section 6. The paper closes out with some conclusions.

2. The economic model

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

2.1 A social network as a graph

Our interest is on interaction between n different members of a social network that can be described by a simple graph $N=(A,L)$. It consists of a finite set $A=1,...,n,\ n>2$ of agents and the set L of links which are unordered pairs of elements of A. The elements of 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 $l_{ij}=1$ indicate that the two agents are neighbors and $l_{ij}=0$ otherwise. The use of the term neighbor does not indicate that the two agents are neighbors that live next to each other but rather that they are linked, i.e., they know and relate to each other. By definition, simple graphs are undirected so that $l_{ij}=1\Leftrightarrow l_{ji}=1$.[1] If every agent is connected with all other agents N forms a complete network.

[1] Moreover, agents are not linked with themselves (self-loops), i.e. $l_{ii}=0$ and there is not more than one link between agent i and j (uniqueness of the link). For each agent i , $N(i)$ denotes her

2.2 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 lead in the long-run either to the depletion of the resource or very low annual private net benefits. For overcoming 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 agents that follow the sustainable extraction path as compliers and the behavior of all other agents as defectors.

Each member either employs the extracted resource as an input for the production of a single good or commercializes it in 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 extracted amount of the resource 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, each member i determines optimal amount of the composite input given a particular value of w and s by solving the following decision problem

$$\max_{x_i} \pi\left(x_i, w_i, s\right). \quad (1)$$

The solution of problem (1) is denoted by $\mathrm{x}_i^*\left(\mathrm{w,s}\right)$. After the determination of the optimal use of the composite input each member i still has to decide to adhere to the social norm or not. The adherence to the social norm supports sustainable extraction while non adherence leads to a non-sustainable extraction path. Non-coordinated individual behavior would result in a sustainable extraction path if all members would take stock dependent costs into account for the determination of the privately optimal

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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 exist a finite sequence of agents $a_1,\ldots,a_K$ such that $a_1=i, a_K=j$ and $a_{k+1}\in N(a_k)$ for $k=1,\ldots K-1$. This means there are no isolated agents in N.

extraction path. These costs will be fully considered if all agents have a private planning horizon of sufficient length. Consequently we define compliers as farsighted agents with a planning horizon of $T >> 1$ years whereas defectors are short-sighted with a planning horizon of 1 year.[2] We assume that the underlying reason for the shortsightedness is either related to socioeconomic factors, for example 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 of the following decision problems. For compliers the resource demand function is given by

$$\mathrm{w}_i^C\left(\xi,t,T,s\left(t\right)\right)= \underset{w_i(\xi)}{\operatorname{argmax}} \int_t^{t+T} e^{-r\xi}\pi\left(x_i^*\left(w\left(\xi\right),s\left(t\right)\right),w_i\left(\xi\right),s\left(t\right)\right)d\xi \quad (2)$$

subject to

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

where r denotes private intertemporal discount rate, $\overline{w}_i^D$ the defectors' resource demand at time t, a dot over a variable the operator d/dt, c the share of compliers within the population of all agents and the function $g\left(s\left(t\right)\right)$ the reproduction or growth function of the resource.

In other words compliers consider the extraction by defectors as constant. The resource demand function (2) is the solution of an open loop strategy. The rational for open-loop strategies is that agents can commit to maintain the determined extraction profile at time t over the planning horizon T because they do not obtain any further information in the future, i.e. neither about the remaining level of the resource nor about the choice made by the other agents. Yet, for the case of natural resource agents can often observe the state of the stock and thus their extraction profile should depend on the observed level of the natural resource. Hence, one could model the resource demand function as the solution of 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

[2] 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.

network it is difficult to envision that every agent plays a non-cooperative game against all other agents. The reasons are threefold. Firstly, the computational burden and complexity is extremely high[3], secondly the agents' rationality may be limited and thirdly compliers seek to implement a cooperative solution and not a non-cooperative one. For these three reasons we discarded the determination of the resource demand as the solution of a feedback strategy and propose a modified open-loop strategy instead. Based on the circumstance that agents can frequently observe the level of the remaining stock we propose that the agents are allowed to revise their extraction profile after x years. In other words the agents determine a new open-loop extraction profile that is based on the observed level of the resource. This profile is maintained until the next revision period when new information about the level of the remaining stock is obtained.

With respect to defectors we assume that the length of their planning horizon is 1 year and thus their resource demand function is given by

$$\mathrm{w}_i^D\left(\xi,1,s(t)\right)=\underset{w_i(\xi)}{\operatorname{argmax}}\int_t^{t+1} e^{-r\xi}\pi\left(x_i^*\left(w(\xi),s(t)\right),w_i(\xi),s(t)\right)d\xi \quad (3)$$

subject to

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

where $\overline{w}_i^C$ the compliers' resource demand at time t.We assume that compliers and defectors differ only with respect to the length of the planning horizon but not with respect to their private discount rate. Both decision problems are subject to equation (1).

2.3 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 of compliers and defectors 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

[3] It requires that every agent solves a large system of partial differential equations.

Somanathan 1996, Osés-Eraso and Viladrich-Grau 2007). We assume that this decision is influenced by the following factors

1. The difference of the defector's net benefits in comparison with the complier's net benefit (the defector's extra benefits) and
2. the interaction with other agents (network effects)

With respect to point 1 we assume that the larger is the difference between the maximal net benefits of the strategy compliance given by $\pi^C\left(x_i^*\left(w_i^C(\cdot),s(t)\right),\mathrm{w}_i^C(\cdot),s(t)\right)$ and the maximal net benefits of the strategy defection given by $\pi^D\left(x_j^*\left(w_j^D(\cdot),s(t)\right),\mathrm{w}_j^D(\cdot),s(t)\right)$ the higher is the chance at moment t that a complier becomes a defector and a defector does not become a complier. The difference between $\pi^D-\pi^C$ not only is important for the agent's strategy but also presents the magnitude of the loss defectors inflict on the members of the network that adhere to the social norm. In the absence of an institution that is technically and legally in the position to punish defectors, compliers may retaliate for the defectors' abstraction of the common property resource via social shunning.

With respect to social pressure we assume that all agents are perfectly informed about the strategy choice of their neighbors (complete monitoring) and there is no time delay between the detection of non-compliance and retaliation.[4] In order to concentrate on the first-order dilemma of public goods (provision of cooperation) we suppose that the retaliation is costless for compliers. In this way we avoid the second-order dilemma of public goods since compliers do not have to agree upon the division of the costs of retaliation among them.

Social pressure and social punishment

If an agent defects she will be exposed to social pressure by the compliers. [5] However, making use of the social network suggests that social pressure on defector i depends on

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

[5] Instead of the male and female possessive pronoun we only use the female form to facilitate the reading.

the number of compliers and defectors in particular within her local neighborhood $N(i)$. Let us define the set of compliers within the neighborhood $N(i)$ by $N_C(i)$ and thus the share of compliers c_i can be defined by $c_i = |N_C(i)| / |N(i)|$. This relation is considered an important factor for the determination of social pressure since it measures the direct influence of the neighborhood on defector i. The higher the number of compliers is in the neighborhood $N(i)$ the more trust agent i has in the action of the other agents. However not only the share of compliers c_i is important for the determination of social pressure but also the relationship between the agents that form part of the set $N_C(i)$. In case none of these agents is linked with another agent of this set one can assume that social pressure on defector i is not so high compared to the situation where every agent of the set $N_C(i)$ is linked with all other agents of this set. In the first case the local cohesiveness between the agents of the set $N_C(i)$ would be zero and in the latter case it would be one. Let us denote the cohesiveness among the compliers of the neighborhood $N(i)$ by $\tau_{c_i} \in [0,1]$. It measures the degree of connectivity among the compliers of the set $N_C(i)$. Finally, we assume that the set of compliers $N_C(i)$ exert less social pressure on defector i if the resource is abundant and more social pressure if the resource is scarce.

After introducing the three key elements of social pressure we can write the social pressure function as $\omega\left(s(t), c_i(t), \tau_{c_i}(t)\right)$. As explained above an increase in the stock reduces social pressure, i.e. $\partial\omega/\partial s < 0$, an increase in the share of compliers in the neighborhood of defector i augments 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 defector's and complier's net benefits, $\pi^D(\cdot) - \pi^C(\cdot)$. Since these extra benefits presents the loss defectors inflict on compliers it can be seen as redemption of the suffered privation. However, the social punishment is not independent of the 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 the social pressure $\omega\left(s, c_i, \tau_{c_i}\right)$. More precisely the product of social pressure and the defector's extra benefits define social punishment given by.

$$\omega(\cdot)\left(\pi^D(\cdot)-\pi^C(\cdot)\right).(4)$$

Agents' 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

$$U_i^C(t)=\pi^C(\cdot),(5)$$

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

$$U_i^D(t)=\pi^D(\cdot)-\left\lfloor \omega\left(s(t), c_i(t), \tau_{c_i}(t)\right)\left(\pi^D(\cdot)-\pi^C(\cdot)\right)\right\rfloor. (6)$$

Equation (5) indicates that the utility of a complier is equal to her private net benefits.[6] It depends on the amount of the extracted resource and the level of the stock. Equation (6) shows that the utility of a defector consists of the net benefits from resource extraction minus social punishment. Like the utility of the complier it depends on the amount of the extracted resource and the level of the stock. However it also depends on the position of the defector in the social network and the characteristics/topology of the social network within her neighborhood.

At each time step every agent decides to maintain the current strategy or to change it. For this purpose every agent i compares the utility associated with her current strategy $U_i(t)$ with the utility of the alternative strategy $U_i'(t)$. Thus even though the utility of a complier is independent of her position in the network and the characteristics/topology of the social network within her neighborhood, the decision to maintain the current strategy or to change it depends on these elements. If the utility of the alternative strategy is greater than the current strategy, $U_i'(t)>U_i(t)$, it is likely that the agent

[6] Although this formulation implies that agents are risk neutral we opted for this specification in order to simplify the model and to concentrate on the interaction between agents within a social network.

adopts the alternative strategy. If $U_i'(t) \le U_i(t)$, the agent maintains her current strategy. In mathematical terms the probability of a change of the current strategy of 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

$$p_i^C(t) = \begin{cases} \dfrac{U_i^D(t) - U^C(t)}{\max\{U_i^D(t) - U^C(t)\}} & \text{, if } U_i^D(t) - U^C(t) > 0 \\ 0 & \text{, if } U_i^D(t) - U^C(t) \le 0 \end{cases}, \quad (7)$$

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

$$p_i^D(t) = \begin{cases} \dfrac{U^C(t) - U_i^D(t)}{\max\{U_i^D(t) - U^C(t)\}} & \text{, if } U^C(t) - U_i^D(t) > 0 \\ 0 & \text{, if } U^C(t) - U_i^D(t) \le 0 \end{cases}. \quad (8)$$

The denominator of the equations (7) and (8) 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 comes about 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 strategy is a 0 - 1 decision in probabilities. For this purpose we generated by the inverse transform method a random number that takes only values of 0 or 1 - see appendix A (Methodological and Technical Aspects of the Implementation of the Social Network). In simple words, if $p_i^D = 0.8$, the methods generates with a probability of 80% a 1 and with 20% a 0. Thus, if the drawn random number is a 1 the defector changes her strategy and otherwise not.

Decisions with respect to the choice of the strategy are taken simultaneously by all agents based on the current distribution of compliers and defectors within the social network and are realized with probability p_i^C or p_i^D .We assume that agents do not act strategically, i.e. they do not consider possible strategy choices of their neighbors as a response to their choice of strategy. Given the large size of the social network and the resulting huge set of possible constellations each player needed to consider for strategic choices, it seems more realistic to base individual strategy-choice on non-strategic behavior as also pointed out by (Gale and Kavir, 2003).

3. Equilibrium concept

In the previous literature (Sethi and Somanathan 1996, Osés-Eraso and Viladrich-Grau 2007) identified equilibrium conditions for the dynamics of a resource and a non-structured population. 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 must require the following three equilibria, a) equilibria with respect to the dynamics of the resource, b) the changes in the agents' strategy choice and c) the agents' resource demand has to be incentive compatible with the equilibria with respect the dynamics of the resource.

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

$$g\left(s\left(t\right)\right)=-\sum_{i}^{c}w_i^C\left(t\right)+\sum_{c+1}^{n}w_i^D\left(t\right).(9)$$

Additional to equation (9) it has to hold that either none of the agents changes her strategy, or the share of compliers of all agents, c, is constant.[7] Hence, an equilibrium b) in expected values is achieved if

[7] The share of compliers can be maintained 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 exist a dynamic equilibrium if $p_i^C\neq 0, p_j^D\neq 0, \forall i, \forall j, i+j<n$ and $p_k^C=0, p_l^D=0,$ and $\forall k, \forall l, i+j+k+l=n$ the share of

$$\sum_{i}^{cn} p_i^C - \sum_{cn+1}^{n} p_j^D = 0 . \quad (10)$$

Finally, equilibrium c) holds if there exist an $w_i^C(t)$ and $w_i^D(t)$ that satisfies the equations (2),(3) and (9). In other words the required amount of the extracted resource that satisfies the balance between reproduction and extraction (equation (9)) has to be also optimal from the economic point of view for compliers and defectors. i.e., none of the agents changes their strategy.

Hence an equilibrium is defined by the equations (2),(3),(9) and (10). Given the great number of agents and the large degree of freedom to satisfy condition (9) and (10) a equilibrium, if it exists, is likely to be not unique and stable. In this case it is possible that the number of compliers and defectors is maintained for a certain period of time but the new constellation in some neighborhoods induces agents to change their strategy. Thus, the equilibrium is likely to be only temporarily.

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 by the all-complier equilibrium. Therefore, the more compliers there are the more efficient is the management of the resource. Consequently, low probabilities of the all-defector equilibrium or any mix equilibrium have to be evaluated positively from a social point of view.[8]

Observation 2: (measurement of distance to a network -equilibrium)

Let denote $\hat{\omega}_i$ *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*

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compliers of all agents is constant. It implies that the strategy-changes from compliers to defectors or vice versa cancel each other out for $i+j$ agents, and $k+l$ agents maintain their current strategy. None of these two equilibria are necessarily steady state equilibria. .

[8] One has to recall that the interpretation of an equilibrium employed in evolutionary game theory is different from the one employed in non-cooperative game theory. In the latter one the equilibrium provides guidance for the agent with respect to the choice of the strategy. In evolutionary game theory, however, an equilibrium simply describes a temporarily or permanent steady state without offering directions for the choice of the strategy.

hold. The sum of the absolute values of all $\hat{\omega}_i$ defines the distance of the actual state of the network from an equilibrium state.

For the definition of the measure $\hat{\omega}_i$ let us assume initially that an equilibrium exists. Therefore the three conditions with respect to the resource, strategy changes and economic incentive mentioned above are satisfied and the value of social pressure is equal to $\bar{\omega}_i\left(\bar{s},\bar{c}_i,\bar{\tau}_{c_i}\right),\forall i$, where the bar over a variable denotes its equilibrium-value. Let us assume no agent has incentive to chance her strategy-choice, i.e., $p_i^C\left(t\right),p_i^D\left(t\right)=0,\forall i$. Thus it holds by the equations (7) and (8) that

$$U_i^C=U_i^D\Rightarrow\pi^C=\pi^D-\bar{\omega}_i\left(\cdot\right)\left(\pi^D-\pi^C\right)\Rightarrow\bar{\omega}_i=1.(11)$$

Thus, provided that no agent has incentives to change her current strategy, equation (11) implies that $\bar{\omega}_i=1$. However, if some agents have incentives to change their current strategy a network equilibrium can only be established if the condition (10) holds. In this case there may exist a dynamic and most likely transitory equilibrium were the probability of the number of compliers and defectors that changes their strategy cancels out. Thus, for agents that changes their strategies it holds that $p_i^C>0$, $p_i^D>0$, which implies that the corresponding social pressure $\hat{\omega}_i$ is given by

$$\begin{aligned}
&\max\left\{U^D\left(t\right)-U^C\left(t\right)\right\}p_i^C=U_i^D-U^C=\pi^D-\hat{\omega}_i\left(\cdot\right)\left(\pi^D-\pi^C\right)-\pi^C\\
&\frac{\max\left\{U^D\left(t\right)-U^C\left(t\right)\right\}p_i^C}{-\left(\pi^D-\pi^C\right)}=\hat{\omega}_i\left(\cdot\right)-1\Rightarrow\hat{\omega}_i\left(\cdot\right)<1\\
&\max\left\{U^D\left(t\right)-U^C\left(t\right)\right\}p_i^D=U^C-U_i^D=\pi^C-\left(\pi^D-\hat{\omega}_i\left(\cdot\right)\left(\pi^D-\pi^C\right)\right)\\
&\frac{\max\left\{U^D\left(t\right)-U^C\left(t\right)\right\}p_i^D}{\left(\pi^D-\pi^C\right)}=\hat{\omega}_i\left(\cdot\right)-1\Rightarrow\hat{\omega}_i\left(\cdot\right)>1.
\end{aligned}\qquad(12)$$

Equations (11) and (12) indicate the values social pressure may take on for a dynamic network-equilibrium to hold (equation (10)).

The interpretation of the value of $\hat{\omega}_i$ is straightforward. It indicates the lack or excess of social pressure that provides incentives for the agents to change their strategies. Thus, the term $0<1-\hat{\omega}_i<1$ denotes the additional share of the *defector-i's* extra benefits

$\pi^D - \pi^C$ that have to be imposed on complier i in 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 her strategy. Likewise, the term $1 < \hat{\omega}_i - 1 < 2$ denotes the share of the *defector-i's* extra benefits $\pi^D - \pi^C$ that have to be passed on to defector i in form of reduced social pressure for an equilibrium to hold. This reduction in social pressure eliminates defector i incentives to change her strategy. Thus, a $\hat{\omega}_i$-value of 1 (0.6, 1.7) indicates that 0% (40%, 70%) of the defector's extra benefits have to be transformed in additional or reduced social pressure in order to establish an equilibrium.

4. 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, little social pressure is exercised. Hence, there is a high probability that the number of defectors rises and the biophysical system is likely to drift on an unsustainable path which may lead to inefficient equilibrium or the depletion of the resource.

4.1 Policy options

In this situation the community may decide to introduce a one-time payment v_i on the defectors' inflicted loss on 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 the higher number of compliers the resource is managed in a more sustainable way.

Observation 3: (one-time payments as a remedy for the tragedy of the commons)

One-time payments are able to increase the number of compliers immediately. Provided that the resulting number of compliers is sufficiently high the increased social pressure allows maintaining the new number of compliers which in turn favor the sustainable management of the resource.

For the plausibility of this argumentation one has to recall that the shortsighted behavior of defectors obstructs the emergence of cooperative behavior. The shortsightedness of defectors is the origin of the tragedy of the commons. However, at the same time it offers an approach for its solution. It allows increasing the number of compliers 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 necessary. Further payments are not necessary if a sufficient number of defectors have changed side so that the risen social punishment has eliminated the incentives to change back to the strategy of defection. If defectors had a longer planning horizon the payment would have to be larger in order to compensate not only the forgone extra benefits of the current period but also of the future periods. A defector is willing to become a complier if her new utility is higher than before, i.e.

$$\pi^D - \omega_i\left(s, c_i, \tau_{c_i}\right)\left(\pi^D - \pi^C\right) < \pi^C + v_i, \quad (13)$$

where v_i denotes the one-time payment. The determination of the one-time payment to defectors depends on the number of compliers necessary to eliminate the economic incentives to change back. Based on equation (13) the community needs to identify the missing number of compliers and the least-cost neighborhoods to reach the targeted share of compliers at the least cost. In practice the community might find it difficult to identify these neighborhoods. However, the experience gathered for the design of reversed auction for payment schemes for environmental services could be used to target these one-time payments (Alston et al. 2013, Schomers and Matzdorf 2013). More details about the determination of the size of the one-time payment can be found in section 6.2.

4.2 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 $\bar{\omega}_i$ that supports a network equilibrium. The missing/excessive social punishment could be substituted by tax or a subsidy so that the sum of each defector's social punishment and the amount of the individual tax/subsidy is equal to equilibrium social punishment $\bar{\omega}_i(\cdot)\left(\pi^D - \pi^C\right)$.[9] Mathematically, the tax/subsidy is given by

[9] 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 is able to compensate the high social pressure and make the defector maintain her current strategy.

$$\omega_i\left(s,c_i,\tau_{c_i}\right)\left(\pi^D-\pi^C\right)+\theta_i=\bar{\omega}_i\left(\cdot\right)\left(\pi^D-\pi^C\right). \quad (14)$$

Although it is difficult to imagine that the community imposes this type of individual tax/subsidy, equation (14) is very informative in other ways.

It allows determining 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. Based on a comparative static analysis we obtain that

Observation 4: (marginal economic value of social punishment)

An increase in the share of complier or local cohesiveness increases the economic value of social punishment, while an increase in the stock leads to a decrease of economic value of social punishment.

The analysis shows that

$$\frac{\partial\theta_i}{\partial c_i}=-\frac{\partial\omega_i\left(\cdot\right)\left(\pi^D-\pi^C\right)}{\partial c_i}<0,\ \frac{\partial\theta_i}{\partial\tau_{c_i}}=-\frac{\partial\omega_i\left(\cdot\right)\left(\pi^D-\pi^C\right)}{\partial\tau_{c_i}}<0. \quad (15)$$

Equation (15) indicates that an increase in the number of compliers in the neighborhood of agent i reduces the required tax/subsidy in order to maintain the steady state-equilibrium pressure. It also specifies that an increase in local cohesiveness among the compliers within the neighborhood of agent i leads to a decrease in the tax/subsidy. Since the tax/subsidy is complementary to the individual social punishment a decrease in the tax/subsidy amount to an increase in the economic value of social punishment. $\omega_i\left(\cdot\right)\left(\pi^D-\pi^C\right)$. The comparative static shows further that

$$\frac{\partial\theta_i}{\partial s}=-\frac{\partial\omega_i\left(\cdot\right)\left(\pi^D-\pi^C\right)}{\partial s}=-\frac{\partial\omega_i}{\partial s}\left(\pi^D-\pi^C\right)-\omega_i\frac{\partial\left(\pi^D-\pi^C\right)}{\partial s}>0 \quad .(16)$$

The sign of equation (16) can be determined unambiguously because the signs of $\partial\omega_i/\partial s$ and $\partial\left(\pi^D-\pi^C\right)/\partial s<0$ are both negative.[10] Based on the complementarity of

[10] The negative sign of $\partial\left(\pi^D-\pi^C\right)/\partial s$ 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

the tax/subsidy and social punishment it follows that social punishment decreases with an increase in the stock. Equations (15) and (16) 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 good: the stock.

5. Structure of the social network

The network itself is not randomly generated but has to meet certain properties. The considered criteria or characteristic are i) scale free, ii) correlation by biological and socioeconomic attributes and iii) small world. The following three paragraphs present the building elements of each of these three characteristics in a non-technical manner. For a more technical description of these characteristics, in particular for the definition of their metrics we refer the reader to (Jackson 2010, Newman 2010).

i) Scale free

An agent j linked to 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 of i. Denote by $P(K = k) = p_k$ the degree distribution of N, that is the probability than an agent i in N chosen uniformly at random has exactly k neighbors. If the links of all agents were formed with the same probability p we would obtain a random network whose degree distribution is approximately given by 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 network have more weight in the tails than random network and thus offer a better match with observed social networks (Jackson 2010). Moreover, scale free networks in comparison with random network allow considering some organizing principles (Rèka and Barabasi 2002) where there are few central agents with a high degree, and many other agents with small degree. In a social system central agents are likely to have more influence,

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corresponding net benefits decreases. This hypothesis is also confirmed by our empirical analysis – see Table A1, Figures C2a) –C2d) of the appendix.

more prestige and/or better access to information with respect to quantity and quality. However, other organizing principles are also possible where the centrality is not based on the degree but on the importance of the link for the social network. Depending on the analyzed question the adequate concept of centrality has to be employed. (Ballester et al. 2006, Bramoullé et al. 2014).

ii) Relation 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 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 that falls within the interval $\left(0,\infty\right]$. Empirical studies have shown that attributes are an important factor for the formation of links between individuals (Jackson 2004). For instance, a known tendency of agents is connect to other agents with similar attributes. This tendency colloquially expressed as "birds of feather flock to gather" is considered for the setup of the network (McPherson et al. 2001). More precisely, the closer are the attributes Φ_i, Φ_j of the individuals i and j the larger is the probability of these two agents to be connected. Thus, similarity attachment is implemented by assuming that the probability of connecting individual i and j is proportional to the similarity of their attributes. Similarity attachment is often referred to as homophily.

Alternatively to similarity attachment individuals might be attracted by certain elements of the attributes of an agent, for example language, wealth or social status. In the case where very few elements or even a single element of the attributes are decisive for the formation of connection between agents the network is constructed on the base of preferential attachments. It is based on the attractiveness of an agent measured by the strength of expression of the dominant attributes. In this case the probability that agent i is connected with 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).[11]

[11] 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.

Since the measurement of preferential or similarity attachments is based on correlation its value is 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 modularity[12] (Newman and Girvan 2004) are other topological properties of social networks that are also helpful for describing characteristics that influence the relationship between agents. However, centrality focuses on the macro-level and modularity at the meso-level of a social network while our approach is at the micro level, i.e. agents take decisions based upon the structure and state of their neighborhood. For this reason centrality and modularity are not considered for our analysis.

iii) Small world

The small-world effect has been observed and studied in a large number of different real networks (Currarini et al. 2015). It can be characterized by two salient properties. Firstly, in most social network agent i is directly connected with agent j, i.e., the path between them is short and normally does not require the intermediation of other agents. Secondly, social network are highly clustered, i.e., agents form close-knit communities that are only loosely connected with other communities. This property measures to which extent the neighborhood of agent i, $N(i)$ forms a complete network and is known as clustering or local cohesiveness. Local clustering is denoted by the term τ_i with $0 \leq \tau_i \leq 1$. For instance the extent to which agent's i friends are friends with one another is one interpretation of cohesiveness. Thus, if $\tau_i = 1$ all neighbors of agent i are connected with each other. Likewise we can define the degree of local cohesiveness of all compliers in the neighborhood of agent i by τ_{c_i} with $0 \leq \tau_{c_i} \leq 1$. It measures to which extent compliers that form part of $N_C(i)$ are connected among each other. To simplify the wording we sometimes refer to it as the "club of compliers". Alternatively to the measurement of cohesiveness at the level of a node or agent it can also be

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

measured at the level of the network. At this scale we define transitivity or average local cohesiveness τ as the average value of local cohesiveness, i.e., $\tau = \frac{1}{n}\sum_{i}^{n}\tau_i$.

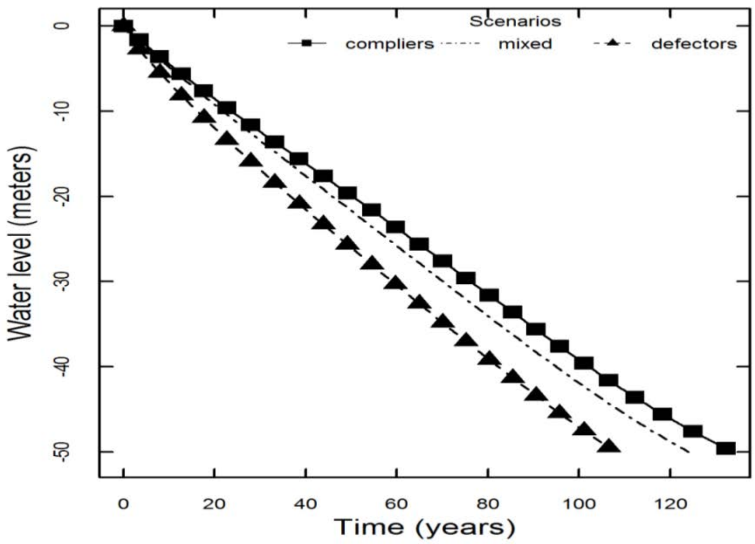
Agents that belong to one community but also connect two another one may act as a bridge between the two communities. If the different communities are only loosely connected the flow of information might be slow or the capacity to reach consensus might be limited. For this purpose (Newman and Girvan 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 upon 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 package igraph of R. Within this programming environment we incorporated the agents' strategy-choice-rules based on the evolutionary-game theoretic approach. Likewise, we incorporated resource demand functions in this programming environment so that the agents can evaluate the utility of 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 the appendix A (Methodological and Technical Aspects of the Implementation of the Social Network).

6. A numerical analysis based on the case groundwater extraction

The social-biophysical system defined by the equations (1) - (6) form the basis for the agents' strategy choice within the social network $N(A,L)$ that is formed by 7500 agents. All considered networks 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 that 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 the case of groundwater extraction for irrigation of agricultural land, more precisely on the aquifer Western La Mancha (Spain). The two resource demand functions were determined by a mathematical programming model that was programmed in GAMS (General Algebraic Modeling System). More details of this part of this model are provided in appendix B (Numerical Analysis and Specification of the Employed Functions).

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 changes her strategies over time. In this case there is no interaction between agents, i.e. there are no network effects. For the analysis of the evolution of the water table of the aquifer the social-biophysical system is based on the equations (1) - (6) with $\omega = 0$. For an initial depth of the water table of 0 m and the hypothetical lifetime of the well of 135 years, the drop of the water tables is presented in Figure 1.



It shows that the water table declines constantly, 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 in 106 years. Finally, if the population of agents consists at least for some period of time of compliers and defectors (mixed case) the aquifer would be depleted some times 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. For both cases it is always optimal to decrease the water table constantly until whatever comes first, either the depth of the well is reached or the economic lifetime of the well.

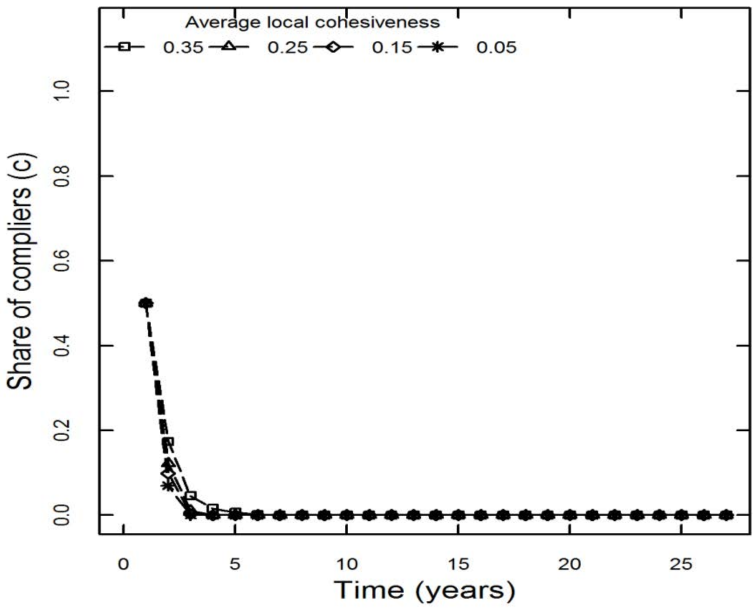
The estimated marginal benefits and the calculated extraction cost of water (appendix B) explain why both types of agents extract up to the depth of the well. Once the depth of the water well has been reached the current social norm cannot be maintained since the natural recharge is not sufficient to satisfy the demand of the agents even if all agents were compliers.[13] Thus, the members of the social network need to agree upon a regime shift and stipulate a new social norm that allows meeting supply and demand once the aquifer is 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., at a level of water table above the depth of the well. For our analysis, however, these considerations are not of real importance since we study social punishment and the factors that influence the agent's decision to comply or not with the norm. The factors we consider are related with the structure and state of the social network, and with the agent's strategy but not with the formulation of the underlying social norm. In this respect the result of our study are also valid if the defined social norm were redefined.

6.1 Cooperation vs. Non-cooperation

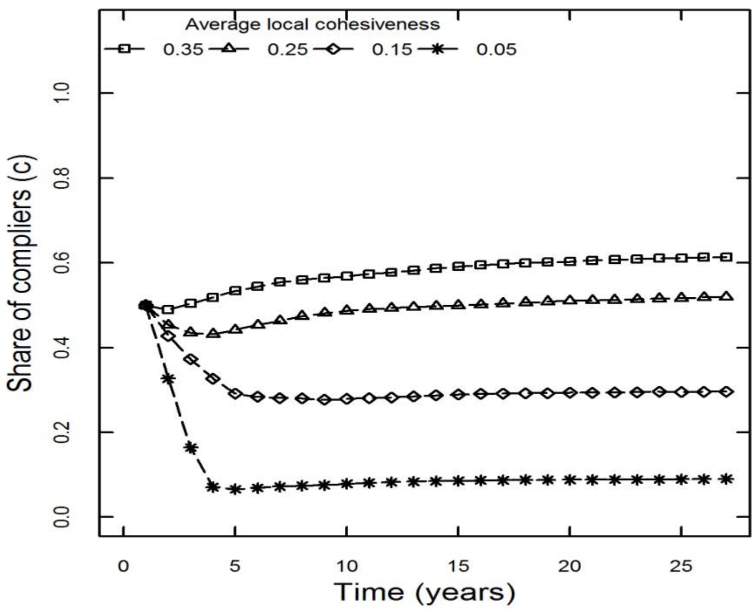
Given the specification of the social-biophysical system (equations (1) - (6)), Figures 2a) - 2d) show the evolution of the share of compliers c and defectors over time for different initial values of the share of compliers $\hat{c}$, the initial depth of the water table $s(0)$ and different degree of 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) : $\hat{c} = 0.65, s(0) = 15$; Figure 2d): $\hat{c} = 0.65, s(0) = 40$.

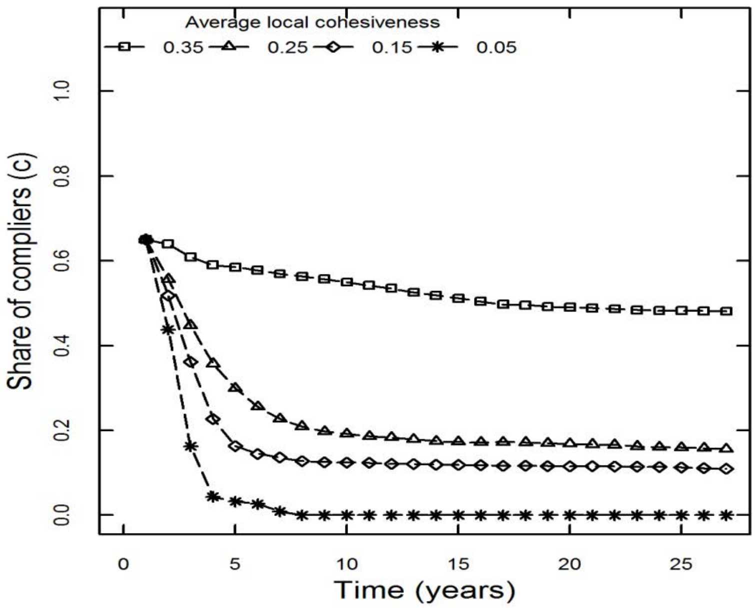
[13] The water table is constantly decreasing over the entire planning horizon even if all agents were compliers. This implies that the natural recharge is always less than the agents' demand. In other words equation (9) in general terms or equation (18) of the appendix B for the case of an aquifer cannot be met.

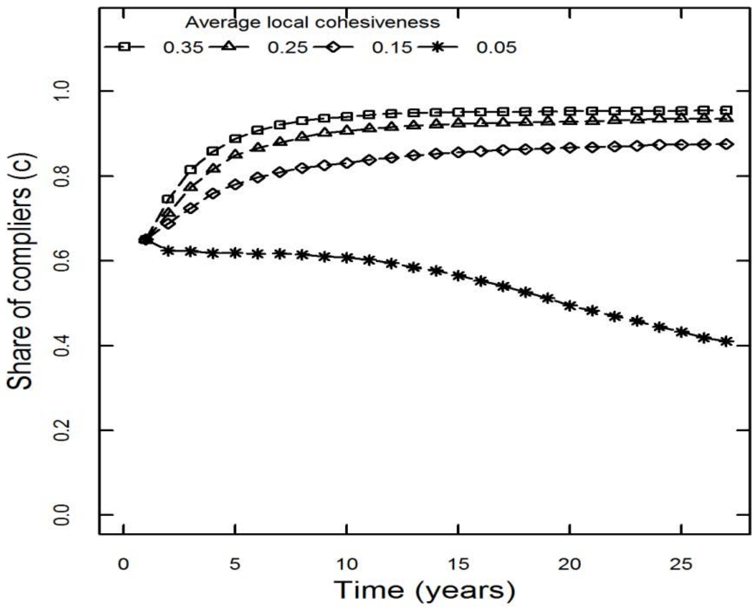


Average local cohesiveness
0.35
0.25
0.15
0.05
Share of compliers (c)
Time (years)



Average local cohesiveness
0.35
0.25
0.15
0.05
Share of compliers (c)
Time (years)





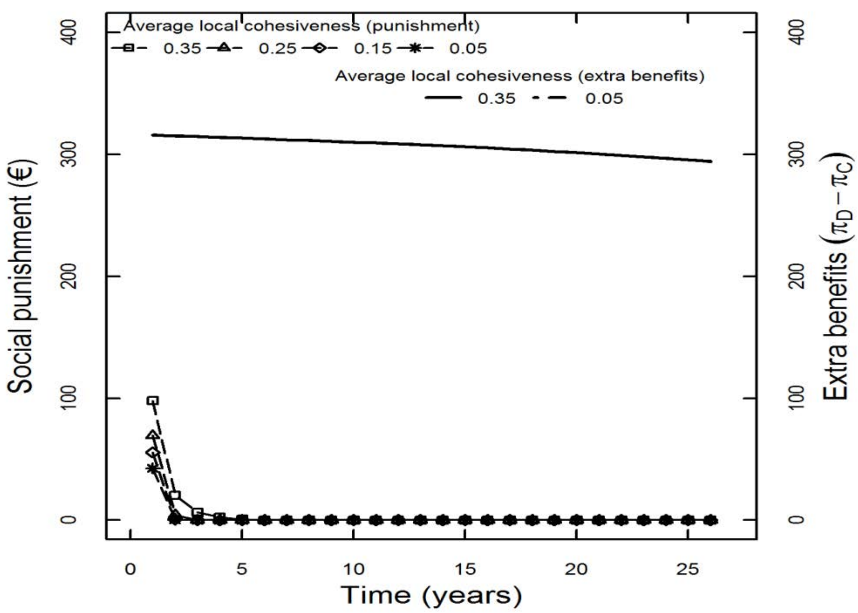
For an initial value of the share of compliers of c = 0.5 Figure 2a) show that even higher values of average local cohesiveness cannot detain the decrease in the share of compliers in the network if the initial depth of water is 15 m. The relatively small scarcity of groundwater leads to ineffective social punishment of defectors so that all compliers abandon their current strategy and become defectors within 5 years. If the initial water table is 40 m only higher values of average local cohesiveness allow maintaining $(\tau = 0.25)$ or increasing $(\tau = 0.35)$ the values of compliers of the network over time (Figure 2b)). In other words provided that groundwater is sufficiently scarce, average local cohesiveness allows building up sufficient social pressure so that compliers maintain their current strategy. If the initial value of the share of compliers is 0.65, Figure 2c) unveil that most compliers are likely to abandon their current strategy as in Figure 2a), however to a lower degree. Only if the average local cohesiveness is 0.35 some compliers are likely to change form compliance to non-compliance. A reversed result is obtained for Figure 2d) where the scarcity of groundwater and values of local cohesiveness above 0.05 lead to sufficiently high social pressure so that the number of compliers increases over time. Only very weak average local cohesiveness $\tau = 0.05$ is not sufficient for building up the necessary social pressure 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 are always a certain but small number of defectors that are not at all or hardly exposed to social pressure. In the case where the defectors neighborhood consists mainly or exclusively of other defectors the social pressure is very small or even does not exist at all. In other words defectors can survive if they live in a fairly isolated community where compliers are absent. Figures C1a) - C1d) of the appendix C (Evolution of Social Pressure) illustrate this phenomena. This observation is analogous to a finding in the non-cooperative game literature where (Bramoullé 2007) observed that agents have incentive to anti-coordinate if they are embedded in a bipartite network. Although these findings are the obtained in very distinct frameworks the underlying force in both cases is heterogeneity of the social network that leads to segregation. These 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 at the macro level)

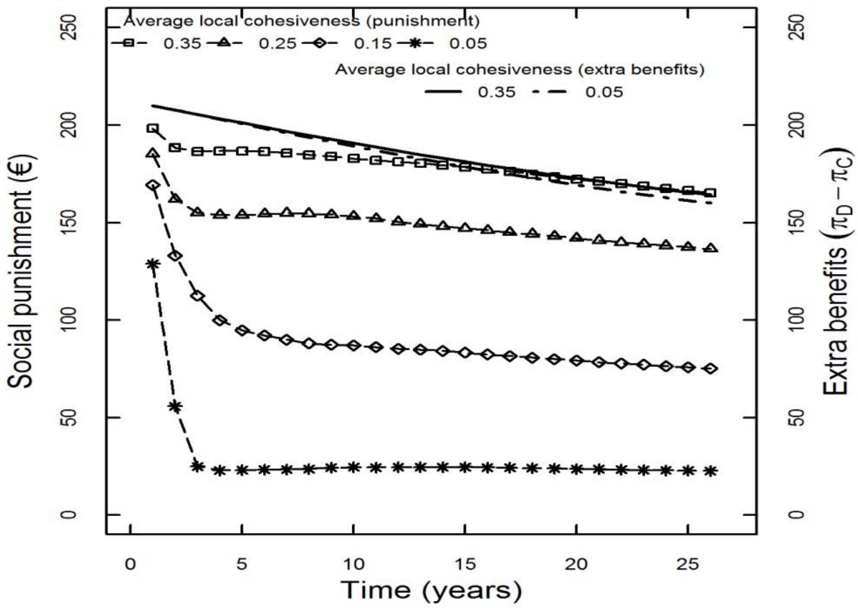
Figures 2a) -2d) show that the resource can only be managed in a sustainable way if the initial number of compliers in the network exceeds the "critical mass". The value of the "critical mass" depends on the strength of average local cohesiveness of the network and the depth of the water table. The share of compliers can be offset within limits by these two factors. Most likely an all-complier equilibrium does not emerge since isolated groups of defectors may evolve that are hardly exposed to social pressure.

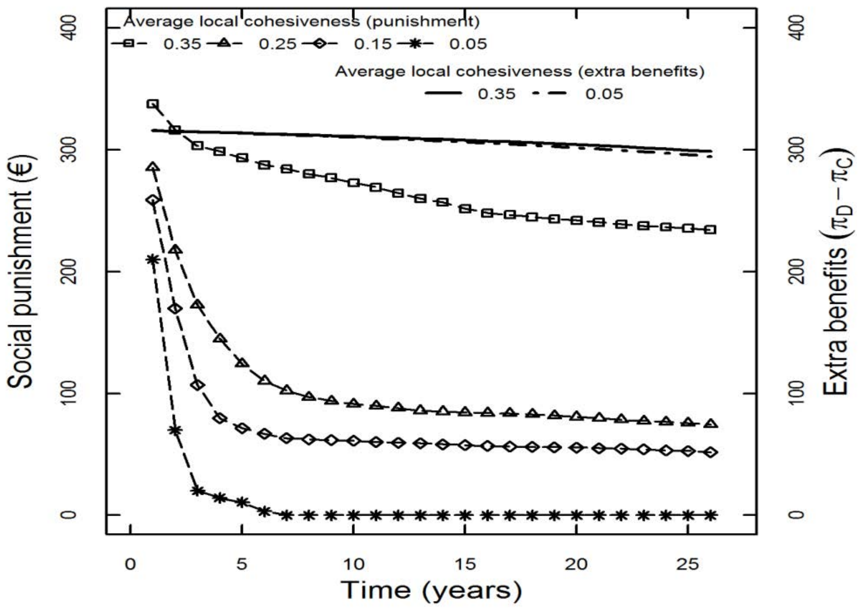
A fundamental element for establishing cooperation is the excise of social pressure on defectors. Figure 3a) – 3d) shows the evolution of social punishment $\omega(\cdot)\left(\pi^D - \pi^C\right)$ for different initial values of the share of compliers $\hat{c}$, the initial depth of the water table $s(0)$ and different degree of average local cohesiveness of the social network τ_c. Likewise, they show the evolution of the defector's extra benefits $\left(\pi^D - \pi^C\right)$ for a average local cohesiveness of 0.35 and 0.05.[14]

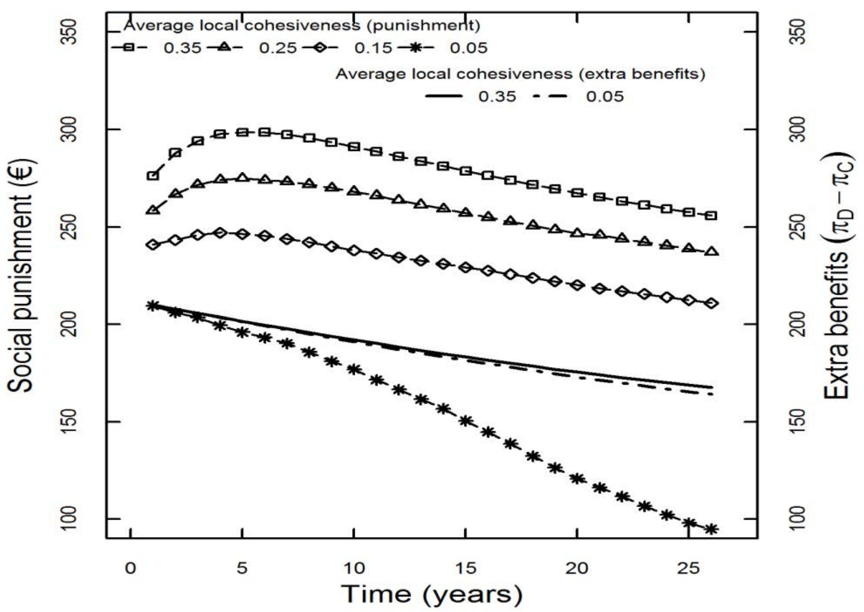
Figures 3a) – 3d): Evolution of social punishment for different degrees of local cohesiveness with $\tau =$ 0.05, 0.15, 0.25 and 0.35. Figure 3a): $\hat{c} = 0.5,\ s(0) = 15$; Figure 3b): $\hat{c} = 0.5,\ s(0) = 40$; Figure 3c) : $\hat{c} = 0.65,\ s(0) = 15$; Figure 3d): $\hat{c} = 0.65,\ s(0) = 40$.



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


Average local cohesiveness (punishment)
0.35 0.25 0.15 0.05
Average local cohesiveness (extra benefits)
0.35 0.05
Social punishment (€)
Extra benefits $(\pi_D - \pi_C)$
Time (years)


Average local cohesiveness (punishment)
0.35 0.25 0.15 0.05
Average local cohesiveness (extra benefits)
0.35 0.05
Social punishment (€)
Extra benefits $(\pi_D - \pi_C)$
Time (years)



Figures 3a) - 3d) demonstrate a qualitative similar pattern as Figures 2a) -2d) For an initial value of the share of compliers of $\hat{c}$ = 0.5 Figure 3a) shows that social punishment breaks down after 3 -4 years independent of the level of average local cohesiveness of the network if the initial depth of the water table is 15 m. Moreover, the defector's extra benefits for both levels of cohesiveness are always superior to social punishment so that defectors have never incentives to abandon their current strategy. If the initial water table is 40 m instead of 15m, only higher values of average local cohesiveness allow deterring initially sharp decreases in social punishment and translate it into an overall moderate decrease (Figure 3b)). Moreover, only in the case of $\tau =$ 0.35 defectors have incentives to change their strategy after approximately 15 years. In other words if groundwater is sufficiently scarce, sufficient social punishment can be maintained if it builds upon strong average local cohesiveness. For an initial value of $c_i = 0.65$ and a depth of the water table of 15 m, Figure 3c) shows that social punishment decreases sharply with time for low and medium values of average local cohesiveness and to a lower extent for the highest value of average local cohesiveness. Further only with average local cohesiveness $\tau = 0.35$ defectors are willing to change their strategy during the initial years. Thereafter they prefer the strategy of non-compliance. If the water table has dropped down to 40 m (Figure 3d)) medium and high values of average local cohesiveness allow maintaining social punishment while low

cohesiveness leads to a rapid decrease in social punishment. Moreover, defectors are likely to adopt the strategy of compliance if average local cohesiveness is larger than 0.05. These results give rise to the following observation

Observation 6: (social punishment and compliance at the macro level)
Figures 3a) -3d) show that only if the initial number of compliers in the network is sufficiently high, the remaining stock is low and average local cohesiveness of the network is relatively high, social punishment is sufficiently strong so that defectors change their strategy from non-compliance to compliance.

Moreover Figure 3a) - 3d) provide information about the concrete monetary value of social pressure at 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 after 3 years. Comparing the level of social punishment between Figure 3a) with Figure 3b) for the same degree of average local cohesiveness offers information about the monetary value of a decrease in the water table from 15 to 40 m. It shows for example that in year 10 the decrease in the water table excise social punishment equivalent to 24.54 € given an average local cohesiveness of 0.05. Similarly an increase in average local cohesiveness by 0.1 in year 10 intensifies social punishment by 87.05 €. Thus, the comparison between Figures 3a) and 3b) and between 3c) and 3d) allows determining the monetary value of social punishment attributable to a change in the water table. Likewise, the distance between the different trajectories of the social punishment in each of the four figures allows defining the monetary value of social punishment attributable to a change in the degree of average local cohesiveness.

6.2 The share of compliers as a catalyst for a sustainable management

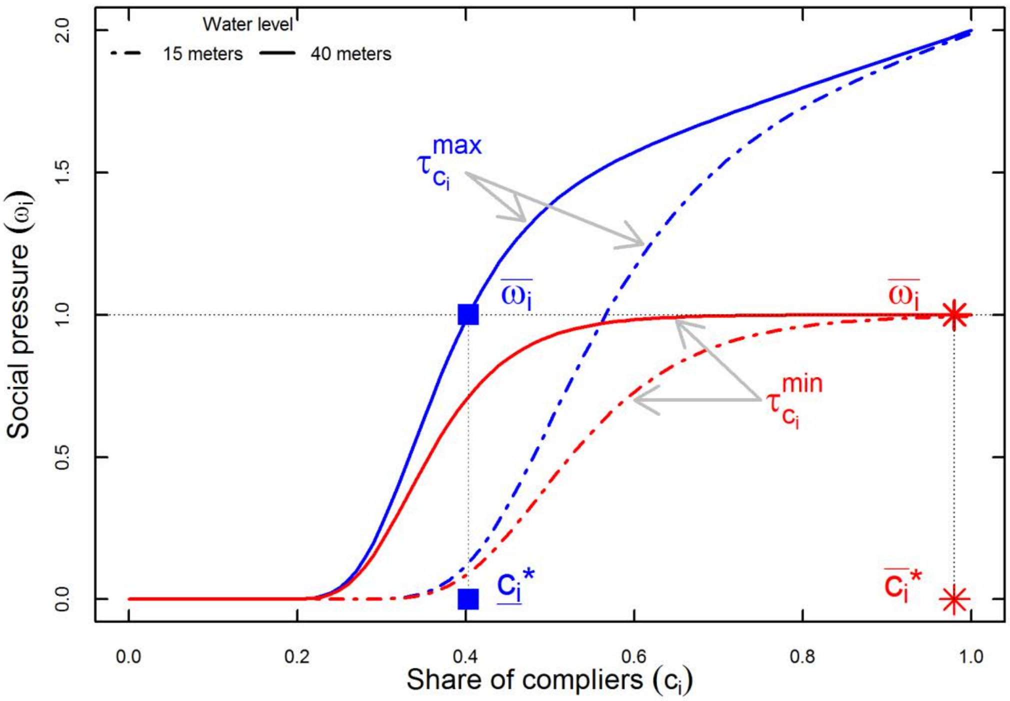
Figures 2a) – 3d) have underlined the importance of the depth of the water table, local cohesiveness and the share of compliers for a sustainable and socially efficient management of the resource. For the choice of the values of local cohesiveness, however, one has to take to into account that the share of complier conditions the maximal magnitude of local cohesiveness of compliers (club of compliers). By definition the less compliers there are in the neighborhood the lower is the maximum value of local cohesiveness of compliers $\tau_{c_i}^{\max}$ since the set of compliers in the neighborhood is a subset of the set of neighbors – see appendix A (Methodological and

Technical Aspects of the Implementation of the Social Network) for more details. For this reason exists a functional relationship between the share of compliers in the neighborhood and the maximum local cohesiveness of compliers that can be achieved. The maximal value of local cohesiveness of compliers is always lower than the corresponding share of compliers. For instance, for a share of compliers of 0.75 (0.5), the maximal local cohesiveness of compliers is 0.562 (0.25).

Figures 2a) – 3d) showed in particular that initial values of the share of compliers below 0.5 foreclose a future increase in the number of complier for most values of the other driving factors whereas initial values of the share of compliers above 0.65 facilitate a future increase in the number of compliers. This observation reflects the fact an increasing number of agents adhere to the social norm the more agents have done so before. It echoes the idea that network effects (local cohesiveness, share of compliers) and stock effect (depth of the water table) shape the individual's incentives of the member of the network. In other words compliers choose to become a complier conditional on other agent's choice to adhere to the social norm.

For the considered values of the average local cohesiveness and the depth of the water table the band width of the initial share of compliers between 0.5 and 0.65 defines the critical mass for a negative or positive evolution of the number of compliers respectively. These critical mass values can be also read off in more general form of the social pressure function as defined in equation (20) of the appendix B (Numerical Analysis and Specification of the Employed Functions). For the sake of brevity of the article we employ in the main text only a graphical presentation of the social pressure function and leave the mathematical details for the appendix B.

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



If social pressure is equal to one $\bar{\omega}_i$, we have seen that agents have no incentive to change their strategy. If the social pressure is below one the defector's utility is positive and consequently compliers are likely to change their strategy to non-compliance. If the social pressure is above one defectors are likely to change their strategy to compliance. The more social pressure differs from one the more the agent is likely to switch from her current to the alternative strategy. Thus, a social pressure of 1 allows determining the critical mass c_i^{crit} of the share of compliers. The minimal required share of compliers that leads to a positive evolution is given by the intersection of the social pressure function with the highest value of the stock ($s = 40$ in Figure 4) and the maximum value of local cohesiveness $\left(\tau_{c_i}^{\max}\right)$ with the straight line that presents the social pressure of 1. The minimal required share of compliers is denoted in Figure 4 by point $\underline{c}_i$. Likewise, the maximal required share of compliers that guarantees its positive evolution is given by the intersection of the social pressure function with the lowest value of the stock ($s = 15$ in Figure 4) and the lowest value of local cohesiveness $\left(\tau_{c_i} = 0\right)$ with the straight line that presents the social pressure of 1. The maximal required share of compliers is indicated by point by $\bar{c}_i$ 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 $\underline{c}_i$ and it will always be positive if the initial number of compliers is larger than $\overline{c}_i$. The two values $\underline{c}_i$ and $\overline{c}_i$ are limiting values of the critical mass, i.e., $c_i^{crit} \in [\underline{c}_i, \overline{c}_i]$. Thus, if we consider initially the least favorable conditions for social pressure (good state of the resource and no local cohesiveness) the critical mass for a positive evolution of the number of compliers is equal to $\overline{c}_i$. 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. It will be equal to $\underline{c}_i$ once the most favorable conditions for social pressure are reached. If the initial depth of the water table were known and immutable $(s = 40 \text{ or } s = 15)$ the interval $[\underline{c}_i, \overline{c}_i]$ would be given by the vertical distance between the two continuous or two discontinuous lines evaluated at $\omega = 1$. It reflects the influence of the strength of local cohesiveness on the evolution of the critical mass of compliers. Likewise, the vertical distance between the continuous and discontinuous line given the local cohesiveness $\tau_{c_i} = 0$ or $\tau_{c_i}^{\max}$ indicates the influence of the depth of the water table on the interval $[\underline{c}_i, \overline{c}_i]$.

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

In particular Figure 4 shows that a critical mass of compliers is necessary for a sustainable and efficient management of the resource, however it is not sufficient. The population dynamics itself is important but need to be accompanied by the dynamics of the network and the dynamics 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 7: (critical mass of compliers and resource and network effects)

Figure 4 shows that a sufficiently high share of compliers is necessary but not sufficient for the sustainable management of the resource

6.3 Social punishment and the social network characteristics at the micro level

Our previous analysis focused on the overall structure of the network (macro perspective). For the remaining part of the analysis we concentrate on the structure of agent's i neighborhood (micro perspective).

As far as the question of an network-equilibrium is concerned we calculate the individual tax or subsidy θ_i that would bring all agents to be indifferent between the choices of the two strategies, i.e., $p_i = 0, \forall i$ with $\bar{\varpi}_i = 1$.[15] As mentioned above the tax itself is not of great interest but its definition allows determining the monetary value of the structural elements of social punishment for a particular state of the network. Since the tax corresponds to the missing/excessive social punishment that supports the network-equilibrium we can calculate monetary value of the structural elements of social punishment as the complement of the tax at the level of agent i. Based on the equations (7), (8) and (14) we determine the tax or subsidy that eliminates the agent's incentive to change its current strategy. The tax or subsidy is determined by the solution of the following equation

$$U_i^D - \theta_i - U^C = \pi^D - \omega_i\left(s, c_i, \tau_{c_i}\right)\left(\pi^D - \pi^C\right) - \theta_i - \pi^C = \left(1 - \bar{\omega}_i\right)\left(\pi^D - \pi^C\right) \quad (17)$$

with respect to the three unknown s, c_i, τ_{c_i}. The plane of the three-dimensional Figure 5a) shows the level curves of social punishment for different values of the share on compliers and local cohesiveness of compliers at time 0 given a water table depth of 15 m. The defectors' extra benefits, $\pi^D - \pi^C$, amount to 316.36 € and are presented by a bold line. These extra benefits are given by a straight line since for a given moment in time they depend only on s but not on c_i and τ_{c_i}. If social punishment is below the bold line the complier's incentives, given by the defector's extra benefit $\pi^D - \pi^C$, to change her current strategy are not sufficiently offset by social punishment ($\omega_i < 1$) so that the imposition of a tax $\left(1 - \omega_i\right)\left(\pi^D - \pi^C\right)$ is needed to offset the agent's incentive to

[15] Alternatively, we could calculate the tax or subsidy θ_i that establishes an equilibrium defined by equation (10) where it holds that $\bar{\varpi}_i \neq 1$. However, to facilitate the graphical presentation and interpretation of the equilibrium analysis we focus on the case were $\bar{\varpi}_i = 1$

abandon the complier's strategy. However, if the agent is a defector and the extra benefits are higher than the social punishment the agent maintains her current strategy. A social punishment that is above the bold line is so strong that defectors want to abandon their current strategy in order to avoid the excessive social punishment $(\omega_i > 1)$. Thus, a subsidy given by $(\omega_i - 1)(\pi^D - \pi^C)$ is needed for establishing a network equilibrium. The payment of the subsidy avoids that a defector wants to change her strategy. The difference between the three-dimensional plane of the monetary value of social punishment and the defectors extra benefits $\pi^D - \pi^C$ presents the tax/subsidy. If this difference is positive it is a tax and if it is negative it is a subsidy. The sum of social punishment and the tax/subsidy eliminates the defector's extra benefits as expressed in equation (17). For the considered case of $\overline{\omega}_i = 1$ the extra benefits are eliminated completely.[16]

As mentioned above the number of compliers in the neighborhood of agent i is another important factor for the determination of social punishment. In addition to the Figures 3a) – 3d) that allow determining the monetary value of average local cohesiveness of compliers and of the depth of the water table at the macro level, Figures 5a) - 5b) provide information about the economic value of the share of compliers in the neighborhood of agent i (micro level). As explained above for their interpretation one has to keep in mind that the value of the share of compliers introduces an upper limit of local cohesiveness of compliers. The higher is the share of compliers the higher is the maximum value of local cohesiveness.

To keep the presentation of the results in the Figures 5a) – 5b) well-ordered we only mark the level-curve which value is equal to 0. The distance between the level curves indicates a decrease or increase in social punishment by 80 €. The level curves to the left (right) of the zero-level indicate a decrease (increase) in social punishment by 80 €. The form of the level curves indicates that the substitution elasticity between the share of compliers and 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

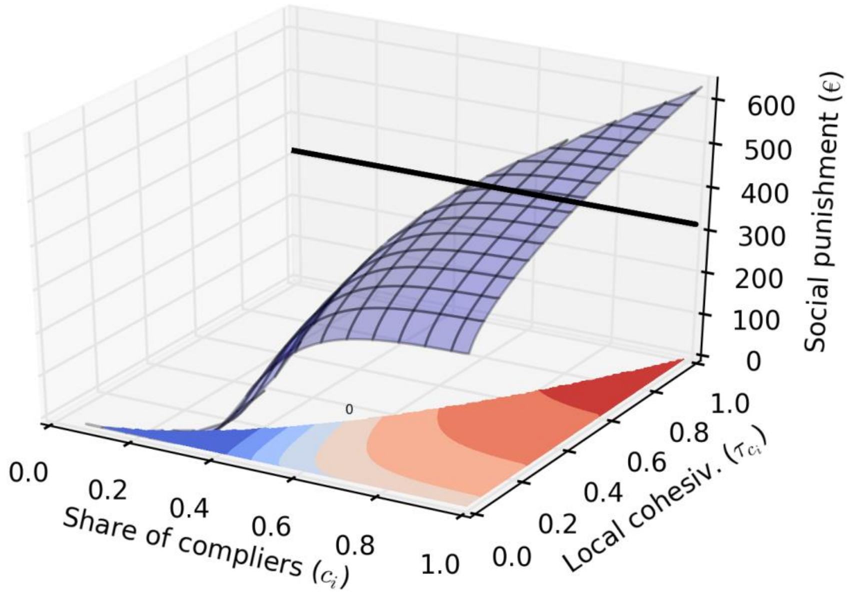
[16] In the case where $\overline{\omega}_i < 1$, the solution of equation (17) could be present in the same way as in the Figures 5a) – 5d). Only the missing or excessive social punishment would now be given by the difference between $\overline{\omega}_i\left(\pi^D - \pi^C\right)$ and the three dimensional plane of the tax/subsidy.

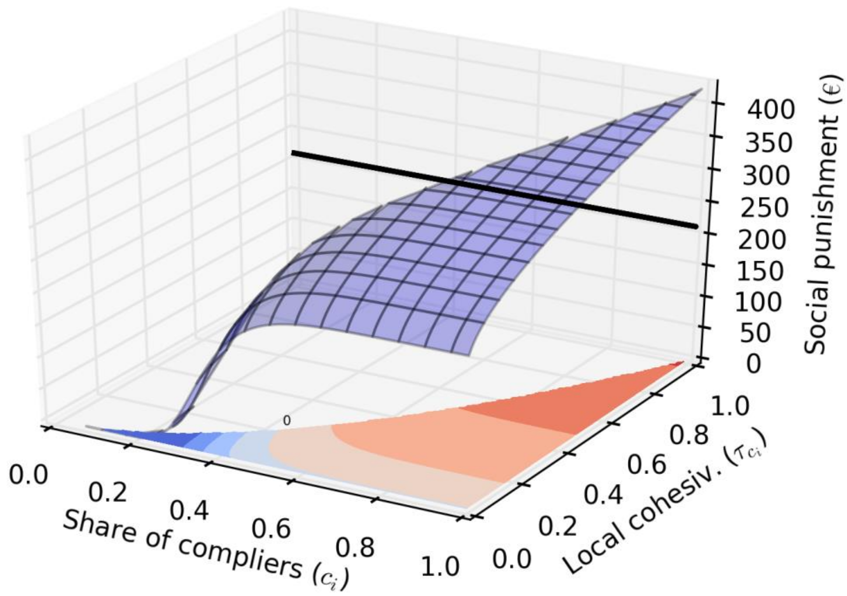
compliers both arguments of the social punishment can substitute each other. The level curves are not even spaced indicating that the greater the distance between the level curves the lower the effect of an increase in the share of compliers or local cohesiveness of compliers on the social punishment.

The marginal monetary value of local cohesiveness of compliers can be read off by the slope of the three-dimensional plane of social punishment. It corresponds to the partial derivatives of social punishment with respect to the share of compliers or local cohesiveness, as defined in the theoretical part of the study in equation (15). Figure 5a) shows that social punishment of agent i is equal to zero, and consequently the tax is equal to 316.36 € as long as the share of compliers is approximately less than 0.3. Once the share of compliers in the neighborhood of agent i has exceeded this critical value, social punishment increases and the tax/subsidy decreases. These increments gradually diminish especially once the share of compliers has reached approximately 0.7. The slope of the plane shows that the marginal value is close to zero if there are either hardly any, or many compliers. The highest marginal value is reached once the share of compliers has exceeded a critical value that is able to exercise sufficiently strong social punishment that alters the strategy choice of the defectors. Figure 5a) differs from Figure 5b) only by the fact that the depth of the water table is 40 m instead of 15 m. Thus the defector's extra benefit $\pi^D - \pi^C$ decrease from 316.36 € to 212.22 €. Figure 5b) shows that the solution of equation (17) is qualitatively identical to the one of Figure 5a). The difference between the extra benefits and the three-dimensional plane of the social punishment is less than in Figure 5a). The lower values of social punishment of agent i and of the tax/subsidy are the result of the decrease in the defector's extra benefits which in turn is the consequence of the decrease in the depth of the water table from 15 to 40 m. Moreover, Figure 5b) shows compared to Figure 5a) that the slope of the three dimensional plane of social punishment is less pronounced, and the necessary critical value to set off the chain reaction of social compliance is lower.

Although both Figures illustrate the low probability of the existence of a network-equilibrium, one has to keep in mind that the number of compliers is important for the existence of a network-equilibrium. The larger the number of compliers is the less important is the location of the agent within the network. This is simply a result of the decrease in the overall social punishment in the network. Thus, the asymmetry of the social network and complexity of the links lose importance and the agents are more and more identical. Consequently, the likelihood of an equilibrium increases with the number of compliers in the network.

Figures 5a) – 5b): Figure 5a): social punishment as a function of the share of compliers c_i and local cohesiveness of compliers τ_{c_i} with $s(0)=15$; 5b): social punishment as a function of the share of compliers c_i and local cohesiveness of compliers τ_{c_i} with $s(0)=40$.





Figures 5a) – 5b) are the result of a snapshot at time 0 and as such they do not provide any information about the evolution of the social punishment over time. Figures 2a – 3d) show the evolution of the compliers and of social punishment over time. Thus, the only missing information for the determination of the social punishment over time is the

evolution of the defector's extra benefit. This information is presented by the Figures C2a) – C2d) in appendix C (Evolution of Social Pressure). The results of this discussion can be summarized in the following observation

Observation 8: (social punishment and network equilibrium at the micro level)

Figures 5a) -5b) show that the share of compliers in the neighborhood of agent i *and local cohesiveness are weak substitutes for magnitude of social punishment if the share of compliers is in the range of 0.3 – 0.7. Outside this range the substitutability of these two arguments tends to zero. The lower or higher is the share of compliers the more likely exists a network-equilibrium. It is given either by an all-defector or a nearly-all-complier network-equilibrium.*

Figures 5a) -5b) analyze the value of social punishment as a variation of the share on compliers and local cohesiveness. Thus, to complete the numerical analysis it remains to investigate the effect of the depth of the water table and the share of compliers on social pressure. The results of this analysis can be summarized in the following observation.

Observation 9: (substitutability between depth of the water table and the share of compliers at the micro level)

Figures D1) of the appendix shows that the depth of the water table and the share of compliers in the neighborhood are substitutes if the defector's extra utility is sufficiently large and tend to be complements otherwise.

For the argumentation of these results see the Appendix D (Social Pressure and the Dynamics of the Resource and the Population of Compliers).

7. Conclusions

The study defines a social norm that is based on the socially optimal management of a renewable natural resource owned by a community. It is obtained by the open loop solution of a dynamic game. On the contrary, the non-compliance of the social norm is linked with short-sighted behavior where agents maximize the net benefits of the current time period. Based on these two extraction strategies we define compliers (compliance of social norm) and defectors (non-compliance). Agents can revise their strategy within an evolutionary game-theoretic approach, i.e. the probability of a change from their current to the alternative strategy increases the higher are the perspective gains from the change. Although agents are free to choose their strategy we consider the case where compliers exercise social punishment that reduces the defectors' 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 to which extent network effects (share of compliers, local cohesiveness) and stock effects (resource) provide incentives for individual agents to comply with the social norm – in particular to what extent the compliance of a social norm is a self-enforcing process, and which are the necessary social and physical conditions to set off 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. Nevertheless, the study provides a measurement of the distance of the current state of the network to the network equilibrium. In the case that the number of compliers is not sufficient for supporting the socially optimal management of the resource the community may decide to realize a one-time payment to defectors that follow the social norm for the next time period. Provided that the number of additional compliers is sufficiently high the increase in social punishment exercised by the compliers allows maintaining or even augmenting the number of compliers which in turn supports a sustainable management of the resource.

Given the limitation for an analytical solution the study analyzes the case of the Western La Mancha Aquifer (Spain). The social network is formed by 7500 farmers. Given the economic conditions and the limited maximal depth of the aquifer there does not exist an economic equilibrium. The results show that a sufficiently high share of compliers is necessary for an efficient management of the resource but not sufficient. The magnitude of the critical mass of compliers depends on the dynamics of the resource and the network. The required initial number of compliers decreases with an increase in average local cohesiveness and decrease in the remaining stock, however, only to a certain degree. There exists a band width of the share of compliers where the resource can be managed in an efficient or inefficient way. The endpoints of the band width identify the initial number of compliers that either prevent or guarantee an efficient management of the resource. The later number is crucial for the determination of the one-time payment. The size of the band width depends on the size of the remaining stock and the strength of average local cohesiveness. Similar results are also obtained at the micro level, i.e., at the level of the neighborhood of agent i. If the critical mass of compliers is not reached initially, an all-defector-network-equilibrium is likely to emerge. However, in contrast with the previous literature the emergence of an all-complier-network-equilibrium is extremely unlikely since isolated communities of defectors may emerge that are immune to social punishment.

The results of this analysis help to understand the observed variety of strategies that coexist within a resource extracting community. Additional they identify targets for the formulation of policies that help to favor the sustainable management of natural resources.

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Appendix A

Methodological and Technical Aspects of the Implementation of the Social Network

As described in section "The social network" the S attributes of each individual (characteristics, attractiveness, fitness) 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 from 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 $\phi_s \in \mathbb{R}_{>0}$. The generation of the network 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 the higher is the probability that the resident is 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 underlying distribution of the agents' characteristics. With this procedure it also not likely that the initially selected agents accumulate more links compared with the later selected agents. Thus, it reduces the positive correlation between the agent's degree and her residence time in the network. Finally, attribute based generation process is also not based on a macro-level structure of the network like the degree. As such it does not hamper the design of the micro-level structure of the network and provides sufficient freedom for variations at the micro-level structure as sought by this study.

The network generation process based on preferential attachment is implemented by 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 $m \le n_0$ the number of agents to whom a newcomer j may connect 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, $0 \le t \le n - n_0$, an agent i already present in the network is selected with a uniform probability $P_i = \dfrac{1}{n_0 + t}$ that is independent of agent's i characteristics Φ_i. If the newcomer j is already linked with agent i, repeat step 3.

4.

With probability $P_i = \dfrac{\Phi_i}{\Phi_{max}}$ the newcomer j connects to agent i, where $\Phi_{max} = max\{\Phi_i\}_{i=1}^{n_0+t}$ denotes maximal value of the characteristics of all agents in the network $(\mathrm{t} < n)$. 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 variable X that results from

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

where u is randomly drawn number from the uniform distribution $Uni\left(0 < P_i \le 1\right)$. This method is commonly known as the inverse transform method and is comparable with a forge coin where the probability to show up head (1) is P_i and tail (0) $1-P_i$.

In case of rejection $\left(X=0\right)$, steps 3 and 4 are repeated. Likewise, steps 3 and 4 are repeated in case of acceptance in order 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 $\rho(\Phi) = Logn(\mu,\sigma)$ and its density function is given by $f(x) = \frac{1}{\sqrt{2\pi}\sigma x} e^{\frac{-(lnx-\mu)^2}{2\sigma^2}}$.

We further assume that $\mu = 0$, and thus the attribute distribution is characterized completely by the parameter σ. If σ is chosen such that it falls within the range of $1 < \sigma < 4$, the degree distribution follows a power-law distribution $P(k) \propto k^{-\gamma}$ where γ satisfy the inequality $2 < \gamma < 3$. If $\sigma = 0$, the network generation process leads to random network. If we have that $0 < \sigma < 1$, the degree sequences of the generated networks are close to the exponential distribution. If it holds that $\sigma > 4$, the generated networks are monopolistic. These types of networks are also called ``winner-takes-it-all'' networks. Within the admissible spectrum for power-law networks, i.e., $1 < \sigma < 4$, we specified the distribution function of the characteristics as $Logn\left(0,1.5\right)$. Moreover, the choice of the parameter m allows defining the network density, d, and the average degree of network, $\langle k \rangle$, since both properties depend on m. More precisely these properties are defined by $d = \frac{2(l_0 + m(n-n_0))}{n(n-1)}$ and $\langle k \rangle = \frac{2\left(l_0 + (n-n_0)m\right)}{n}$, where l_0 corresponds to the initial set of links at $t = 0$. If the initial network is complete, it holds that $l_0 = \frac{n_0(n_0-1)}{2}$. As we are assuming that all agents add links at a constant rate m, it holds that $d = \frac{2m}{n-1}$ and $\langle k \rangle = 2m$. 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.[17]

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 exit the network and/or links are newly formed or cut. Despite these simplifications, the generation 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 agents' degree), local cohesiveness, modularity (strength of division into subgroups) and hierarchical clustering are maintained. For the economic analysis null networks are important since they allow isolating the effects of specific meso- and micro-level topological characteristics on the agents' behavior.

Once the social network has been generated by the process described above directional rewiring (reorientation of existing links) is applied in order 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 larger the probability of agents i and j to be connected. The rule consists of the two following three steps:

---

[17] 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 replacing by defining $P_i = \frac{\Phi_i}{\Phi_{max}}$. It allows obtaining better computational performance while maintaining the qualitative properties of the previous approach.

1.

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

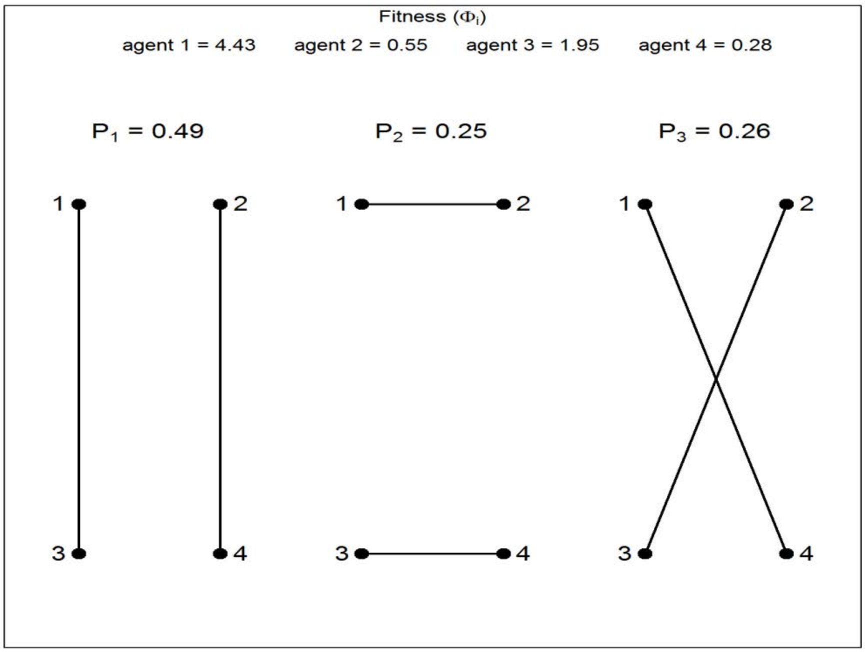
2.

The four agents associated with these two links are ordered with respect to their characteristics completely. 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 agent's degree. With probability P_q , the links are rewired in such a way that the new links connect the two agents that have the lowest characteristics and the two agents that have the highest characteristics. 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. It is given by $\left.\exp\left(-\sqrt{\left|\Phi_{i_q} - \Phi_{j_q}\right|}\right)\right|_{(i_q, j_q)\in C_q}$ and the probability of establishing the new link by $P_q = 1 - \frac{\left.\sum_{i_q, j_q} \exp\left(-\sqrt{\left|\Phi_{i_q} - \Phi_{j_q}\right|}\right)\right|_{(i_q, j_q)\in C_q}}{\sum_{i<j} \exp\left(-\sqrt{\left|\Phi_i - \Phi_j\right|}\right)}$. Since the objective of rewiring is connecting agent 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 agents with the lowest characteristics. In the case that one or both of these new links already exists in the network, step 2 is discarded and step 1 is repeated. Based on $\max P_q$ and the inverted transform method described above, it is decided whether the rewiring step is realized or not.

3.

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

Figure A1 Rewiring of links that reduces preferential attachment and increases 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 agent's degree that are connected by the i^{th} link. The measure lies in the range of $-1 \le r \le 1$, where 1 indicates the maximal assortativity. For random networks it follows that $r = 0$ when the generated networks are sufficiently large $(n \to \infty)$, since agents are placed at random.

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

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

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

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

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

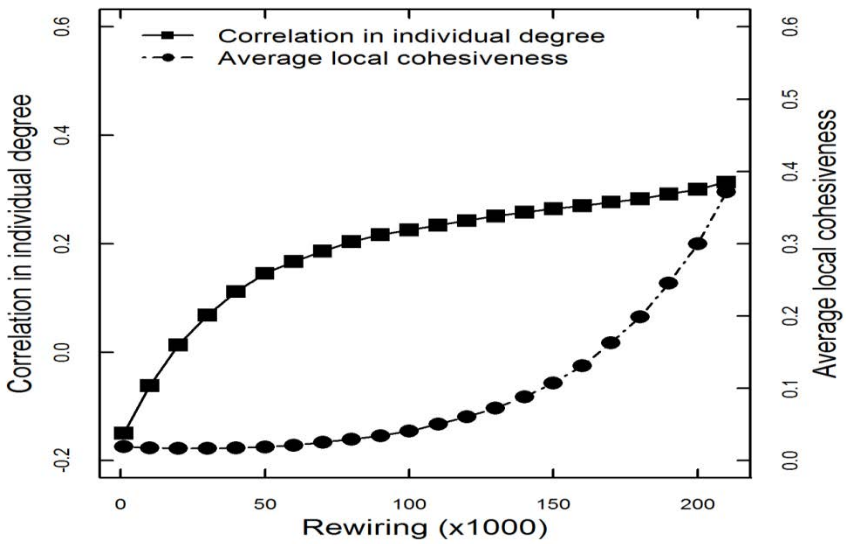
The upper value of local cohesiveness $\tau_{c_i}^{\max}$ can be approximated by

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

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 if given by 0.0625 (0.09, 0.25, 0.562).

Figure A2 shows how average cohesiveness and the type of attachment (from preferential to similar) changes as more and more agents are disconnected and reconnect (rewiring) such that the new connection increases the average local cohesiveness. It allows us to identify the interrelation between the different topological properties of the network. Figure A2 also illustrates that individual degree is positively related with average local cohesiveness, i.e., higher assortativity leads to an increase in 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 constitute a complete network. It is the basis for this study where we determine the effects of the structure and state of the network on the agent's decision to comply with the social norm or not.

Figure A2: The effects of rewiring on individual degree and average local cohesiveness



So far we have described the generation of the social network but not its initialization with respect to complier 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 1 year. Let us denote this results as $\hat{\omega}$. However, depending on the initial distribution of compliers and defectors within the network, the value of $\hat{\omega}$ may vary strongly. To evaluate the magnitude of this bias we used the Monte Carlo method and repeated $n-$times the calculations of $\hat{\omega}$. The variance of the $n-$times repeated calculations $\sigma_{\hat{\omega}}^{n}$ is employed for the determination of 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 $(1-\alpha)$.[18,19] 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 presented in this study with 100 different initial assignments. The presented results throughout the article are average values over the 100 repetitions.

[18] It would have been possible to evaluate the social pressure function in later years. However, the effect of the initial assignment dilute over the years. Thus, limiting the error term of the first year presents the stringent test.

[19] The formula for the calculation of the necessary simple size is given by $n=\frac{\left(1.96\ \sigma_{\hat{\omega}}^{n}\right)^{2}}{\varphi^{2}}$.

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

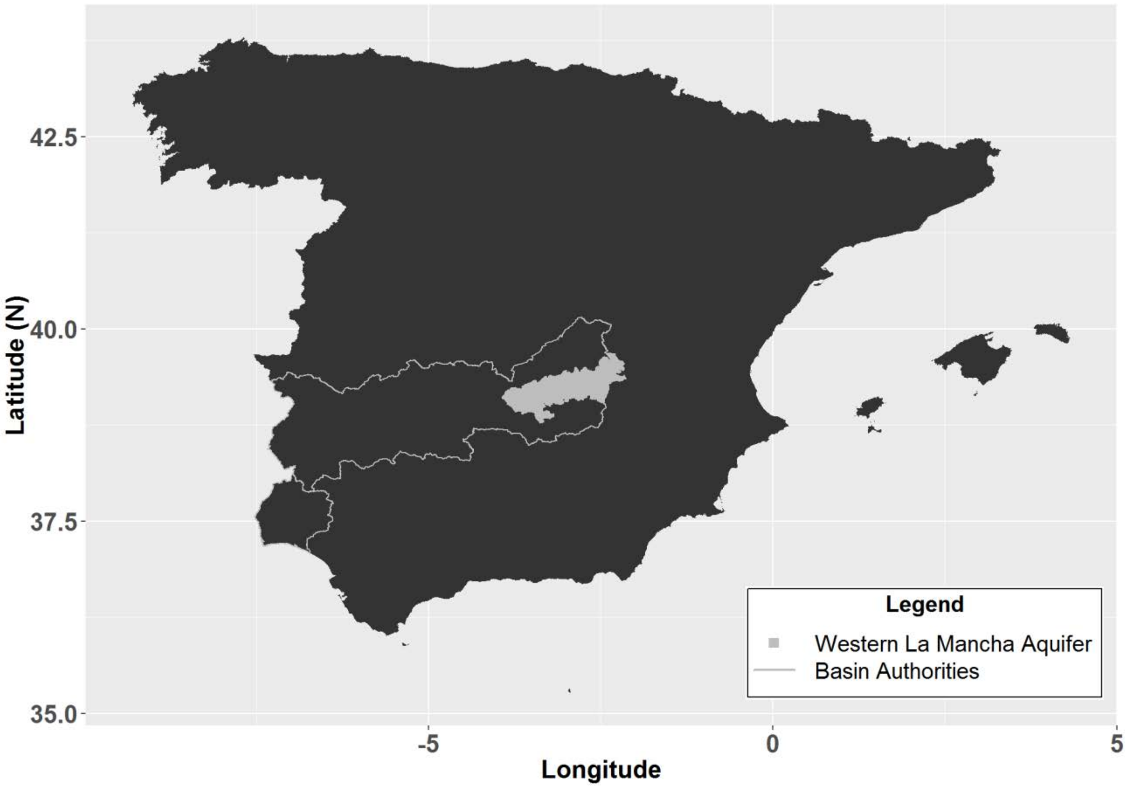
The differential equation $\dot{s} = g(s) - \sum_{i}^{cn} w_i^C - \sum_{cn+1}^{n} w_i^D$, was solved analytically for the case of pure strategies: all agents are compliers or all agents are defectors. However, for the case of mixed strategies an analytical solution cannot be provided because the share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

Appendix B

Numerical Analysis and Specification of the Employed Functions

As an example of high policy relevance we focus on the situation of the Western La Mancha Aquifer situated within the upper Guadiana basin which is located in the inland region of Castilla La Mancha, Spain and extends over 5000km^2 - see Figure B1. The constant overdraft of this aquifer has led to a variety of policy measures with the objective to curb the deterioration of this aquifer and to comply with the Water Framework Directive of the European Union (European Comission 2000, Blanco-Gutiérrez et al. 2011).

Figure B1: Geographical location of the Western La Mancha Aquifer



Hydrological model

We start out with the specification of the dynamics of the aquifer, $\dot{s}(\xi)=g\left(s(\xi)\right)-\sum_{i}^{cn} w_i^C\left(\xi\right)-\sum_{cn+1}^{n} w_i^D,\ s\left(\xi\right)=s_t$. For the case of an aquifer natural reproduction of the resource is independent of the stock and thus the term $g\left(s\left(\xi\right)\right)$ is equal to R that denotes natural recharge. 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 extracted water 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 water extraction. Moreover, a part of the extracted water for irrigation percolates back to 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 is now given by

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

Esteban and Albiac (2011) report that the cultivated land for agricultural production comprised 191400 ha in the year 2007. Esteban and Albiac (2010, 2011) calculated that the farmers' irrigation practices lead to a gross extraction of 1km^3 of water from the aquifer and an extension of the irrigated area by 62000 ha. As a consequence 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 1.000.000.000m^3/253400ha= 3946,3299131807 m^3/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 are caused by a total extraction of 3946,3299131807 m^3/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 2,66666m/29597474,34885525m^3 = 0.0000009009778m/ m^3. Although we downscaled the aquifer we kept the number of agents approximately identical. However, we had to adjust the size of the firm. 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=1420,678768m^3. This number links well with the reported rainfall of 415 mm/ha by (Martínez-Santos et al. 2008). In term of cubic meters it results in 10000m^2 times 0.415 m = 4150 m^3 /ha.

Water extraction costs

We calculated the extraction costs as 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 area of the Western La Mancha Aquifer the cost of the well given a lifetime of 25 years and a depth of 46.83m are 371€ per ha that is 7.94€ per lineal meter of the constructed well depth. Assuming an average price raise of 2003 of 4% p.a. over 10 years, the nominal costs per lineal meter for the year 2014 are 11.75 € per lineal meter. As reported by Llamas and Garrido (2007) the energy required to lift 1 m^3 of water by 1 meter requires 0,004 kWh. Given a price of 0.12 € per kWh the lifting costs per m^3 of water 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 farm types that characterize the variety of production systems and farm types in the area of the Western La Mancha Aquifer. Subject to economic, agronomic and policy constraints the authors calculate the farm net income for different water allocation schemes. In other words they calculate the best response of the farmer with respect to changes in the level of the allocated water per ha. for the coming agricultural campaign, i.e., the changes in other inputs than water or in the type of crop in order to maximize the farm net income to adjust for changes in the allocated water. The reported results by Varela-Ortega et al. allowed us to relate the maximal net farm income with respect to composite input as a function of the assigned water per ha, i.e. $\pi\left(x^*\left(w\right)\right)$. The optimal farm income and the assigned water 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 the farm net income and water consumption for the four different farm types. Unfortunately, the collected and presented data only reflects the upward sloping section of the farm net benefit function. Yet, the same authors report that prior to the implementation of water restriction at the beginning of the 21 century the economic optimum corresponded to an extraction of 4300 m^3 of water per ha and year. Adding this information in form of a decrease of the farm net benefit function beyond a consumption of 4300 m^3 allowed estimating the farm net benefits as a function of water consumption. Additionally, we incorporated the extraction costs of water. The function that best fitted the data was a quadratic function with an R^2 adjusted of 0.94. It is given by

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

(19)

Equation (19) is the specification of equation (1).

In the next step we need to obtain the solution of the dynamic optimization problem, detailed in equations (2) and (3). For this purpose we substitute the general resource dynamics $\dot{s}$ and the term $\pi\left(x^*\left(w,s\right)\right)$ in equations (2) and (3) by their specifications given in equations (18) and (19) respectively. Thereafter, the dynamic solution problem was solved numerically in GAMS. The compliers' and defectors' strategy differs by the length of their planning horizon. Compliers adhere to the social norm by having a farsighted perspective while defectors deviate from it by having only a planning horizon of 1 year. The choice of a planning horizon of 25 years is obviously debatably but this period of time coincides with the generational succession of the farm business and with the economic life time of the investment.[20]

The obtained data from the solution of the dynamic optimization model for different initial value of s_0 allowed to estimate the compliers' and defectors' water demand that maximizes theirs farm net benefits, $\mathrm{w}_i^C\left(t,T,s(t)\right)$ and $\mathrm{w}_i^D\left(t,1,s(t)\right)$, as a function of the depth of the water table. Likewise, the optimal water demand for each strategy for different initial value of s_0 allowed us to calculate the optimal farm net benefits $\pi^C\left(x_i^*\left(w_i^C(\cdot),s(t)\right),\mathrm{w}_i^C(\cdot),s(t)\right)$ and $\pi^D\left(x_i^*\left(w_i^D(\cdot),s(t)\right),\mathrm{w}_i^D(\cdot),s(t)\right)$ as a function of the depth of the water table.[21] The results both estimations are presented in Table A1.

	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)

[20] 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 the investment.

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

		$- 0,81859727\ s(t)^2 + 0,023769413\ s(t)^3 - 0,000212445\ s(t)^4$

Table B1: Water demand and optimal farm net benefits as a function of the depth of the water table.

Although the compliers maximize over 25 years all agents – compliers and defectors - may change her strategy at each moment of time. For this purpose every agent compares the utility of her current of strategy with the utility of the alternative strategy. The probability of a change in strategies is given by the equations (7) and (8) and takes into account – among elements – the optimal farm net benefits π^C and π^D.

Cooperative behavior and groundwater management

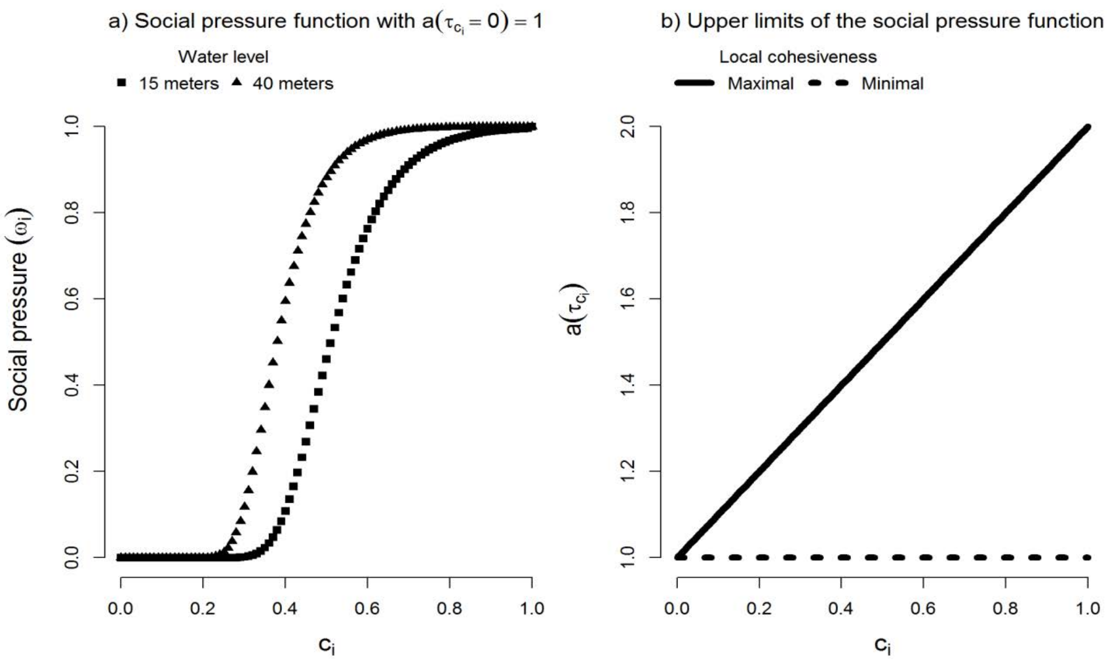
As mentioned above social pressure exercised by the compliers is an informal mechanism to support the enforcement of the social norm. It allows compliers to retaliate for the defectors' higher extractions rate of the groundwater. These abstractions, lead as a result of the faster decrease of the water table to higher pumping and scarcity costs for all agents.

After having specified the optimal farm net benefits 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 by 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 that correspond respectively to the upper asymptote, the displacement along the origin and the growth rate of the function. 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 by the functions $a\left(\tau_{c_i}\right)$ and $g(s)$ respectively. Hence the modified Gompertz function depends on the characteristics of the neighborhood with respect to its share of compliers and its cohesiveness, and the depth of the water table and is given by

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

Figure B1a) shows its form as a function of the share of compliers for a given depth of the water table of 15 m and 40 m and $a\left(\tau_{c_i} = 0\right)$=1. Figure B1b1) illustrates its scaling factor that determines the upper limit of the social pressure function. Higher values of local cohesiveness lead to a higher values of the upper limit (asymptote) but the shape of the social pressure function stays unchanged. The specification of the functions and parameters is explained in detail below.

Figure B1 a) – b): a) Social pressure as a function of the share of compliers for given depth of the water table of 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's i neighborhood $\left(c_i\right)$, the stock levels $\left(s\right)$

, the effectiveness of sanctioning (d) and the number of compliers in agent's neighborhood who are connected $\left(\tau_{c_i}\right)$.

Compliers are aware about the evolution of the stock and they 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 on defectors as before. 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 $a\left(\tau_{c_i}\right)$ defines the upper asymptote it reflects the maximal social pressure that compliers can exercise. Provided that agent i is a defector social pressure on agent i increases if the compliers of the neighborhood of agent i coordinate their action against agent i. Thus, the cohesiveness of the compliers of the neighborhood of agent i is a precondition for their cooperation and it likely increases social pressure of defectors. For this reason we introduced the function $a\left(\tau_{c_i}\right)$ that measures to which extent compliers in the neighborhood of agent i are connected among each other. The specification of the cohesiveness function $a\left(\tau_{c_i}\right)$ is given by

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

If all neighbors of agent i were compliers $c_i = 1$ and connected among 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. $\omega \leq 2\left(\pi^D - \pi^C\right)$.

Obviously the choice of the parameters and the specification of the social pressure function ω is debatable and we cannot defend its choice on grounds of the literature or realized experiments. However, the choice of limiting ω to be smaller or equal to two seems reasonable on grounds 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 not only if all neighbors of agent i are compliers that are perfectly connected among each other.

The definition of the social pressure function however is not only motivated by economic reasoning but it also allows linking the structure and state of the network with the decisions that have to be made by each agent. Finally the choice of the boundaries of 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 of her alternative strategy by $U_i^{'}$. Thus, based on equations (5) - (8) we observe that the probability of a change in the agent's current strategy to the agent's alternative strategy is given by

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

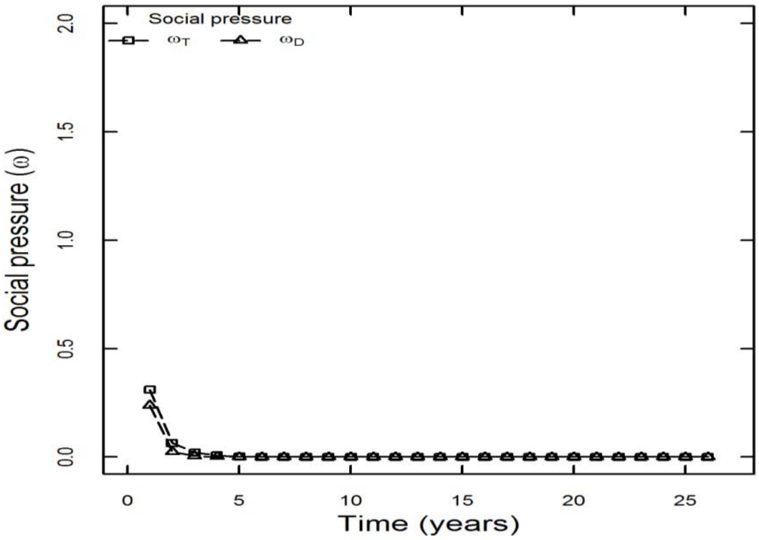
If $U_i'(t)-U_i(t)\geq 0$ we have $0\leq p_i(t)<1$ and if $U_i'(t)-U_i(t)\leq 0$ we have $0\geq p_i(t)\geq -1$. Thus, equation (22) shows that the probability is limited by $-1\leq |p_i(t)|<1$ and links to the mathematical conception of probability. In the equations (7) and (8) we set the probability of a change in strategies equal to zero if it would lead 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 with the mathematical concept of probability.

Appendix C

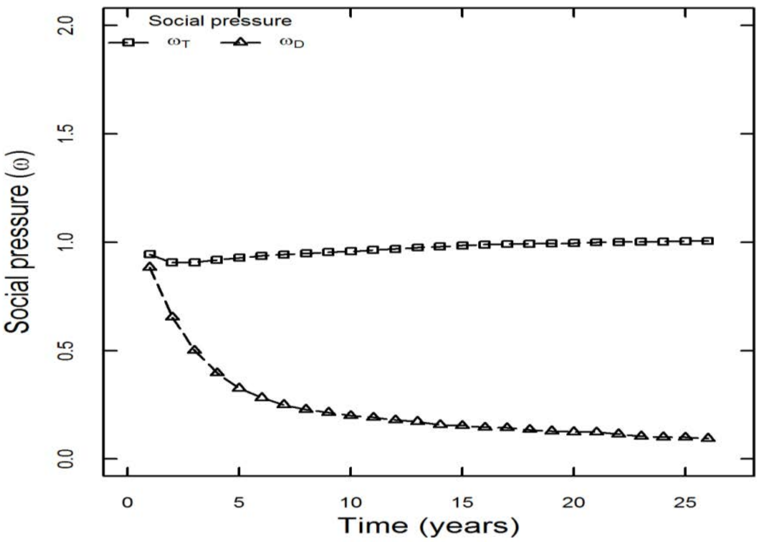
Evolution of Social Pressure

Figures C1a) –C1d) show the evolution of the average social pressure within the network, ω_T. It consists of the social pressure received by all agents, i.e. the social pressured received by defectors and the potential social pressure that compliers would receive if they decided to abandon their current strategy. Alternatively we calculated the average social pressure that only defectors 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.

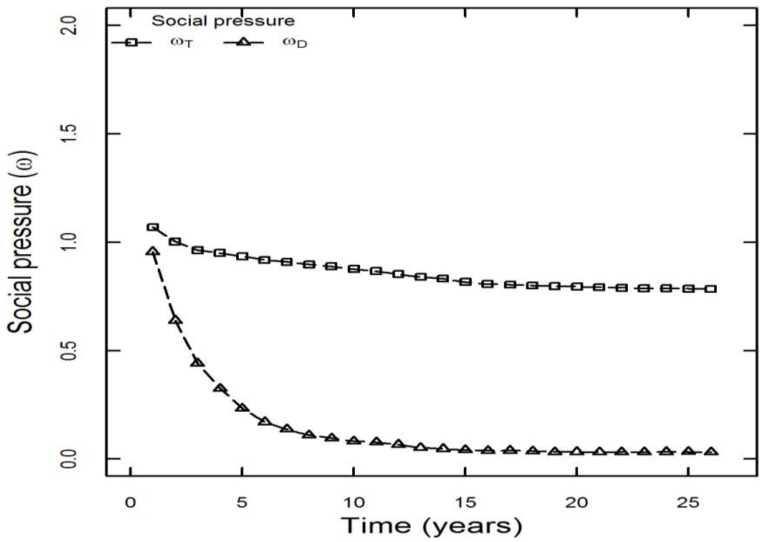
Figure C1a) – C1d): Evolution of social pressure ω . Figure C1a): $c_i=0.5, s(0)=15$; Figure C1b): $c_i=0.5, s(0)=40$; Figure C1c) : $c_i=0.65, s(0)=15$; Figure C1d): $c_i=0.65, s(0)=40$.

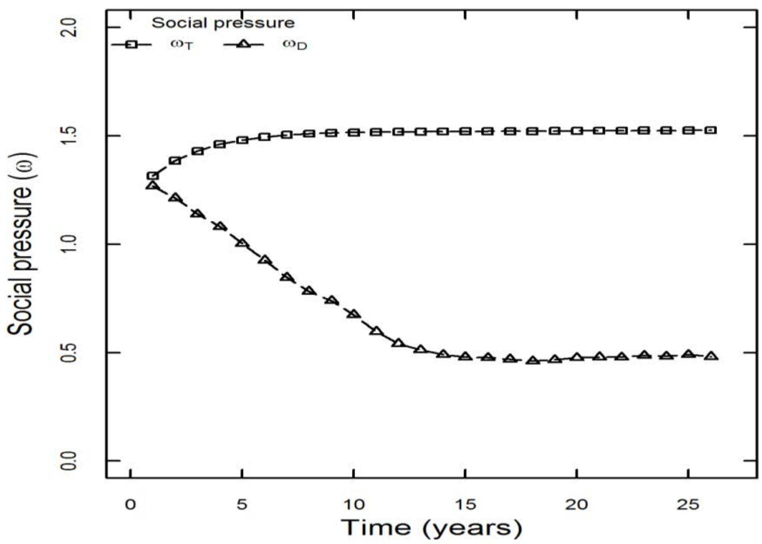

Social pressure
ω_T
ω_D
Social pressure (ω)
Time (years)
0.0
0.5
1.0
1.5
2.0
0
5
10
15
20
25

1553

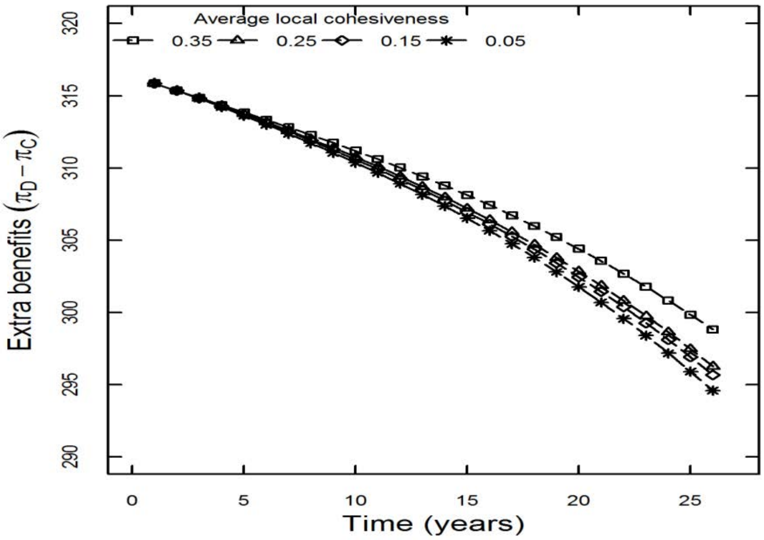

Social pressure
ω_T
ω_D
Social pressure (ω)
Time (years)
0.0
0.5
1.0
1.5
2.0
0
5
10
15
20
25

1554

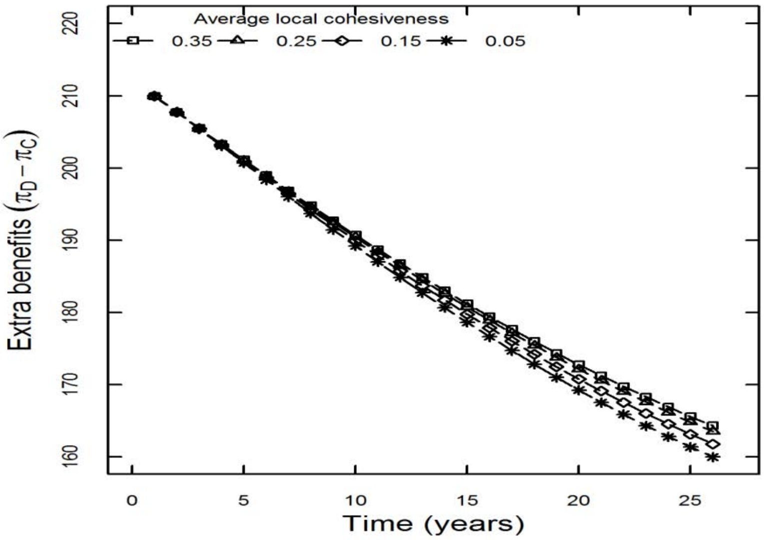




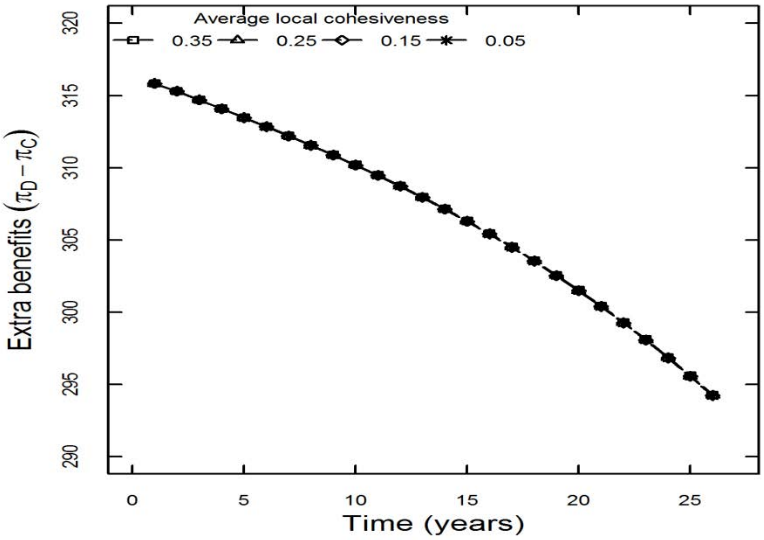
Figures C2a) – C2d): Evolution of the defector's extra benefits for different degrees of average local cohesiveness with $\tau = 0.05,\ 0.15,\ 0.25$ and 0.35 . Figure C2a): $c_i = 0.5, s(0) = 15$; Figure C2b): $c_i = 0.5, s(0) = 40$; Figure C2c) : $c_i = 0.65, s(0) = 15$; Figure C2d): $c_i = 0.65, s(0) = 40$.

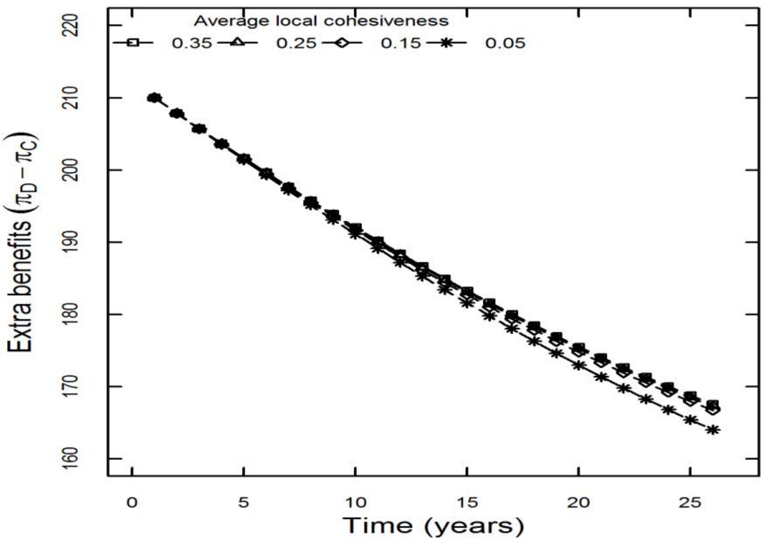

Average local cohesiveness
0.35
0.25
0.15
0.05
Extra benefits ($\pi_D - \pi_C$)
Time (years)

1564


Average local cohesiveness
0.35
0.25
0.15
0.05
Extra benefits ($\pi_D - \pi_C$)
Time (years)

1565





Appendix D

Social Pressure and the Dynamics of the Resource and the Population of Compliers

Figure D1 shows the relationship between two arguments of the social pressure function in form of level curves of the defector's extra utility, $U^D - U^C$. The level curve of $U^D - U^C = 0$ indicates the locus where defectors are indifferent between compliance and non-compliance and thus, it draws the separation line of non-compliance and compliance. The level curve of 0 (continuous line) indicates the substitution between depth of the water table and the share of compliers given that the maximum local cohesiveness of compliers is achieved. As long as the level curve is positive defectors have little incentive to abandon their current strategy. For negative values, however, the probability that defectors change their strategy to compliance increases with a decrease in the value of the level curve. Figure 4 also indicates the level curve 0 (discontinuous line) in the absence of local cohesiveness between compliers (minimal local cohesiveness $\tau_{c_i} = 0$). These two level curves limit the area where other combinations of the share of compliers and local cohesiveness of compliers would bring about a level curve of 0.

As long as the level curves are greater than approximately -75 the depth of the water table and the share of compliers tend to be substitutes while they tend to be complements if the value of the level curve is below -75.

Figure D1: Level curves of the defector's extra utility as a function of the depth of the water table and the share of compliers given the maximum and minimum local cohesiveness (club of compliers).