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Potential disasters can turn the tragedy into success

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POTENTIAL DISASTERS CAN TURN THE TRAGEDY INTO SUCCESS*

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ABSTRACT

This paper presents a novel experimental design that allows testing how users of a common resource respond to potential endogenously driven drastic changes in the supply of the resource. We show that user groups will manage a resource more efficiently when confronted with such a non-concave resource growth function. Even among cooperative groups there is a significant difference in behavior, although theory predicts there should not be. We argue that effectiveness of communication is endogenous to the problem; the threat of reaching a critical tipping point, beyond which the growth rate will drop drastically, triggers more effective communication within the group, enabling stronger commitment for cooperation and more knowledge sharing, which together explains the results.

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I. INTRODUCTION

An increasing amount of empirical evidence suggests that growth functions of many resources are non-concave, characterized by several domains of attractions and multiple equilibria.

Trespassing some critical threshold causes an abrupt and potentially persistent change in the growth of and in the supply of the resource. While such drastic changes are widespread and can be found in many different systems, such as the human body (heart attacks), epidemiological (sudden outburst of diseases), social (shifts in public opinions) and economic (stock market collapses) (Scheffer [2009]; Scheffer et al. [2012]), perhaps most documented examples stem from the biosphere (Carpenter et al. [2011]), nevertheless of high relevance for human welfare.

Case studies have documented so-called regime shifts¹ in many different types of ecosystems (e.g. lakes, coral reefs, grasslands, forests) and on various scales, ranging from local to global (see e.g. the Regime Shifts Database for an overview of case studies: www.regimeshifts.org). The Barents Sea, for example, hosting one of the most productive fish stocks in the world, is one region where we can expect such drastic and persistent changes to occur (ACIA [2005]; Wassmann and Lenton [2012]). There are even indications that the Earth system's capacity to absorb green house gases can change drastically above some critical value of greenhouse gas levels in the atmosphere (Lenton and Schellnhuber [2007]; Lenton et al. [2008]). These observations suggest that high welfare impacts and economic consequences are at stake in terms of expected changes in both the aggregate and in the distribution of human welfare (MA [2005]; Stern [2007]; Crépin et al. [2012]). The fact, that human activities trigger such shifts to an increasing extent, (e.g. due to pollution, resource extraction, climatic warming) and that their frequency seems to be increasing (Folke et al. [2004]; Steffen et al. [2004]; Scheffer

¹ Regime shifts are large, abrupt, persistent changes in the structure and function of a system (Biggs et al. [2012]).

[2009]) emphasizes the importance of studying how people react to and deal with the potentiality of such abrupt changes which can be triggered by their management actions (i.e. endogenously driven changes).

From an economic viewpoint, there is one additional critical aspect to consider about these resources - the institutional structure. The climate system, the Barents Sea, freshwater supply are all examples of common resources, typically associated with over-exploitation, a *tragedy of the commons* (Hardin [1968]), unless users find ways to cooperate.

How will a potential abrupt and persistent shift in the resource growth rate influence strategies for cooperation and resource management? Should we expect an increase or a decrease of the frequency of tragedies of the commons? The purpose of this study is to address exactly these questions, which is, to our knowledge, the first attempt. The prevalence of common resources and their often associated inefficiencies have given rise to an extensive literature aiming at identifying factors influencing management (see e.g. Bromley et al. [1992]; Baland and Platteau [1996]; Ostrom et al. [2002] for comprehensive overviews). Although there are some exceptions (which we will get back to), most of the behavioral/experimental studies in this research area focus on institutional aspects thereby ignoring the resource dynamics or implicitly or explicitly assuming a fixed or simple resource dynamics.

We will rely on the experimental method for collecting data. The reason is that collecting field data on human behavior under the influence of ecosystem regime shifts is very challenging. Sufficient data (both ecological and economic) must contain precise information about the resource and management situation before and after the shift for the studied system. This is hardly available (Walker and Meyers [2004]). It is challenging to transform this

complex decision problem, involving not only strategic elements but also complex resource dynamics, into a comprehensive decision task for the experiment participants. This paper introduces a novel experimental design which allows precisely that.

Our experimental results show that the potentiality of an endogenously driven abrupt drop in the resource renewal rate leads to more cautious exploitation and more efficient resource management. We argue that the threat of reaching the threshold triggers more effective communication within the group. This enables commitment for cooperation and knowledge sharing about the resource dynamics, which leads to better performance. These results stem from laboratory experiments. More specifically, we compare two experimental treatments. In both these treatments users play a dynamic common resource game, but whereas some groups face a simple (a logistic type of) resource dynamics, other groups face a more complex resource dynamics with a potential endogenously driven abrupt change.

Theoretical studies on optimal management of resources entailing potential regime shifts show that management can be difficult when even marginal changes can cause radical, potentially irreversible, system transformations (see Crépin et al. [2012] for a review and Weitzman [1974]; Nævdal [2001]; Brock and Starrett [2003]; Crépin [2003]; Crépin [2007]; Crépin, Norberg, and Mäler [2011] for different aspects of this issue). The nature of the impact of resource users' actions on resource dynamics also matters for management and policy implications. A shift can be driven by an external driver and would then be manifested as a natural catastrophe or disaster, in which case actions have no impact on the probability of a shift. We know from previous studies that such a case motivates more aggressive exploitation strategies in order to secure resources now rather than to risk losing them (Reed and Echavarría Heras [1992]; Tsur and Zemel [1998]). In contrast, the risk of an

endogenously driven regime shift can motivate precaution in optimal management (Polasky, De Zeeuw, and Wagener [2011]). To isolate the effect of an endogenously driven regime shift there is no exogenous driver in our model, the resource dynamics in our setting and the probability of a shift is driven positively and *solely* by the users' actions.

In a common resource system, theory suggests that a potential regime shift can magnify the externality associated with non-cooperation (Mäler, Xepapadeas, and De Zeeuw [2003]; Kossioris et al. [2008]) or cause other kinds of suboptimal outcomes depending on parameter values and the initial state of the system (Crépin and Lindahl [2009]). However, the outcomes of these common pool game theoretic settings depend very much on underlying behavioral assumptions: do users cooperate or not and how do users update their strategies and respond to changes in the resource stock? Theory alone cannot provide answers to these questions. To improve our understanding of these systems and to be able to speak to the optimal set of policies, we need empirical data. This study thereby contributes to filling this research gap by showing that the probability of cooperation can be endogenous to the problem; particular resource dynamics can result in more cooperative outcomes.

Laboratory experiments have previously proven to be valuable for gathering empirical data on human behavior in common resource systems (see e.g. Kopelman, Weber, and Messick [2002] and Ostrom [2006] for comprehensive overviews) and recently, studies have also demonstrated the advantage of using experiments for analyzing the potential impact of specific ecological features in such systems (Cardenas, Janssen, and Bousquet [2013]). Janssen (2010) and Janssen et al. (2010), for example, find that spatial resource dynamics can have a significant influence on the institutional rules that arise and that this element of complexity amplifies the importance of communication between resource users.

Numerous case studies and experiments indicate that communication *per se* is important for determining whether groups will cooperate or not and, hence, prevent the tragedy of the commons (see e.g. Pretty [2003]; Ostrom [2006] for overviews). However, this observation is mostly based on a comparison of experimental outcomes where groups play a common resource game, without the opportunity to communicate in a first stage, and then, at a second stage of the experiment, with the opportunity to communicate. The difference between the two stages is then substantial. In our experiment, all groups, regardless of treatment, are given the same opportunity to communicate. Our study thus adds to the existing literature on common resources by showing that just because resource users have the opportunity to engage in communication does not necessarily mean they will take it. As a matter of fact, our study demonstrates that the effectiveness of communication, which underlies cooperation, can be endogenous to the problem.

In the next section, we explain and motivate the experimental design and procedure. In Section III, we provide some theoretical predictions. Section IV presents the results and Section V concludes the paper with a discussion.

II. EXPERIMENTAL DESIGN AND PROCEDURE

In the resource economics literature, the logistic growth function is often used to model resource growth (see e.g. Clark [1990]). This function has the advantage that one can easily capture resource dynamics with a potential endogenous abrupt change by adding a sigmoid term (e.g. a Holling-type III predation term, see Ludwig, Jones, and Holling [1978]). Such a model can simulate the dynamics of relatively complex systems like forests, grasslands, coral reefs and other systems (Scheffer and Carpenter [2003]; Crépin [2007]; Graß [2012]). It has also recently been used in the resource management literature (see e.g. Crépin and Lindahl

[2009]; Crépin, Norberg, and Mäler [2011]). Figure I illustrates resource growth for different stock levels with a logistic growth function (dashed curve) and a resource growth as modeled in Ludwig et al. (1978) (solid curve) for comparison.²

[Figure I about here]

A model where resource users maximize an objective under the constraint of a logistic growth function typically has one unique interior stable solution and a boundary solution where the stock gets extinct, which is unstable (see e.g. Clark [1990].) A model with a Ludwig et al. kind of constraint may have up to three interior solutions of which two are stable and one unstable (Graß [2012]). In such a model there are also critical thresholds (bifurcation points) at which the system dynamics change abruptly; at such a point, a marginal change in exploitation may shift the system into another stable domain where resource growth differs significantly from the previous stable domain. The critical threshold for going from one stable domain to another often differs from the critical threshold for going back to the original stable domain once the system has shifted. This is called hysteresis and results from the presence of internal feedback loops that maintain the system state, making it difficult to reverse (Biggs et al. [2012]).

In the experiment we represented resource growth as discrete versions of the logistic model and the Ludwig et al. model. This experimental design presents the advantage that it is easy to describe to a non-expert audience. We introduced a minimum stock size to allow possible reproduction, here 5 resource stock units. We limited the stock size to 50 units, a measure of the carrying capacity. The maximum sustainable yield was then set to 9 units and we let resource renewal rates change by steps of 5. Figure IIa and Table AI (in the appendix) show the renewal rate of the logistic model, as we presented it to the subjects.

² See the appendix A1 for details about Figure I and the underlying functions.

For the case with a potential regime shift, we represented the dynamics for high stock levels in the same way as with no shift. However, for a stock size below the threshold of 20 units the regeneration of the resource dropped dramatically. We also introduced hysteresis. For lower stock sizes than 20 units, if users wanted to recover a high regeneration rate, it was not enough to let the stock rebuild to 20 units; instead the users must let the stock rebuild up to 25 units or more. Figure IIb and Table AII (in the appendix) illustrate these dynamics. From now on we refer to our two treatments as the threshold treatment (an endogenous shift in the resource growth rate is possible) and the no threshold treatment (logistic type of resource dynamics).

[Figure II about here]

The experiment was carried out in May 2010 and fall 2011 with 150 subjects recruited (with the help of a show-up fee of SEK 150³) from Stockholm University. Each subject was randomly assigned to a group of three to four subjects⁴. Each group participated only once and only in one treatment. None of the subjects had previously participated in a similar experiment. We gathered 20 observations (groups) for the threshold treatment and 21 observations for the no threshold treatment. Because the main focus of this study is the dynamics of the resource, we kept the institutional structure of the experiment simple, but still complex enough to mimic the field as much as possible and allow comparisons with earlier experimental results on common pools. For example, we used a *framed laboratory experiment*; we employed a standard set of subjects (students) but with a real resource problem description⁵. Moreover, the subjects were allowed to communicate orally with each

³ SEK 1 corresponds to approximately Euro 0.57 Euro or USD 0.75.

⁴ We aimed for four subjects but performed the experiment also with three subjects in those cases where one of them did not show up.

⁵ There are other types of experiments, ranging from laboratory experiments to natural field experiments. For a more complete classification see Harrison and List (2004).

other (face-to-face) as it has been observed that communities dealing with common resources keep up frequent face-to-face communication (Pretty [2003]).

Upon arrival the subjects were given instructions to read⁶ after which they were given time for clarifying questions. The subjects were told that they each represented a resource user and that they together with the other participants in their group had access to a common resource stock. In each period each subject took an individual and anonymous decision about how many units of the resource to harvest. The experiment was a pen and paper experiment and the individual decisions were communicated via protocols. After each round of decisions, the experimenter calculated the sum of harvest, and the new resource stock size (based on tables A1 and A2 in the appendix) and communicated (written and orally) the new stock size to the group. Each harvested unit was worth SEK 5. The experiment lasted several periods, but we chose to approximate an infinite time horizon by letting the exact number of periods be unknown to the subjects (the experiment lasted between 12-18 periods, most groups played for at least 14 periods). However, if the group's total harvest was equal to or exceeding the number of available resource units in one period (s_t), the resource regeneration was zero and the experiment ended. The payment (p_{it}) of subject (i) in that period t was based on her harvest share (h_{it}) of the group's total harvest in period t , n denoting group size (see Equation 1).

$$p_{it} = \frac{h_{it}}{\sum_{i \in n} h_{it}} s_t \quad (1)$$

After the experiment the subjects filled in a questionnaire specifically designed to identify and analyze individual and group attributes. For example, we asked the subjects to state their age, gender, and educational background. We also asked them to indicate on a five-level Likert

⁶ The instructions are available as supplementary material.

scale (Likert [1932]), ranging from strong disagreement (scale value of 1) to strong agreement (scale value 5), if they understood the resource dynamics, if their group managed to cooperate, and if their communication was effective (in the following we will refer to these variables, which display mean group values, as group knowledge index, group cooperation index and group communication index). To complement the questionnaires, the experimenters also took notes on these matters⁷.

III. FORMULATING HYPOTHESES

To formulate hypotheses we rely on methods from repeated game theory and assume an infinite time horizon as it is a better approximation compared to a finite horizon when players think the game extends one more period with high probability. The discount factor, which is subjective, then represents the possibility that the game may or may not terminate at the end of the period (Fudenberg and Tirole [1998]). Although there are many types of equilibriums, we only consider equal sharing equilibriums⁸; i.e. if an equilibrium is sustained, it is based on equal shares of the stock size X and we focus on pure strategies. The players receive an update on the stock level X_t at the beginning of each period which implies that the players can deduce information on the other players' actions. For example, they know if someone deviated from an agreed cooperative strategy. They can thereby condition their strategies on the stock variable. In fact, we assume that they *only* condition their strategies on this piece of information, i.e. they use Markov strategies (Maskin and Tirole [2001]).

The optimal outcome of the game is the one where the group is able to maximize joint earnings. This outcome is obtained if the group harvests 25 units in the first period, and then, in each subsequent period, harvests the maximum sustainable yield, here 9 units. This is true

⁷ Questionnaires are available upon request from the authors

⁸ This was actually consistent with observed behavior in the experiment.

for both treatments. If, for some reason, the stock falls lower than 25 units, the optimal strategy is to let the resource recover until it again reaches 34 units (most rapid approach) and then harvest 9 units for the subsequent periods.⁹ Over-exploitation (tragedies) is then collective exploitation above what is optimal (and vice versa for under-exploitation). Efficiency is measured as the share of actual joint earnings over the maximum possible earnings.

Proposition I: Each stock size $X \in [5,50] \in \mathbb{N}$ can be sustained as an equal sharing Markov Perfect Equilibrium if the discounted value of one resource unit is large enough for each player i in the game and for the entire game. The critical discount factor δ associated with stock sizes $X \in [5,9] \cup [20,50] \in \mathbb{N}$ is the same for both treatments while for stock sizes $X \in [10,19] \in \mathbb{N}$ the critical discount factor associated with a specific stock size is higher in the threshold treatment.

The formal proof of Proposition I can be found in the appendix. The critical discount factor associated with each stock size and each treatment (and for group sizes of three and four) is also depicted in Figure III below.

[Figure III about here]

To formulate hypotheses, we need to make some assumptions about the distribution of the subjective probabilities that the game will continue one more period (true discount factors). We denote this distribution $F(\delta_{true})$. We assume that the range of the critical discount factors $[0.907, 0.995]$ is a subset of the range of $F(\delta_{true})$. Moreover, the distribution $F(\delta_{true})$ is independent of treatment.

⁹ Table AIII in appendix gives the optimal harvest strategy for the group for each stock level.

Hypothesis I: We expect less over-exploitation in the threshold treatment compared to the no threshold treatment. We also expect the average efficiency to be higher in the threshold treatment.

The intuition behind Hypothesis I stems from the idea that between stock sizes of 10 and 19, the incentive to deviate from an equilibrium is higher in the threshold treatment because the regeneration rate (and hence the incentive to play according to the equilibrium) is lower. Thus, equilibriums for stock sizes between 10 and 19 (where we find over-exploitation) are harder to sustain in the threshold treatment. For the remaining stock sizes, $X \in [5,9] \cup [20,50] \in \mathbb{N}$, where the resource growth of both treatments is identical, equilibriums are equally hard to sustain. As a result, we expect less cases of over-exploitation in the threshold treatment. To clarify, consider the example where at least one of the players in the group has a subjective discount factor below 0.966. Table I illustrates the stock sizes that can be sustained in equilibrium (SusE) depending on group size and treatment for that particular subjective discount factor. It is clear that stock sizes where we find over-exploitation equilibriums, i.e. stocks below 20, can only be sustained for the no threshold treatment.

[Table I about here]

Equilibriums that can be sustained are equally likely. Because we assume that the distributions of the subjective discount factor are identical for the two treatments, we expect less equilibrium outcomes associated with over-exploitation and, hence, we also expect efficiency to be higher in the threshold treatment.

There are many potential equilibrium outcomes but only one which is optimal. Thus, if a group makes full use of the communication opportunity and cooperates, we do expect them, regardless of treatment, to follow the optimal group strategy and stay at the maximum

sustainable yield. We define a group as cooperative if they are able to reach agreements on actual exploitation (for the entire game) and if these agreements are also being followed by all group members.

Hypothesis II: We expect cooperative groups to follow the optimal strategy and be equally efficient in their management of the resource regardless of treatment.

The intuition behind Hypothesis II stems from this latter idea that both treatments are identical for all remaining stock sizes and from the fact that the game starts with the maximum possible resource stock. Proposition I then implies that the optimal outcome can be obtained as a Markov Perfect Equilibrium regardless of treatment if the expected discounted value of one resource unit is large enough for all players i in the game.

IV. EXPERIMENT OUTCOME

IV.A. Statistics

For the statistical analysis we have used STATA 12 (StataCorp: www.stata.com). Because experiments often lead to skew distributions (which is also the case here¹⁰), we report significance levels from non-parametric Mann-Whitney U tests along with standard independent t-tests. To compare proportions across the two treatments, we use a Pearson's chi-square test (D'Agostino, Chase, and Belanger [1988]). All reported p-values are two-sided. In the regressions we let * denote significance at the 10-percent level, ** on the 5-percent level and *** on the 1-percent level. Because we can reject normality on most variables, we have bootstrapped the standard errors for all our regressions (Goncalves and White [2005]).

¹⁰ According to a Shapiro Wilk test, we can reject the normality assumption at the 5% level for all continuous variables of Table II.

IV.B. Results

We first look at the overall picture of the data, comparing means and proportions of the threshold with the no threshold treatment. Table II illustrates that there are indeed significant differences between the two treatments. Threshold treatment groups cooperated more, reported more effective communication, achieved a higher efficiency, experienced fewer tragedies and, hence, earned more money on average than groups in the no threshold treatment.¹¹ There are no structural differences with respect to age, gender, and group size.

[Table II about here]

Figure IV illustrates over- and under-exploitation in resource stock units for 14 periods¹². For the no threshold treatment (Figure IVa), although some of the groups under-exploited the resource, more than half (12/21) of the groups over-exploited and of these, half (6/12) even depleted the resource. For the threshold treatment, Figure IVb illustrates something quite different. Almost no group over-exploited the resource; only four, of which one depleted the resource. In fact, in the threshold treatment, most groups actually under-exploited the resource.

[Figure IV about here]

We have also calculated how efficient the groups were at managing the resource. Figure V clearly demonstrates the significant difference in average efficiency we found (see Table II) between the two treatments; no threshold treatment groups were not as efficient as threshold treatment groups. Given the pattern illustrated in Figure IVa, it is not that surprising to see that no threshold groups become less efficient over time. Once they have depleted the resource, efficiency drops to zero for these groups, bringing down the average efficiency.

¹¹ Note that these differences are significant on the 5-percent level even when we adjust for multiple testing, using, for example, the Bonferroni correction (Abdi [2007]).

¹² The experiment lasted between 12-18 periods and we report the results from 14 periods.

From Figure IVb we can also deduce that most inefficiencies in the threshold treatment stems from under-exploitation.

[Figure V about here]

Result I: Based on Table II and Figures IV and V we accept Hypothesis I. There are more cases of over-exploitation in the no threshold compared to the threshold treatment. Moreover, the average obtained efficiency in the no threshold treatment is significantly lower.

To answer Hypothesis II we look into the behavior of cooperating groups. For this purpose we use a stringent categorization and single out those groups with an average group cooperation index of 5 (this means that all participants in the group gave the highest value to the question how well their group managed to cooperate). We also made sure that for these cooperative groups there were no inconsistencies between reported cooperation indexes and observed behavior, which we extracted from actual behavior and the experimental notes (see section II)¹³. We found no inconsistencies and in total, we could identify 16 cooperative groups in the threshold treatment and 9 cooperative groups in the no threshold treatment.

[Figure VI about here]

If we first look at Figure VI, where we illustrate average efficiency for cooperative groups across periods for the two treatments, we see that the efficiency of no threshold groups is now closer to the efficiency obtained by threshold groups (compare Figures V and VI). However, the average achieved efficiency for cooperative groups that participated in the threshold treatment was 0.851 (with a standard deviation of 0.031). For cooperative groups in the no threshold treatment the average efficiency was 0.691 (with a standard deviation of 0.074). A

¹³ For example, some groups agreed to keep the individual shares equal in all rounds, other groups agreed to keep a rotating schedule in order to make sure to maximize joint returns. There were also groups that agreed to deplete the resource.

Mann-Whitney U test reveals that this difference is significant on the 1-percent level (p-value = 0.000).

Result II: We cannot accept Hypothesis II that states that the treatment should not have an effect on the efficiency of cooperative groups.

To summarize, the different treatments produced a significant difference in user group behavior (as we predicted). However, the effect was even stronger than predicted. We now explore the experimental results further to gain some insights and understanding about why this is the case. Table III illustrates the results from three linear regressions. We use efficiency as the dependent variable with 14 observations (periods) for each group. The first regression is with all groups, the second only with cooperative groups, and the third only with non-cooperative groups. To capture potential within group correlation, we employed a random effects structure. The models presented in Table III were chosen among several alternative specifications based on their performance with respect to model test and explanatory power.¹⁴ Other specifications show that none of the variables; average group age, gender composition, nor group size can significantly explain the variation of observed efficiency. Table III reveals instead that groups that played the threshold treatment, groups that cooperated and had a good average understanding of resource dynamics achieved on average a higher efficiency. These results are consistent for other model specifications too. We can also identify differences in behavior between cooperative and non-cooperative groups. For example, efficiency decreases with the number of periods played for non-cooperative groups but not for cooperating groups (at least not significantly). This is not surprising as we typically find over-exploitation and depletion among non-cooperative groups. The treatment is significant for both groups.

¹⁴ Other specifications are provided as supplementary material.

According to the theoretical predictions it should not have any effect for cooperative groups, thus, validating our rejection of Hypothesis II. How well group members thought they understood the resource dynamics plays a role for cooperative groups but not for non-cooperative groups, which is to be expected. Because we control for cooperation, effectiveness of communication does not seem to play any role in determining how well the groups performed with respect to efficiency.¹⁵

[Table III about here]

Besides the treatment, whether a group managed to cooperate or not seems to play a crucial role in explaining how the group performed with respect to efficiency. If the group had on average a good knowledge of the resource dynamics also seems to influence achieved efficiency. But what triggers cooperation and what lies behind the knowledge variable?

A linear regression, with the group cooperation index as dependent variable shows that groups with effective communication are more likely to cooperate (see Table IV, regression I). No other variables, including the treatment, can significantly explain how well a group managed to cooperate.¹⁶ Also for effectiveness of communication we made sure that there were no inconsistencies with reported values and observed behavior. We define effective communication as one where the group takes advantage of the communication possibility and moreover, the communication leads to collective decisions.¹⁷

[Table IV about here]

¹⁵ We only have information on communication for about 75 percent of the observations (30/41). To be able to use all our observation in the regression analysis, we have replaced missing variables for the remaining 11 groups based on averages from threshold respectively no threshold groups (see Table II).

¹⁶ Table IV presents the best (with respect to model test and explanatory power) models. Other model specifications are provided as supplementary material.

¹⁷ It is worth noting that our definitions of cooperation and effective communication imply that cooperation can be achieved only if there is effective communication.

Table IV (regression II) also reveals that the most influential variable for the average group knowledge index is how effective the group was at communicating. The threshold treatment is, as we know from Table II, associated with a less understanding of the resource dynamics, which also becomes evident here (although only at the 10-percent level). How effective the group was at communicating can explain how well they cooperated and how well they understood the resource dynamics, which in turn explains the variation of efficiency observed. So which groups are more likely to communicate effectively? Table IV (regression III) shows that the only influential variable is the treatment. Threshold groups communicate more effectively. It seems that the effectiveness of communication is endogenous to the problem, which in turn suggests that communication is a “bad” control in the first regression (I). To capture the causal effect of communication we therefore have to use a two stage least square (2SLS) regression where we use predicted values from regression III in regression I. Regression IV presents these results. Effective communication causes a higher level of cooperation. Based on our results we propose the following linkage:

Result III: The threat of reaching a critical tipping point triggers more effective communication within the group, which in turn enables not only stronger commitment for cooperation but also knowledge sharing, which can explain why threshold groups manage the resource more efficiently, even when we only consider cooperative groups.

V. DISCUSSION

The purpose of this study was to experimentally assess the effects of potential endogenous, abrupt and persistent changes in the resource growth rate on resource users’ management of common resources. We find that the existence of such shifts significantly influences resource users’ strategies for cooperation and resource exploitation. We observe more cooperative

outcomes and more efficient resource management. This kind of behavior is to some extent consistent with other experimental and theoretical findings on commons management. Santos and Pacheco (2011) show, for example, by using an evolutionary dynamics approach, how decisions within small groups under more stringent resource conditions significantly raise the chance of coordinating actions and escaping the tragedy of the commons. It is the common threat that fosters more cooperative behavior. Moreover, Samuelson (1991) showed experimentally that when giving the choice of assigning a leader (who alone would decide group harvest) and thereby being able to escape the tragedy, groups were more inclined to assign a leader when they thought that the task before them was more difficult.

So what is the value-added of this study? Our results suggest that one important linkage between the level of cooperation and resource management decision is the *effectiveness* of communication. When rules cannot be enforced internally or externally, face-to face communication should by game theoretic predictions be irrelevant (cheap talk). However, communication has been identified as one of the most influential variables to ensure cooperative outcomes (see overviews in Sally [1995]; Ostrom [2006]). Group discussions enhance group identity and solidarity which foster commitments to cooperate (Dawes, Van der Kragt, and Orbell [1990]; Kopelman, Weber, and Messick [2002]). In our experiment, all groups, regardless of treatment, face the same opportunities to engage in face-to-face communication, but we do not observe the same level of communication and cooperation in our treatments, because the extent to which groups take advantage of the communication possibility is endogenous to the problem. Policy recommendations for successful commons management often centers on how we can enhance and support arenas for communication and conflict resolutions (Ostrom et al. [2002]). Our results suggest that how the problem is described to and perceived by the different actors may also matter. Theoretical results and

outcomes on commons management under the influence of endogenously driven abrupt changes in the resource growth rate hinges on whether the user group is assumed to be cooperative or not, but usually nothing is said on when we should expect cooperation or not. These results can thus directly inform theory.

Another significant contribution of this paper is that it introduces and evaluates an experimental design that is comprehensive for its subjects while still allowing for a high degree of complexity of the underlying resource supply function. This design can thus be used for similar future studies (e.g. to test other associated features of regime shifts in the laboratory and/or in the field) and may even be helpful for introducing the concept of tipping points and regime shifts to resource users, other stakeholders, and policy makers.

Our results are relevant for other types of economic problems too. Consider for example a bargaining problem. It is in both parties interest to reach an agreement but inefficiencies (due to bargaining impasse) may arise when each party strives to attract most of the surplus.¹⁸ Should we expect a higher probability of reaching an efficient agreement if the impasse can lead to substantial and potentially persistent losses? Our results suggest we should. One can also think of cases where a potential threat of substantial losses can lead to market inefficiencies. Consider, for example, the decision to enter a new market with imperfect competition; there are only a few potential competitors and excess entry can lead to substantial losses in terms of sunk costs. Our results would then imply that the probability of cooperation in the form of a cartel arising is endogenous and positively dependent on the nature of the market structure.

¹⁸ The bargaining impasse can be described as an endogenous drastic change in the bargaining process.

We have left some critical questions for future research. For example, in order to isolate the effect of an endogenously driven abrupt shift on users' strategies, we abstracted away from exogenous drivers; the probability of a shift is driven positively and *solely* by the users' actions. This implies, of course, that there are no other uncertainties (but strategic) in our model. We know from related experimental studies that uncertainty about the location of a critical point, at which huge welfare losses are to be expected, can have substantial effects on public good contribution and that uncertainty about the resource stock size uncertainty or regeneration rate in commons dilemmas (where subjects cannot communicate) can increase individual requests (Budescu, Rapoport, and Suleiman [1990]; Rapoport, Budescu, and Suleiman [1993]; Gustafsson, Biel, and Gärling [1999]; Barrett and Dannenberg [2012]). How would uncertainties related to the tipping point in our commons dilemma, where users can communicate, influence our results? We have to leave this question for future research.

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APPENDIX

A1. Details on Figure 1 in Section 2

Figure 1 in Section 2 is based on equation (A1) which represents stock dynamics of a stock x that change with time t , with growth rate r and carrying capacity K . In the Holling type III

predation term b denotes the maximum uptake rate, a half saturation, and exponent θ introduces the non-convexity. The term h represents exploitation and can be controlled.

$$\frac{dx}{dt} = rx \left(1 - \frac{x}{K} \right) - b \frac{x^\theta}{a^\theta + x^\theta} - h \quad (\text{A1})$$

The figure was simulated based on the following parameter values:

Logistic model $r=0.6$; $K=9,5$; $h=0$

Ludwig et al model $r=1$; $K=11$; $a=1$; $b=1,3$, $h=0$ and $\theta=4$)

A2. Tables of Resource Dynamics as Presented to Subjects

[Table AI about here]

[Table AII about here]

A3. Proofs of Theoretical Results in Section III

1. Optimal claims for all stock sizes

[Table AIII about here]

2. Proof of Proposition 1: Assume the following Markov strategy profile for each player $i \in \{1, \dots, n\}$, where n is the total number of players: In the first period, take $(50-X)/n$ units of the resource (to reach a stock size of X) and then from the second period and onwards take H_X/n units, where H_X denotes the sustainable yield to keep stock size X . If in some period t , someone deviates from this strategy profile (i.e. the new stock size is not X), then deplete the resource in the next period, $t+1$, i.e. claim the entire stock size. The maximum possible amount to claim is the current resource stock size and in case of depletion each player gets a payoff which corresponds to his/her percentage of the sum of all claims that period (see

equation 2). Hence for a deviating player, the optimal deviation is then to deplete the resource in period t i.e. claim the current stock size (s_t). Equation (A2), gives the payoff p_{DC} of a player i who deviates when all other players play according to the strategy profile which sustain the stock size X . h_{jt} represents the claimed harvest of player j where $j \neq i$.

$$p_{DC} = s_t \frac{s_t}{s_t + \sum_{j \in n, j \neq i} h_{jt}} \quad (\text{A2})$$

If all players deplete the resource in the same period, the associated payoff for each player is s_t/n . Let δ_i denote the expected discounted value of 1 unit harvested capturing the subjective probability of player i that the game will continue for one more period. Let r denote the rate of time preference, Δ the period length, and μ_i the probability that the game will continue to the next period. Then 1 unit tomorrow, to be collected only if the game lasts that long, is worth 0 with probability $1-\mu_i$ and $\rho = e^{-r\Delta}SEK$ with probability μ_i , and yield the expected discounted value $\delta_i = \mu_i \rho$.

Equation (A3) shows the total payoff, for player i who follows the optimal cooperative strategy for the entire game, given that all other players do so as well. The first term refers to the payoff in period 0 and the second term the sum of the continuation payoffs in all subsequent periods.

$$p_{CC}(n, \delta_i) = \frac{50-X}{n} + \sum_{t=1}^{\infty} \delta_i^t \frac{H_x}{n} \quad (\text{A3})$$

From equations (A2-A3) we can derive the necessary conditions for the optimal cooperative outcome to be sustainable as a Markov (subgame) perfect equilibrium. In the very first period, the optimal cooperative outcome can be obtained if equation A4 holds:

for all i

$$\begin{aligned}
\frac{50-X}{n} + \sum_{t=1}^{\infty} \delta_i^t \frac{H_x}{n} &\geq \frac{50^2}{50 + \frac{50-X}{n}(1-n)} \\
\Leftrightarrow \frac{1}{1-\delta_i} &\geq \frac{50^2 n^2}{((100-X)n - (50-X))H_x} - \frac{50-X-H_x}{H_x} \\
\Leftrightarrow \frac{((100-X)n - (50-X))H_x}{50^2 n^2 - ((100-X)n - (50-X))(50-X-H_x)} &\geq 1-\delta_i \\
\Leftrightarrow \delta_i &\geq \frac{50^2 n^2 - ((100-X)n - (50-X))(50-X)}{50^2 n^2 - ((100-X)n - (50-X))(50-X-H_x)}
\end{aligned} \tag{A4}$$

In the subsequent periods, because each period is a proper subgame, we need to check that the continuation payoff at time t , is larger than the deviation payoff. Thus, the following needs to hold:

for all i

$$\begin{aligned}
\sum_{\tau=t}^{\infty} \delta_i^{(\tau-t)} \frac{H_x}{n} &\geq \frac{(X+H_x)^2}{X+H_x + \frac{H_x(n-1)}{n}} \\
\Leftrightarrow \frac{1}{1-\delta_i} &\geq \frac{(X+H_x)^2 n^2}{((X+H_x)n + H_x(n-1))H_x} \\
\Leftrightarrow \frac{((X+H_x)n + H_x(n-1))H_x}{(X+H_x)^2 n^2} &\geq 1-\delta_i \\
\Leftrightarrow \delta_i &\geq \frac{(X+H_x)^2 n^2 - ((X+2H_x)n - H_x)H_x}{(X+H_x)^2 n^2}
\end{aligned} \tag{A5}$$

For all parameters in our model, we have verified that if equation A4 holds then equation A5 also holds.¹⁹

¹⁹ These calculations are available upon request.

In Table AIV we present the critical discount rates (from equation A4) associated with equal sharing equilibriums for all stocks. From the table we can see that equal sharing equilibrium outcomes are harder to sustain for stock sizes between 10 and 19 in the threshold treatment while for all other stock sizes $x \in [5,9] \cup [20,50] \in \mathbb{N}$ they are equally easy to sustain. Moreover, equilibriums are harder to sustain in groups of 4 players compared to groups of three players. Table AIV proves Proposition I.

[Table AIV about here]

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Table I

Illustration of Stock Sizes that Can Be Sustained in Equilibrium (SusE) for the Case where, at Least One of the Group Members has a Subjective Discount Factor below 0.966.

Stock sizes	N=3, Threshold	N=4 Threshold	N=3 No threshold	N=4 No threshold
5-9				
10-14			SusE	
15-19			SusE	SusE
20-24	SusE	SusE	SusE	SusE
25-29	SusE	SusE	SusE	SusE
30-34	SusE	SusE	SusE	SusE
35-39	SusE		SusE	
40-45				
46-50				

Table II
Comparing Averages

	No Threshold (st.dev)	Threshold (st.dev)	p-value	
			t-test	Mann-W.
Average individual total earnings (SEK)	141.990 (58.877)	176.417 (44.448)	0.000	0.000
Average efficiency	0.510 (0.091)	0.840 (0.041)	0.000	0.000
Average cooperation index	3.896 (1.518)	4.534 (1.094)	0.004	0.002
Average age	29.896 (10.760)	28.233 (9.906)	0.327	0.276
Average knowledge index	4.90 (1.002)	4.493 (0.784)	0.484	0.791
Average communication index	4.196 (1.102)	4.768 (0.713)	0.002	0.000
Pearson's chi-square				
Prop. of females	0.571	0.600	0.721	
Prop. of tragedies (over-exploiting groups)	0.571	0.200	0.015	
Prop. of groups with 4 subjects	0.727	0.712	0.446	

Table III

Random Effects Linear Regression Models

	All groups	Cooperating groups	Non- cooperating groups
	Efficiency	Efficiency	Efficiency
	Coefficient	Coefficient	Coefficient
	(st. error, bootstrap)	(st. error, bootstrap)	(st. error, bootstrap)
	p-value	p-value	p-value
Treatment: Threshold =1	0.244***	0.125**	0.342**
No threshold =0	(0.054)	(0.049)	(0.157)
	0.000	0.011	0.030
Average group communication index	-0.068 (0.049)	0.017 0.056	0.110 0.126
	0.169	0.756	0.383
Average group knowledge index	0.087** (0.043)	0.145*** (0.053)	0.030 (0.118)
	0.045	0.006	0.800
Average group cooperation Index	0.130*** (0.021)		
	0.000		
Ln period	-0.044* (0.027)	-0.013 0.024	-0.097* 0.057
	0.097	0.575	0.088
Rho (fraction of variance due to u_i)	0.216	0.107	0.403
Model test: Wald chi2	1133.82*** 0.000	1735.43*** 0.000	93.75*** 0.000
Adj. R square			
# of observations	14*41=574	14*25=350	14*16=224

Table IV
Four Regression Models

	(I) Group cooperation (OLS)	(II) Group knowledge of resource dynamics (OLS)	(III) Group communication (OLS)	(IV) Group cooperation (2SLS)
	Coefficient (st. error, bootstrap) p-value	Coefficient (st. error, bootstrap) p-value	Coefficient (st. error, bootstrap) p-value	Coefficient (St. error, bootstrap) P-value
Constant			4.221*** (0.182) 0.000	
Treatment: Threshold = 1	0.045	-0.400*	0.566***	
No threshold = 0	(0.385)	(0.227)	(0.199)	
	0.906	0.077	0.004)	
Average group communication Index. In the 2SLS (4), predicted values from reg. (3) are used.	1.173*** (0.301) 0.000	1.121*** (0.137) 0.000		0.672** (0.334) 0.016
Average group knowledge of resource dynamics	-0.236 (0.301) 0.431			0.277 (0.344) 0.420
Average group cooperation index		-0.102 (0.134) 0.447		
Adj. R-square	0.947	0.978	0.141	0.925
Model test	1509.75***	2923.31***	8.09***	546.95***
Wald chi2	0.000	0.000	0.005	0.000
# observations	41	41	41	41

Table AI

Regeneration for each Resource Stock Size, No Threshold

Resource stock size	Re-generation	Resource stock size	Re-generation	Resource stock size	Re-generation
50	0	32	7	14	3
49	1	31	7	13	3
48	1	30	7	12	3
47	1	29	9	11	3
46	1	28	9	10	3
45	1	27	9	9	1
44	3	26	9	8	1
43	3	25	9	7	1
42	3	24	7	6	1
41	3	23	7	5	1
40	3	22	7	4	0
39	5	21	7	3	0
38	5	20	7	2	0
37	5	19	5	1	0
36	5	18	5	0	0
35	5	17	5		
34	7	16	5		
33	7	15	5		

Table AII

Regeneration for each Resource Stock Size, Threshold

Resource stock size	Re-generation	Resource stock size	Re-generation	Resource stock size	Re-generation
50	0	32	7	14	2
49	1	31	7	13	2
48	1	30	7	12	2
47	1	29	9	11	2
46	1	28	9	10	2
45	1	27	9	9	1
44	3	26	9	8	1
43	3	25	9	7	1
42	3	24	7 alt. 1	6	1
41	3	23	7 alt. 1	5	1
40	3	22	7 alt. 1	4	0
39	5	21	7 alt. 1	3	0
38	5	20	7 alt. 1	2	0
37	5	19	1	1	0
36	5	18	1	0	0
35	5	17	1		
34	7	16	1		
33	7	15	1		

Table AIII
Optimal Claims

No threshold treatment				Threshold treatment			
Stock size (s)	Optimal claim	# rounds until s = 34 =R	Harvest during R	Stock size (s)	Optimal claim	# rounds until s = 34 =R	Harvest during R
50	25	1	25	50	25	1	25
49	24	1	24	49	24	1	24
48	23	1	23	48	23	1	23
47	22	1	22	47	22	1	22
46	21	1	21	46	21	1	21
45	20	1	20	45	20	1	20
44	19	1	19	44	19	1	19
43	18	1	18	43	18	1	18
42	17	1	17	42	17	1	17
41	16	1	16	41	16	1	16
40	15	1	15	40	15	1	15
39	14	1	14	39	14	1	14
38	13	1	13	38	13	1	13
37	12	1	12	37	12	1	12
36	11	1	11	36	11	1	11
35	10	1	10	35	10	1	10
34	9	1	9	34	9	1	9
33	8	1	8	33	8	1	8
32	7	1	7	32	7	1	7
31	6	1	6	31	6	1	6
30	5	1	5	30	5	1	5
29	4	1	4	29	4	1	4
28	3	1	3	28	3	1	3
27	2	1	2	27	2	1	2
26	1	1	1	26	1	1	1
25	0	1	0	25	0	1	0

24	4	2	6	24	4 alt. 0	2	6 alt. 0
23	3	2	5	23	3 alt. 0	2 alt. 3	5 alt. 0
22	2	2	4	22	2 alt. 0	2 alt. 4	4 alt. 0
21	1	2	3	21	1 alt. 0	2 alt. 5	3 alt. 0
20	0	2	2	20	0	2 alt. 6	2 alt. 0
19	4	3	6	19	0	7	0
18	3	3	5	18	0	8	0
17	2	3	4	17	0	9	0
16	1	3	3	16	0	10	0
15	0	3	2	15	0	11	0
14	2	4	4	14	0	11	0
13	1	4	3	13	1	12	1
12	0	4	2	12	0	12	0
11	1	5	3	11	1	13	1
10	0	5	3	10	0	13	0
9	0	6	3	9	0	14	0
8	0	7	3	8	0	15	0
7	0	8	3	7	0	16	0
6	0	9	3	6	0	17	0
5	0	10	3	5	0	18	0

Table AIV
Critical Discount Factors

Stock size	δ_i for NT treatment	δ_i for T treatment	NT: 3 subjects	T: 3 subjects	NT: 4 subjects	T: 4 subjects
5	$\frac{50^2 n^2 - 45(95n - 45)}{50^2 n^2 - 44(95n - 45)}$	$\frac{50^2 n^2 - 45(95n - 45)}{50^2 n^2 - 44(95n - 45)}$	0.980	0.980	0.987	0.987
6	$\frac{50^2 n^2 - 44(94n - 44)}{50^2 n^2 - 43(94n - 44)}$	$\frac{50^2 n^2 - 44(94n - 44)}{50^2 n^2 - 43(94n - 44)}$	0.981	0.981	0.987	0.987
7	$\frac{50^2 n^2 - 43(93n - 43)}{50^2 n^2 - 41(93n - 43)}$	$\frac{50^2 n^2 - 43(93n - 43)}{50^2 n^2 - 41(93n - 43)}$	0.981	0.981	0.987	0.987
8	$\frac{50^2 n^2 - 42(92n - 42)}{50^2 n^2 - 41(92n - 42)}$	$\frac{50^2 n^2 - 42(92n - 42)}{50^2 n^2 - 41(92n - 42)}$	0.982	0.982	0.988	0.988
9	$\frac{50^2 n^2 - 41(91n - 41)}{50^2 n^2 - 40(91n - 41)}$	$\frac{50^2 n^2 - 41(91n - 41)}{50^2 n^2 - 40(91n - 41)}$	0.982	0.982	0.988	0.988
10	$\frac{50^2 n^2 - 40(90n - 40)}{50^2 n^2 - 37(90n - 40)}$	$\frac{50^2 n^2 - 40(90n - 40)}{50^2 n^2 - 38(90n - 40)}$	0.951	0.967	0.966	0.978
11	$\frac{50^2 n^2 - 39(89n - 39)}{50^2 n^2 - 36(89n - 39)}$	$\frac{50^2 n^2 - 39(89n - 39)}{50^2 n^2 - 37(89n - 39)}$	0.952	0.968	0.967	0.978
12	$\frac{50^2 n^2 - 38(88n - 38)}{50^2 n^2 - 35(88n - 38)}$	$\frac{50^2 n^2 - 38(88n - 38)}{50^2 n^2 - 36(88n - 38)}$	0.954	0.969	0.968	0.978
13	$\frac{50^2 n^2 - 37(87n - 37)}{50^2 n^2 - 34(87n - 37)}$	$\frac{50^2 n^2 - 37(87n - 37)}{50^2 n^2 - 35(87n - 37)}$	0.955	0.969	0.968	0.979
14	$\frac{50^2 n^2 - 36(86n - 36)}{50^2 n^2 - 33(86n - 36)}$	$\frac{50^2 n^2 - 36(86n - 36)}{50^2 n^2 - 34(86n - 36)}$	0.956	0.970	0.969	0.979
15	$\frac{50^2 n^2 - 35(85n - 35)}{50^2 n^2 - 30(85n - 35)}$	$\frac{50^2 n^2 - 35(85n - 35)}{50^2 n^2 - 34(85n - 35)}$	0.931	0.985	0.951	0.990
16	$\frac{50^2 n^2 - 34(84n - 34)}{50^2 n^2 - 29(84n - 34)}$	$\frac{50^2 n^2 - 34(84n - 34)}{50^2 n^2 - 33(84n - 34)}$	0.933	0.986	0.952	0.990
17	$\frac{50^2 n^2 - 33(83n - 33)}{50^2 n^2 - 28(83n - 33)}$	$\frac{50^2 n^2 - 33(83n - 33)}{50^2 n^2 - 32(83n - 33)}$	0.934	0.986	0.953	0.990
18	$\frac{50^2 n^2 - 32(82n - 32)}{50^2 n^2 - 27(82n - 32)}$	$\frac{50^2 n^2 - 32(82n - 32)}{50^2 n^2 - 31(82n - 32)}$	0.936	0.987	0.954	0.990

19	$\frac{50^2 n^2 - 31(81n - 31)}{50^2 n^2 - 26(81n - 31)}$	$\frac{50^2 n^2 - 31(81n - 31)}{50^2 n^2 - 30(81n - 31)}$	0.938	0.987	0.955	0.991
20	$\frac{50^2 n^2 - 30(80n - 30)}{50^2 n^2 - 23(80n - 30)}$	$\frac{50^2 n^2 - 30(80n - 30)}{50^2 n^2 - 23(80n - 30)}$	0.917	0.917	0.917	0.917
21	$\frac{50^2 n^2 - 29(79n - 29)}{50^2 n^2 - 22(79n - 29)}$	$\frac{50^2 n^2 - 29(79n - 29)}{50^2 n^2 - 22(79n - 29)}$	0.919	0.919	0.940	0.940
22	$\frac{50^2 n^2 - 28(78n - 28)}{50^2 n^2 - 21(79n - 28)}$	$\frac{50^2 n^2 - 28(78n - 28)}{50^2 n^2 - 21(79n - 28)}$	0.921	0.921	0.942	0.942
23	$\frac{50^2 n^2 - 27(77n - 27)}{50^2 n^2 - 20(77n - 27)}$	$\frac{50^2 n^2 - 27(77n - 27)}{50^2 n^2 - 20(77n - 27)}$	0.922	0.922	0.943	0.943
24	$\frac{50^2 n^2 - 26(76n - 26)}{50^2 n^2 - 19(76n - 26)}$	$\frac{50^2 n^2 - 26(76n - 26)}{50^2 n^2 - 19(76n - 26)}$	0.924	0.924	0.944	0.944
25	$\frac{50^2 n^2 - 25(75n - 25)}{50^2 n^2 - 16(75n - 25)}$	$\frac{50^2 n^2 - 25(75n - 25)}{50^2 n^2 - 16(75n - 25)}$	0.907	0.907	0.930	0.930
26	$\frac{50^2 n^2 - 24(74n - 24)}{50^2 n^2 - 15(74n - 24)}$	$\frac{50^2 n^2 - 24(74n - 24)}{50^2 n^2 - 15(74n - 24)}$	0.909	0.909	0.932	0.932
27	$\frac{50^2 n^2 - 23(73n - 23)}{50^2 n^2 - 14(73n - 23)}$	$\frac{50^2 n^2 - 23(73n - 23)}{50^2 n^2 - 14(73n - 23)}$	0.911	0.911	0.933	0.933
28	$\frac{50^2 n^2 - 22(72n - 22)}{50^2 n^2 - 13(72n - 22)}$	$\frac{50^2 n^2 - 22(72n - 22)}{50^2 n^2 - 13(72n - 22)}$	0.913	0.913	0.934	0.934
29	$\frac{50^2 n^2 - 21(71n - 21)}{50^2 n^2 - 12(71n - 21)}$	$\frac{50^2 n^2 - 21(71n - 21)}{50^2 n^2 - 12(71n - 21)}$	0.914	0.914	0.936	0.936
30	$\frac{50^2 n^2 - 20(70n - 20)}{50^2 n^2 - 13(70n - 20)}$	$\frac{50^2 n^2 - 20(70n - 20)}{50^2 n^2 - 13(70n - 20)}$	0.934	0.934	0.950	0.950
31	$\frac{50^2 n^2 - 19(69n - 19)}{50^2 n^2 - 12(69n - 19)}$	$\frac{50^2 n^2 - 19(69n - 19)}{50^2 n^2 - 12(69n - 19)}$	0.935	0.934	0.951	0.951
32	$\frac{50^2 n^2 - 18(68n - 18)}{50^2 n^2 - 11(68n - 18)}$	$\frac{50^2 n^2 - 18(68n - 18)}{50^2 n^2 - 11(68n - 18)}$	0.936	0.936	0.952	0.952
33	$\frac{50^2 n^2 - 17(67n - 17)}{50^2 n^2 - 10(67n - 17)}$	$\frac{50^2 n^2 - 17(67n - 17)}{50^2 n^2 - 10(67n - 17)}$	0.938	0.938	0.953	0.953
34	$\frac{50^2 n^2 - 16(66n - 16)}{50^2 n^2 - 9(66n - 16)}$	$\frac{50^2 n^2 - 16(66n - 16)}{50^2 n^2 - 9(66n - 16)}$	0.939	0.939	0.954	0.954

35	$\frac{50^2 n^2 - 15(65n - 15)}{50^2 n^2 - 10(65n - 15)}$	$\frac{50^2 n^2 - 15(65n - 15)}{50^2 n^2 - 10(65n - 15)}$	0.957	0.957	0.967	0.967
36	$\frac{50^2 n^2 - 14(64n - 14)}{50^2 n^2 - 9(64n - 14)}$	$\frac{50^2 n^2 - 14(64n - 14)}{50^2 n^2 - 9(64n - 14)}$	0.957	0.957	0.968	0.968
37	$\frac{50^2 n^2 - 13(63n - 13)}{50^2 n^2 - 8(63n - 13)}$	$\frac{50^2 n^2 - 13(63n - 13)}{50^2 n^2 - 8(63n - 13)}$	0.958	0.958	0.969	0.969
38	$\frac{50^2 n^2 - 12(62n - 12)}{50^2 n^2 - 7(62n - 12)}$	$\frac{50^2 n^2 - 12(62n - 12)}{50^2 n^2 - 7(62n - 12)}$	0.959	0.959	0.969	0.969
39	$\frac{50^2 n^2 - 11(61n - 11)}{50^2 n^2 - 6(61n - 11)}$	$\frac{50^2 n^2 - 11(61n - 11)}{50^2 n^2 - 6(61n - 11)}$	0.960	0.960	0.970	0.970
40	$\frac{50^2 n^2 - 10(60n - 10)}{50^2 n^2 - 7(60n - 10)}$	$\frac{50^2 n^2 - 10(60n - 10)}{50^2 n^2 - 7(60n - 10)}$	0.976	0.976	0.982	0.982
41	$\frac{50^2 n^2 - 9(59n - 9)}{50^2 n^2 - 6(59n - 9)}$	$\frac{50^2 n^2 - 9(59n - 9)}{50^2 n^2 - 6(59n - 9)}$	0.977	0.977	0.982	0.982
42	$\frac{50^2 n^2 - 8(58n - 8)}{50^2 n^2 - 5(58n - 8)}$	$\frac{50^2 n^2 - 8(58n - 8)}{50^2 n^2 - 5(58n - 8)}$	0.977	0.977	0.983	0.983
43	$\frac{50^2 n^2 - 7(57n - 7)}{50^2 n^2 - 4(57n - 7)}$	$\frac{50^2 n^2 - 7(57n - 7)}{50^2 n^2 - 4(57n - 7)}$	0.977	0.977	0.983	0.983
44	$\frac{50^2 n^2 - 6(56n - 6)}{50^2 n^2 - 3(56n - 6)}$	$\frac{50^2 n^2 - 6(56n - 6)}{50^2 n^2 - 3(56n - 6)}$	0.978	0.978	0.983	0.983
45	$\frac{50^2 n^2 - 5(55n - 5)}{50^2 n^2 - 4(55n - 5)}$	$\frac{50^2 n^2 - 5(55n - 5)}{50^2 n^2 - 4(55n - 5)}$	0.993	0.933	0.955	0.955
46	$\frac{50^2 n^2 - 4(54n - 4)}{50^2 n^2 - 3(54n - 4)}$	$\frac{50^2 n^2 - 4(54n - 4)}{50^2 n^2 - 3(54n - 4)}$	0.993	0.993	0.995	0.995
47	$\frac{50^2 n^2 - 3(53n - 3)}{50^2 n^2 - 2(53n - 3)}$	$\frac{50^2 n^2 - 3(53n - 3)}{50^2 n^2 - 2(53n - 3)}$	0.993	0.993	0.995	0.995
48	$\frac{50^2 n^2 - 2(52n - 2)}{50^2 n^2 - (52n - 2)}$	$\frac{50^2 n^2 - 2(52n - 2)}{50^2 n^2 - (52n - 2)}$	0.993	0.993	0.995	0.995
49	$\frac{50^2 n^2 - (51n - 1)}{50^2 n^2}$	$\frac{50^2 n^2 - (51n - 1)}{50^2 n^2}$	0.993	0.993	0.995	0.995
50	$\frac{50^2 n^2}{50^2 n^2 + 50n}$	$\frac{50^2 n^2}{50^2 n^2 + 50n}$	0.993	0.993	0.995	0.995

Figure I

Two Types of Resource Dynamics. Logistic type stock dynamics (dashed curve) in comparison to stock dynamics involving a potential endogenous abrupt change (solid curve).

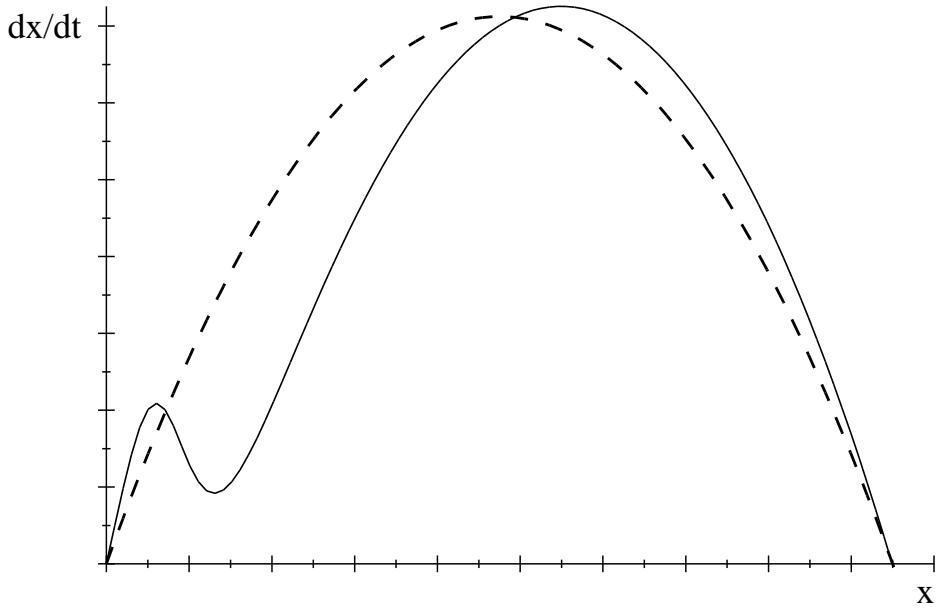


Figure II

Graphical Illustration of Resource Dynamics As Presented To The Subjects. Without (a) and with threshold (b).

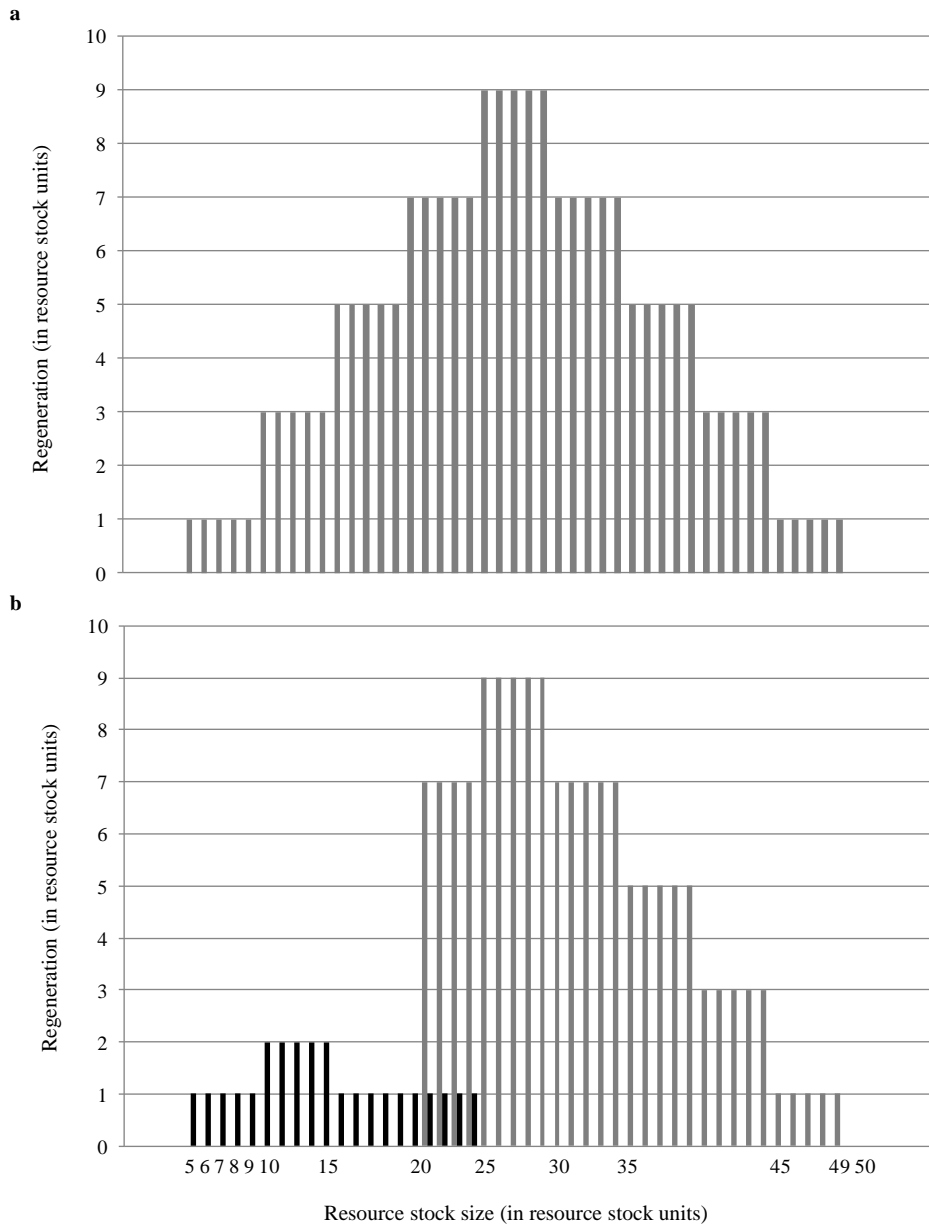


Figure III

Critical Discount Factors. The critical discount factor associated with each equilibrium stock size for each treatment and both group sizes.

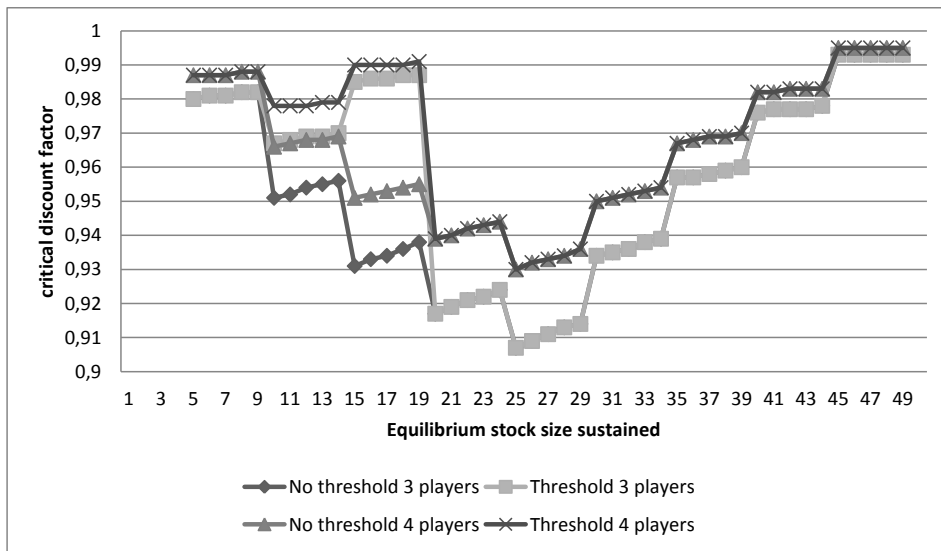


Figure IV

Over And Under Exploitation. Data points above zero indicate over exploitation and data points below under exploitation.

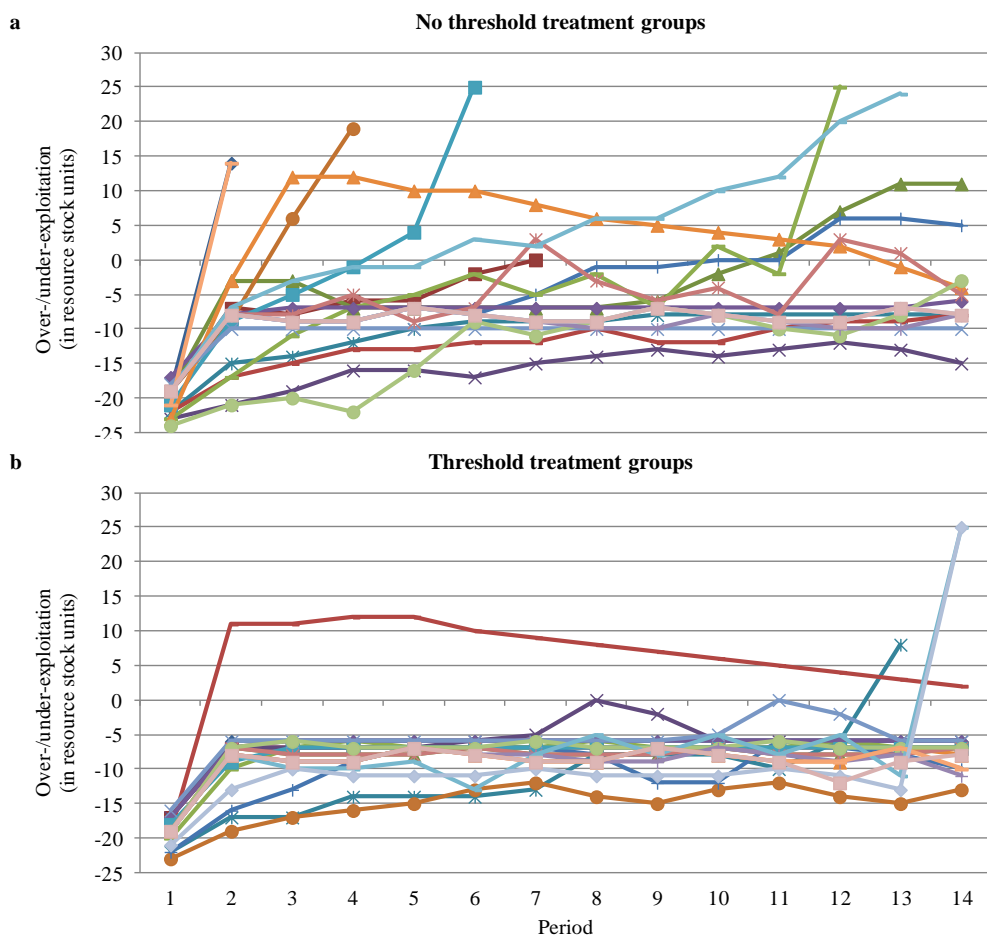


Figure V

Average Efficiency, Given Current Stock Size.

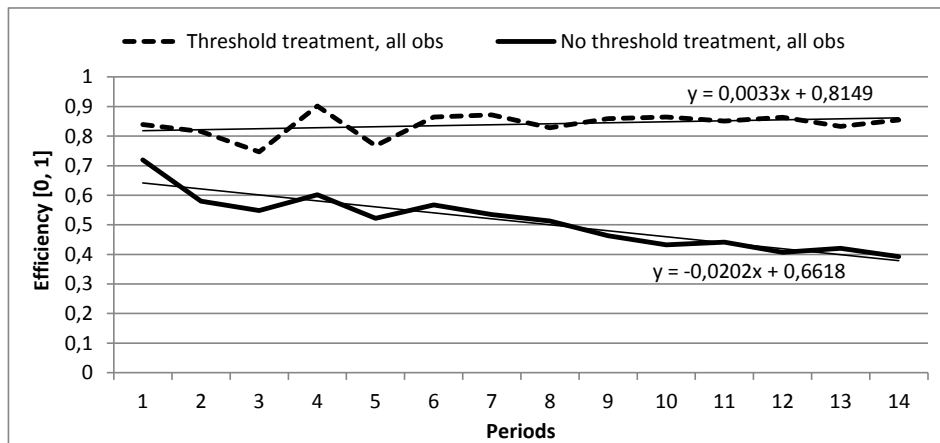


Figure VI

Average Efficiency For Cooperative Groups, Given Current Stock Size.

