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Risk, Networks, and Ecological Explanations for the Emergence of Cooperation in Commons Governance

Abstract:

The commons literature increasingly recognizes the importance of contextual factors in driving collaboration in governance systems. Of particular interest are the ways in which the attributes of a resource system influence the dynamics of cooperation. While this may occur through many pathways, we investigate the mechanisms by which ecological factors influence both the risk of cooperation as well as the density of networks in which strategic interactions take place. Both of these factors influence the co-evolutionary dynamics of network structure and cooperative behavior. These dynamics are investigated through agent-based simulations, which provide preliminary evidence that: 1) low-density networks support higher levels of cooperation, even in high-risk Prisoner's Dilemma scenarios; and 2) in high-risk scenarios, networks that develop higher levels of clustering generally enjoy higher societal gains.

1. Introduction

Empirical work on commons governance is increasingly oriented towards understanding the ways in which contextual variables influence the dynamics of cooperation and sustainability outcomes (Dietz and Henry 2008). An important set of contextual variables are ecological factors, or characteristics of the natural environment in which a particular resource system is embedded. The direct and indirect influence of ecological factors on cooperation and governance has long been recognized in theoretical work (Mazmanian and Sabatier 1980; Ostrom 2007; Sabatier 1999) and there is a growing body of empirical research linking ecological factors and emergent patterns of cooperation (Heinrich et al. 2005; Leibbrandt et al. 2010; Nisbett 2003; Prediger et al. 2011). This paper seeks to build upon existing research in this area by positing general but precise models of how fixed or slowly-changing ecological factors influence the dynamics of cooperation in commons governance systems.

Our investigation of the influence of ecological factors on cooperation focuses on two distinct, but related, pathways. First, ecological factors influence the density of social networks that both constrain and enable strategic interaction. While some ecological settings are likely to support greater opportunities for in-

teraction within an action arena (and more dense networks), other settings may support only infrequent interactions (and more sparse networks)—this may, for example, be related to population density or the transaction costs inherent in working with others across natural obstacles such as mountains or waterways between islands.

Second, ecological factors partially determine the benefits and costs of cooperation within any particular setting. These costs and benefits help to define the risk that is inherent in any actor's decision to engage in collective action, since increasing incentives to 'free-ride' also increase the risk that any particular cooperator will pay the costs of cooperation without enjoying any of the benefits. Benefits of defection, for example, may be especially high in an environment where the resource grows slowly (as with high value timber) or has slow regeneration rates (as with certain types of fish stocks).

These dynamics are explored through a series of computational, agent-based simulations of strategic interaction within a hypothetical action arena using a small number of plausible assumptions. Strategic interaction takes place through multi-player games that are played within random networks, which are allowed to evolve over time as the simulation progresses. The network layer allows us to represent the particular structure of opportunities for interaction in the system. While the system may be large, individual actors interact with only subsets of other players—thus, in any given system there is an 'ecology' of overlapping games being played (Long 1958; Lubell et al. 2010). The networks that constrain and enable interaction not only exercise an important influence on the evolution of cooperation in social systems (Nowak 2006; Ohtsuki et al. 2006), but might also be influenced by cooperative strategies as a system matures (Skyrms and Pemantle 2000).

By allowing actors to adjust their local network and choose their collaborators as the model progresses, we are able to explicitly model these co-evolutionary dynamics. Risk is represented in the structure of the games being played. Risk and network density are both fixed as exogenous factors representing the ecological setting in which interactions occur; we then examine the emergent patterns of cooperation within different ecological settings.

We find that, consistent with theoretical expectations, the level of cooperation decreases with increasing network density and levels of risk. On the other hand, cooperation is still possible in high-risk scenarios when network density is low. Regarding the types of network structures that emerge under varying ecological conditions, we find that high-risk settings favor high levels of transitivity (such that actors tend to share common partners), whereas low-risk settings provide no clear incentives for actors to form transitive network relationships.

2. Model Overview

We model how actors within a commons governance system (an 'action arena') make strategic decisions using a game theoretic perspective. In particular, we

assume that actors are linked together in a network and play repeated games with their *network neighbors*, or other actors with whom they share a linkage. The following sections discuss the model itself, as well as the ways in which fixed model parameters are likely to be influenced by ecological factors.

2.1 The Role of Network Density

Interaction within the action arena is described by a network $G = (V, E)$, on $n = |V|$ vertices and $m = |E|$ edges. The vertex set V represents all n actors in the action arena, $V = \{v_i\}$ for $i \in \{1, 2, \dots, n\}$. The edge set E represents all relationships between actors within the system, where $v_i v_j \in E$ if and only if actors v_i and v_j share a relationship. Ties are interpreted as undirected; therefore $v_i v_j \in E$ implies that $v_j v_i \in E$, and vice-versa. When two actors share a relationship, they will have an opportunity to strategically interact. Although the set of vertices remains fixed, the set of interactions among vertices may evolve over time. The edge set at time t is denoted E_t , and the full network G at time t is thus described by $G_t = (V, E_t)$.

The density of the network in which interactions occur is fixed—network density is defined as the proportion of all possible actor-actor pairs in which a network linkage exists, and is a function of model parameters n and m . Thus, although the contents of the set E are allowed to change over time, the overall size of the set is fixed throughout the course of a simulation.

Network density is one measure of the overall intensity of interactions within a particular system, or the frequency with which any two actors are likely to interact (since the model assumes that, at each time step, a single interaction occurs within each linkage). Ecological factors may play an important role in network density. For example, network density may reflect the population density in a given action arena—when individuals live or work in closer proximity to one another, the opportunities for interaction also increase. Thus, larger density parameters may represent more urbanized environments whereas smaller density parameters may be more consistent with rural communities or communities that face high transaction costs for managing their resource base (for example, in resource systems dispersed across islands or in high mountains). It is important to note, however, that it is also possible to have situations where localized subgroups experience frequent interactions, although the density of the global network may remain small—for example, within ‘segregated’ networks partitioned into several disconnected communities (Henry et al. 2011).

Network density may also be influenced by resource characteristics—for example, resources with higher productivity may increase local populations if they attract new residents or support higher fertility rates. Similarly, some resource characteristics may require higher levels of interaction, which is tantamount to increasing the density of the underlying network—for example; the extraction of some resources requires greater interdependencies among actors, as with

some species of fish that can be encircled by several boats in order to maximize harvest.¹

2.2 Risk of Cooperation and Model Parameter b

In a single iteration of the game considered here, all actors simultaneously play a multi-person game with their network neighbors. Each actor chooses a strategy, either *cooperate* (C) or *defect* (D). Actors who choose cooperation receive a payoff of 1 for every other cooperators they are connected to, and lose b for every other defector they are connected to. Actors who choose defection receive no payoff for other defectors in their network neighborhood, but receive a payoff of b for every other cooperators they are connected to. In this scenario, the parameter b represents the benefits of defection and is hence a measure of the riskiness of the underlying game—when $b > 1$, this game is a high-risk Prisoner’s Dilemma, while $b < 1$ yields a low-risk coordination game where both players prefer the same Nash equilibrium outcome {C,C} (Berardo and Scholz 2010; Hegselmann and Flache 1998).

We apply a rather narrow definition of riskiness for the underlying game. Our risk parameter is not related to uncertainty of payoffs and predictability of the resource. Rather, our risk parameter captures the benefits of defection that arise from resource characteristics such as varying growth or replenishment rates. As noted above, resources that grow slowly may correspond with larger risk parameters, whereas rapidly-growing resources may correspond with smaller risk parameters. This is because slow-growing resources will demand greater investments over time, and if these resources are highly valued then the potential benefits of free-riding on the prior investments of others will increase. These differences may be observed across resources such as fast growing eucalyptus or palm trees for timber production versus slow growing, high value timber such as teak or mahogany, or across fish stocks with varying reproduction rates.

2.3 Network Structure, Risk, and Cooperation

We now turn to the question of how network structure and risk—represented by model parameter b —exercise their influence on cooperative dynamics.

For a particular iteration of the game, let us focus our attention on one actor named ‘Ego’ and represented by the network vertex v_{Ego} . Suppose that Ego is connected to k other players in the network such that $v_{Ego}v_i \in E$ for all $i \in \{1, 2, \dots, k\}$. Also, let $p(i)$ denote the objectively-determined probability that player v_i will cooperate. The probability $p(i)$ is based on v_i ’s history of cooperation, and is equal to the proportion of rounds in which v_i has cooperated. All agents have full knowledge of all other agents’ prior strategies, and so $p(i)$ does not vary from one Ego to another.

¹ Fish traps consisting of several boats were frequently used to capture migrating bluefin tuna and albacore. Nowadays, such traps are still used to harvest tuna in the Mediterranean Sea and Japan.

	v_i cooperates ($C_i = 1$)	v_i defects ($C_i = 0$)
Ego cooperates ($C_{Ego} = 1$)	1	-b
Ego defects ($C_{Ego} = 0$)	b	0

Table 1: Payoff to Ego given C_i and C_{Ego}

For housekeeping purposes, let the variable C_i denote the strategy played by actor v_i , where $C_i = 1$ if and only if v_i cooperates, and $C_i = 0$ if and only if v_i defects. In order to support cooperation in the first round, all actors begin with the optimistic assumption that all other players will cooperate (such that $p(i) = 1$ for all actors).

Given any set of probabilities $p(i)$, Ego may now estimate her expected payoffs given her own strategy C_{Ego} . Note that for a particular alter v_i , Ego will receive payoffs as summarized in table 1.

From Ego's point of view, v_i will cooperate with probability $p(i)$, and defect with probability $1 - p(i)$. Thus, Ego's *expected* payoff for a particular alter is:

$$P_{Ego} = \begin{cases} p(i) - b(1 - p(i)) & \text{if } C_{Ego} = 1. \\ b \cdot p(i) & \text{if } C_{Ego} = 0. \end{cases}$$

Across all of Ego's k network neighbors, it follows that Ego's expected payoff is:

$$P_{Ego} = \begin{cases} \sum_{i=1}^k p(i) - b(1 - p(i)) & \text{if } C_{Ego} = 1. \\ \sum_{i=1}^k b \cdot p(i) & \text{if } C_{Ego} = 0. \end{cases}$$

Given these expected payoffs, how does Ego choose a strategy? She begins by considering two key values: her expected payoff if she cooperates (the *expected benefit of cooperation*, or *EBC*), and the difference between the expected benefits of defection and the expected benefits of cooperation (the *marginal benefit of defection*, or *MBD*). Ego is then assumed to choose a strategy according to the following decision rules:

1. If the marginal benefit of defection is zero or less, then Ego will cooperate.
2. If the marginal benefit of defection is positive, and the expected benefits of cooperation are zero or negative, then Ego will defect.
3. If the marginal benefit of defection is positive and the expected benefits of cooperation are positive, then Ego will defect with probability proportional to the marginal benefit of defection.

These decision rules imply that if Ego is in a position to choose between cooperation and defection, there is always some possibility of cooperation. On the other

hand, this probability shrinks as the benefits of defection increasingly outweigh the benefits of cooperation. In particular, we assume that the probability that Ego chooses cooperation, or p_{Ego} , is exponentially decreasing in the size of the marginal benefit of defection:

$$p_{Ego} \propto \frac{1}{e^{B_{Ego}}}, \text{ where } B_{Ego} = \text{Ego's marginal benefit of defection.}$$

In choosing a precise functional form for p_{Ego} , it is useful to note that a long line of research has shown that observed behaviors—both in the field and in controlled experimental settings—deviate greatly from theoretical expectations in contexts outside of highly competitive markets. While individuals commonly choose strategies below social optimums, one generally observes substantially more cooperation than predicted by Nash equilibrium. Thus, we introduce into the model a mechanism through which cooperation is possible even if such a choice involves a strategy dominated in substantive payoffs (that is, when $b > 1$).

In particular, let $a \in [0,1]$ be an exogenously-fixed, global model parameter that reflects an inherent preference for cooperation ('a' is chosen for 'altruism'). In this model, smaller values of a reflect greater self-interest and larger values of a capture stronger preferences for cooperation versus defection. A parameter value of $a = 1$ reflects the (very rare) situation where all actors are unconditional cooperators.

Given a , Ego chooses cooperation according to the function:

$$p_{Ego} = \frac{1}{e^{B_{Ego}(1-a)}}.$$

Larger values of a therefore have the effect of shrinking the perceived marginal benefit of defection—since a may be no greater than 1, it follows that altruism cannot change dominant strategies, but it can shrink the perceived differences between payoffs based on defection versus cooperation.

This functional form implies a few principles of cooperation that are reflected in the model. Of course, these principles reflect contestable hypotheses that should be tested in field and/or experimental work, however in general these principles are consistent with empirical research on collective action:

1. *The probability of cooperation is never zero.* Even though actors may not have an inherent preference for cooperation, there is always some non-zero possibility that a strictly rational actor (with parameter $a = 0$) will still cooperate. This reflects the notion that we are dealing with stochastic, rather than deterministic, strategic decisions (Selten 1975).
2. *In cases where the expected payoffs from defection equal the expected payoffs from cooperation, actors will always choose cooperation.* This idea is reflected in the property that $p_{Ego} = 1$ when the marginal cost of defection is zero (when $B_{Ego} = 0$). While in practice this may be a rare phenomenon, it has important theoretical implications. All else being equal,

actors are likely to prefer cooperative strategies as they tend to result in more socially-desirable outcomes, and because they bring additional benefits (in the form of reputation, trust, and social capital) to individual actors. This may also reflect the Hobbesian notion that humans are more averse to exploitation than they are prone to exploit others—thus, all else being equal they will prefer defensive strategies motivated by fear rather than outright exploitation motivated by greed (Kliemt 2005).

3. *Even altruistic agents are likely to defect when the expected marginal benefit of defection is large.* While the probability of cooperation decreases exponentially in B_{Ego} , B_{Ego} decreases only linearly in a . Thus, while altruism may be a powerful force behind cooperation, even highly altruistic actors will seek to protect themselves when surrounded by frequent defectors. Alternatively, even altruistic agents may be tempted to defect when the benefits of defection are very high.

2.4 The Co-evolution of Networks and Cooperation

In this model, players are allowed to dynamically rewire their network; thus, the set of actors with whom any particular Ego interacts may not be static over time. Network rewiring gives individual players greater control over their well-being in competitive situations. Individual actors are assumed to maximize their individual well-being by abandoning unproductive relationships for others that hold greater promise for beneficial outcomes. In other words, actors have the opportunity to adjust the set of actors they ‘play the game with’ as the model progresses, which may yield results that deviate from theoretical expectations where interactions are fixed.

The network rewiring process is as follows: At each time step, every actor assesses their network linkages and independently decides whether each linkage is to be rewired. Specifically, the probability that Ego will rewire their linkage with a given actor (say, actor v_i) is given by $R_{Ego}(i)$, where

$$R_{Ego}(i) = \text{maximum} \{ L, 1 - W_{Ego}, 1 - p(i) \}.$$

In this formula, L is a fixed model parameter representing the *elasticity* of the network. Network elasticity L ranges from 0 to 1, and gives a minimum probability that any particular tie will be rewired. For example, setting elasticity to 1 will force all linkages to be rewired at each time step, whereas a small value (say, elasticity = 0.05) will ensure that all linkages are rewired with at least 5% probability. This parameter reflects the inherent stability of relationships in the system.

W_{Ego} represents Ego’s well-being (in terms of net payoffs), and is defined as the percentile score of Ego’s net payoffs as compared to others in the system. Given the formulation for R_{Ego} , actors are more likely to rewire their local network when they fall at the lower end of the distribution of net payoffs.

The parameter $p(i)$ is the posterior probability that v_i will cooperate (as discussed above); this is also a measure of v_i 's positive reputation. Setting a minimum probability of $1-p(i)$ for the rewiring of the link $v_{Ego}v_i$ reflects the notion that Ego will tend to cut ties with defectors more frequently than she will cut ties with cooperators.

When a particular linkage is terminated, it is then assigned to the actor that made the decision to cut the link. If both actors simultaneously choose to cut the link between them, then the linkage is assigned (uniformly at random) to one of the two. The actor that 'owns' the terminated link then chooses a random actor from the system to form a new relationship with. This process holds network density constant since the total number of linkages is fixed; however, the distribution of actor degrees may change as some actors (frequent defectors in particular) lose linkages that they themselves did not choose to terminate.

3. Simulation Runs and Results

The model described above is used to simulate the dynamics of cooperation in varying ecological conditions, represented by the density of networks and the risk inherent in cooperation.

The results presented here are based on 1,000 individual simulation runs. In each simulation an action arena was defined with $n = 25$ agents, and model parameters were randomly assigned as follows: risk (parameter b) ranged from 0.5 to 1.5; network density (parameter m) ranged from 0.05 to 0.5; preferences for altruistic behavior (parameter a) ranged from 0 to 1; and network elasticity (parameter L) ranged from 0 to 0.1. These parameters are randomly assigned at the beginning of each simulation run, but remain fixed throughout the course of each simulation. Each simulation was run for 20 time periods.

An example of a single simulation is illustrated in *figure 1*. In this figure, actors are represented by the circular network nodes, and interactions are represented by the linkages between nodes. The size of nodes are proportional to the actors' net payoffs, and the number beside each node is $p(i)$, or the proportion of time periods in which the corresponding actor played a cooperative strategy. One may observe the evolution of the network structure and relative size of payoffs as the model progresses.

In the following sections we investigate the situations that tend to emerge under varying conditions. We not only examine how fixed model parameters (with a particular focus on risk and density) produce varying expectations of wealth and cooperation, but we also take a look at the types of emergent network structures that tend to be favored by these exogenously-fixed factors.

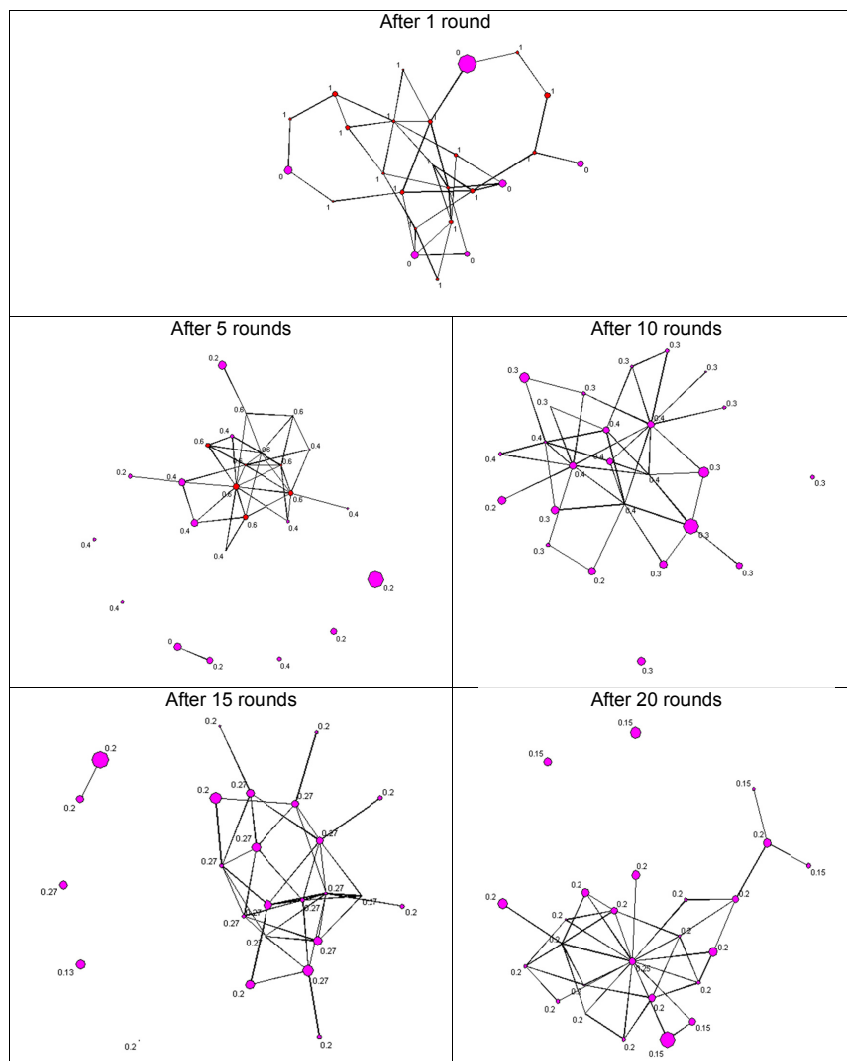


Figure 1: Sample simulation over 20 time periods; expected density = 0.15; $b = 1.2$; $a = 0.2$; elasticity = 0.1

3.1 The Emergence of Cooperation in Varying Ecological Conditions

One of the most important outcomes of interest is the degree of cooperation that is observed in various conditions. We operationalize agents' overall propensity to cooperate as the average strategy played by all players over all rounds; similarly, this variable may be defined as the average cooperation shown in the final round. Since '0' is viewed as a defective strategy and '1' as a cooperative strategy, average cooperation will take on a value of 0 to 1, indicating the average proportion of actors who play cooperative strategies.

Figure 2 depicts average levels of cooperation observed across all rounds, plotted against the fixed risk parameter (b) for each simulation (left panel) and average levels of cooperation observed across all rounds, plotted against the density of the network in each simulation (right panel). In very low-risk scenarios where the benefits of cooperation outweigh the benefits of defection (when $b < 1$), all agents cooperate all of the time. This follows from the structure of the model—when $b < 1$, the marginal benefit of defection is always negative; therefore all agents will cooperate unconditionally. On the other hand, it is possible that cooperation still survives in situations where $b > 1$, and agents are facing a classic Prisoner's Dilemma at each time period. Indeed, figure 2 suggests a high degree of variance in average levels of cooperation when $b > 1$. We also find a negative relationship between network density and average cooperation.

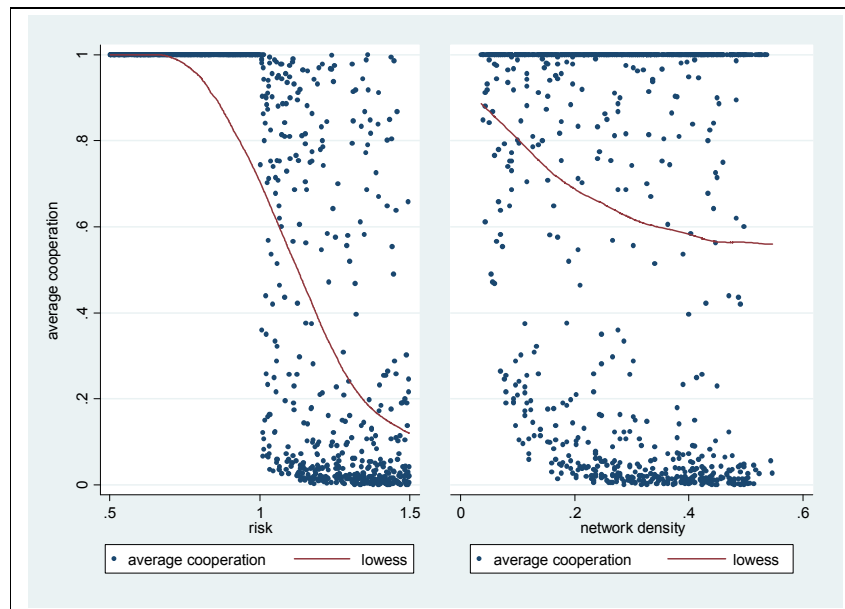


Figure 2: Cooperation is possible when $b > 1$

Time series data were recorded for each simulation, allowing us to examine the proportion of actors who cooperate at each time step. To better understand the role of risk and network density in cooperative behavior when actors face Prisoner's Dilemma games ($b > 1$), *figure 3* depicts the average levels of cooperation across all actors at each time step for four basic scenarios: high and low levels of risk (but where $b > 1$ in any case), and high and low levels of network density.

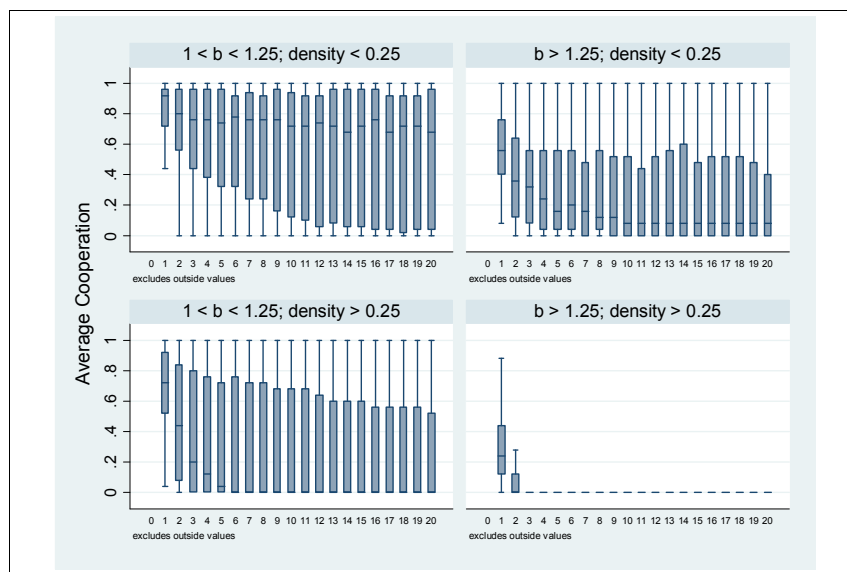


Figure 3: Evolution of cooperation when risk and network density are high/low

Figure 3 demonstrates a clear pattern linking risk and network density to cooperation—controlling for network density, higher levels of risk lead to lower levels of average cooperation over the 20 time periods studied here. This is an unsurprising result, and follows simply from the fact that all agents perceive larger marginal benefits of defection as b increases. On the other hand, lower densities tend to support higher levels of cooperation controlling for risk. This is because actors perceive smaller marginal benefits of defection when they have fewer network partners, thereby increasing incentives to cooperate. The result is that cooperative behavior is almost never observed when both risk and density are high (lower-right quadrant of *figure 3*), however high-density and high-risk scenarios may both support moderate levels of cooperation even when the other parameter is very large.

These results are further supported by a set of Tobit regression models, summarized in *table 2*. Here we model average levels of cooperation over all time periods (estimation 1), average wealth over all time periods (estimation 2) and the cumulated standard deviation of wealth (estimation 3) as a function of fixed simulation parameters.

	(1) Average cooperation in 20 rounds	(2) Average wealth in 20 rounds	(3) Cumulated standard deviation of wealth
Risk (b)	-1.125*** (0.148)	40.06*** (10.30)	-0.252 (2.520)
Altruism (a)	0.714*** (0.0328)	-5.995* (3.125)	4.761*** (0.699)
Network density (m)	-2.030*** (0.599)	267.1*** (40.61)	1.741 (10.03)
Risk * Network density	0.626 (0.476)	-184.2*** (31.43)	5.875 (7.564)
Clustering increase	0.124 (0.120)	11.44 (8.247)	7.943*** (1.948)
Elasticity	-0.279 (0.326)	25.48 (21.53)	-4.604 (5.081)
Avg. coop		15.91*** (5.424)	12.19*** (1.159)
Std. wealth		2.872*** (0.142)	
Avg. wealth			0.168*** (0.00825)
Constant	1.692*** (0.191)	-76.08*** (13.81)	-1.148 (3.446)
Observations	494	494	494
Left censored	12	46	12
Right censored	4	-	-
Log likelihood	73.89	-1814	-1258
Chi-squared	581.6	1090	1280

Notes: Robust standard errors clustered for each simulation run in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 2: Cooperation, wealth and standard deviation of wealth as a function of simulation parameters when $b > 1$

The model parameters representing ecological factors—network density and risk of cooperation—both have a significant negative influence on average levels of cooperation. These results are consistent with the observations above, but also show that cooperation decreases as both risk and network density increase, even controlling for other factors such as actors' inherent preference for cooperation (or altruism, model parameter a) and interaction effects across simulation parameters. While altruism has a strong positive influence on cooperation (as expected), network elasticity has no significant effect—thus, these results appear to be robust even to small degrees of random mutations that are introduced in the network structures. The interaction effect of risk and network density is positive and insignificant, which suggests that there is no reinforcing effect of high risk and high density even though both effects are strong independent predictors for average cooperation over 20 rounds.

3.2 Societal Wealth

It makes sense that higher levels of cooperation would promote greater societal wealth, operationalized here as the average net payoffs for all actors across all 20 time periods. In fact, we observe high levels of variance in societal wealth even when cooperation is high (see *figure 4*). This suggests the need to examine the relative influence of various factors in providing more or less desirable outcomes, controlling for overall levels of cooperation.

Table 2 also presents the results of a Tobit regression model predicting societal wealth (estimation 2). The model demonstrates that, controlling for average cooperation levels and the distribution of wealth, the total payoffs observed are strongly determined by both network density as well as risk. However, when controlling for cooperation levels, risk and network density are both positively related to wealth. This indicates that, for constant average cooperation levels, high risk and high networks generate higher wealth—this is most likely due to higher benefits of defection combined with the possibility of finding enough linkages. The significantly negative interaction effect between these two variables suggests that when both risk and density are high, societal payoffs do increase in absolute terms ($123 = 40 + 267 - 184$) compared to situations with high risk and low networks density (40), low risk and low network density (0) but decreases relative to a situation with high network and low risk (267).²

Interestingly, neither risk nor network density account for inequality of wealth once we control for average cooperation and average wealth (*table 2*, estimation 3). We find that higher levels of altruism increase inequality, possibly since actors cooperate unconditionally and are thus willing to incur losses for themselves.

² When further subtracting the constant (-76) from the coefficients one can see that wealth is actually decreasing in situations with high risk and low networks density ($40 - 76 = -36$) and in situations with low risk and low network density ($0 - 76 = -76$).

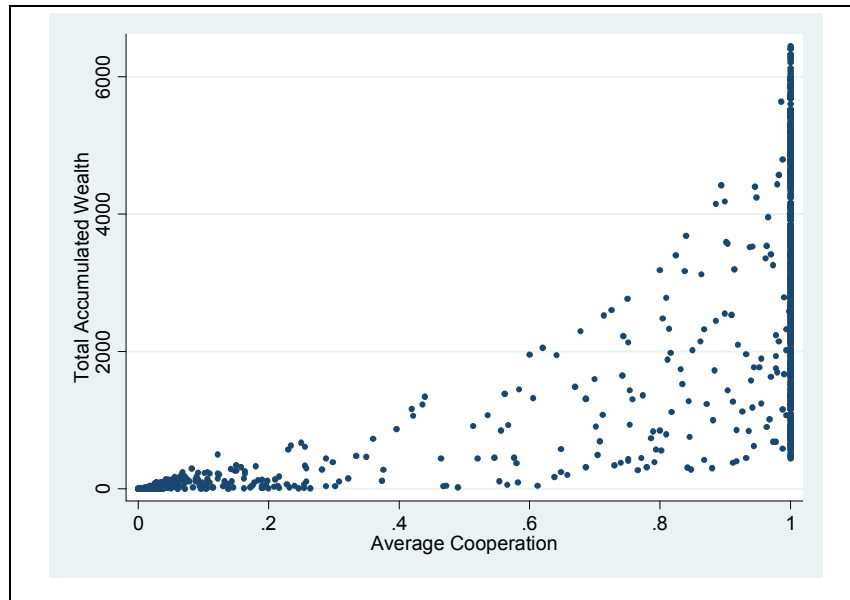


Figure 4: Total accumulated wealth varies even when cooperation is high

3.3 Favored Network Structures

These preliminary model runs also reveal some useful insights regarding the evolution of networks and cooperative dynamics. For a given simulation, the variable *clustering increase* represents the change in actors' average clustering coefficient between the initial and final time periods—a single actor's clustering coefficient is the proportion of linkages that exist between the actor's network neighbors. Higher clustering coefficients reflect more redundant, transitive relationships in the network, which are hypothesized to support legitimacy and trust within dyadic relationships (Berardo and Scholz 2010; Henry and Dietz 2011; Henry et al. 2011). Thus, positive values of *clustering increase* indicate scenarios where networks have become more clustered as the simulation progresses.

While this model assumes that actors will terminate linkages with higher probability if these links appear to correlate with negative well-being, agents are also not assumed to follow any explicit calculus (other than random selection) in choosing new network linkages. On the one hand, this assumption does lack some realism. It stands to reason that agents would use their information about other players' cooperative history to find other network partners that will be more likely to cooperate in future rounds. On the other hand, random rewiring of the network allows for a simpler model but also poses a conservative standard for network evolution. Under an assumption of random rewiring, it is likely that whatever network characteristics emerge over time are a result of

agents' increased well-being, and not because they reflect specific (and potentially artificial) preferences that are programmed into the model.

What network structures do we expect will be 'learned' over time? Berardo and Scholz (2010) advance the *Risk Hypothesis*, that actors engaged in games where there is a high risk of defection (i.e., large b parameters) will seek out transitive, clustered relationships. Indeed, we do see a positive effect of *clustering increase* in all three models in *table 2*; this suggests that actors who develop higher levels of clustering do tend to be better off in the sense that cooperation is more likely and more societal wealth is generated. However, additional research is needed to understand the co-evolving relationships between network structure and cooperation, and how these relations are conditional upon exogenous contextual factors. Given these initial results, it may be that agents would learn to form clustered networks with higher probability if the number of iterations were to be substantially increased.

The implications for network evolution are clearer in low-risk scenarios. As noted above, cooperation is always dominant when $b < 1$. While societal wealth varies when $b < 1$, this outcome is completely determined by density (correlation = 1.0). This makes sense, given that actors always cooperate under these conditions—thus, payoffs are always proportional to the number of individuals in one's network. The more interactions one has, the more they will gain. Thus it follows that the worse-off actors will be those with relatively few network links; they will tend to rewire their linkages with higher probability and will ultimately seek (if allowed to learn optimal strategies) network positions with higher levels of centrality.

4. Conclusion

With the pioneering work of Elinor Ostrom (1990), scholars have worked to develop a predictive theory of successful commons governance. While Ostrom's earlier work emphasized certain design principles that characterize the governance system as well as the attributes of the resource users, more recent frameworks have focused on both the social and the ecological system (Ostrom 2007). However, empirical work often does not allow for strong causal inferences regarding the effect of ecological factors on cooperation. This paper contributes to a small but growing body of research that links exogenous ecological factors (that we assume influence networks of interaction and risk) with cooperation in a social dilemma situation. We defined two major influences of ecology on cooperation and tested their influence on cooperation and resulting societal wealth.

Table 3 summarizes our main results: The best situations seem to be low-risk scenarios coupled with low-density networks. This is the case of small communities with secure access rights harvesting a fast growing resource. When network density increases and risk remains low, *ceteris paribus* cooperation rates drop to an intermediate level but wealth increases. Thus, it seems that people are cooperating too much in the low-risk, low-density scenario. When a community has

	Low network density	High network density
Low risk	High cooperation (60%) and high wealth (30)	Intermediate level of cooperation (31%) and high wealth (39)
High risk	Intermediate level of cooperation (29%) and low wealth (7)	Low cooperation (7%) and low wealth (8)

Table 3: Classification of our main results based on mean values and thresholds used in figure 3

low network density but faces a high risk of resource extraction, cooperation is at intermediate levels and wealth is low. Thus, lower network densities may support cooperation despite the risk; however, in these situations cooperators are not able to generate large amounts of societal wealth because they have relatively few opportunities to interact with others. Finally, high-risk, high-density cases have both low cooperation levels and low wealth. When taking societal wealth as an evaluative criterion, our result suggests that network density matters less compared with riskiness of cooperation. Our findings underscore the importance of sustaining cooperation in high-stakes commons governance scenarios.

These results suggest a number of future research directions. First and foremost, the simulation results presented here yield plausible hypotheses regarding expected cooperation levels that will be observed under varying ecological conditions. Testing these hypotheses in the field is an important direction for future research. At the same time, empirical work is needed to link environmental factors, including characteristics of the resource system, with the structure of the game being played as well as the structure of the networks that define opportunities for strategic interaction.

Understanding the role of evolving network structures in cooperative dynamics is an emerging area of research. Our model suggests that network density and risk interact in important ways, but further research is needed on several counts. First, the results presented here are for relatively few time periods, and likely represent the “burn-in” period where results at the final time step are heavily influenced by the initial conditions. In further research it will be important to examine the conditions under which cooperation is an evolutionary stable strategy, in the sense that cooperative strategies can survive over infinitely many time periods (Nowak 2006). It is possible that, in the models presented here, situations that appear to favor cooperation (such as the low-density, low-risk scenario) will still lead to defection in the long run. Thus, our results should be interpreted in terms of short-term trends rather than long-term equilibria—that is, cooperation survives *longer* in low-density scenarios than in high-density scenarios.

Further research will also examine variations on the game structure, as well as additional effects in the evolution of the network. Many variants of the game introduced here may be examined; for example, where strategic interaction occurs in the dyads (rather than a single strategy being applied to all network neighbors) or using continuous strategies. In terms of network evolution, understanding how actors learn both efficient strategies and efficient network positions is an important area for future research—these learning dynamics are likely to include social influence processes, where agents learn or imitate norms of cooperative behavior from others in the system. Understanding these dynamics through rigorous modeling and theoretical development will ultimately help us to understand how institutions may be designed to effectively and sustainably govern common pool resources.

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