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Crossing the Point of No Return:
A Public Goods Experiment

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Abstract

Participants in a public goods experiment receive private or common signals regarding the so-called "point of no return", meaning that if the group's total contribution falls below this point, all payoffs are reduced. An individual faces the usual conflict between private and collective interests above the point of no return, while he incurs the risk of damaging everyone by not surpassing the point. Our data reveal that contributions are higher if the cost of not reaching the threshold is high. In particular if the signal is private, many subjects are not willing to provide the necessary contribution.

Keywords: Public goods, provision point mechanism, experiments, reduction factor, signal

JEL classification H41, C92, C72

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1. Introduction

Greenhouse gas emissions are a primary concern of the Kyoto protocol and various courses of action could be taken to reduce them – they vary in the scale of their effect, their cost, and potential contribution. Although no consensus has been reached concerning the measures to be adopted and the share of responsibilities among countries, it is undoubtedly crucial that some investments are made in order not to jeopardize mankind's future. Motivated by the importance of this kind of public goods requiring multilateral effort to reach a target and avoid losses to all members, this paper examines an experimental scenario where the failure to achieve a prespecified contribution level results in a universal damage. We refer to such a critical level as the "point of no return" because if contributions fall short of this point, everybody suffers. Although arguments and examples for points of no return have been put forward (see, e.g., Dasgupta and Mäler 2001), we simply presuppose that points of no return do exist.

Our main aim is to explore whether the threat caused by the point of no return facilitates the coordination of contributions even when self-interest renders zero-contribution a dominant strategy. To this end, we combine the essential characteristics of a provision point mechanism (PPM) with those of a voluntary contribution mechanism (VCM). These two mechanisms have been extensively investigated in separation (see Ledyard 1995 for a survey). Yet, few experimental economics studies have combined them into a unified framework.[1]

The most commonly implemented PPM (Isaac et al. 1989; Bagnoli and McKee 1991; Suleiman and Rapoport 1992; Cadsby and Maynes 1998, 1999; Marks and Croson 1998; Croson and Marks 2000; Asher et al. 2009; Spencer et al. 2009) uses a step-level function that requires, for providing the public good, a minimum level of group contributions.[2] This minimum level is referred to as the "threshold" or "provision point" and usually corresponds to the cost of the public good. If enough contributions are made to reach the threshold, the

[1] Some previous work has been devoted to understanding the relative performance of the two mechanisms (e.g., Rondeau et al. 2005) or to critically assessing the differences between them (Abele et al. 2010). The experiment most similar to ours is Freytag et el. (2010), who consider a VCM with a discontinuity in the linear payoff function. Differently from us, however, Freytag et el. focus on the effectiveness of "milestones" (i.e., intermediate contribution stages) in preventing a potential environmental catastrophe.

[2] The provision point can also be defined in terms of the number of players who need to contribute (see, e.g., van de Kragt et al. 1988; Offerman et al. 1998; Rose et al. 2002).

good is provided.[3] Otherwise, it is not provided at all. Unused contributions are frequently refunded, but can also be lost (like in, e.g., van Dijk and Grodzka 1992).[4]

Our game involves the step-level characteristic of the earlier studies, but has some distinctive features. First, the threshold does not represent the cost of the public good, but – as mentioned above – it stands for the target to be met in order to protect the good and not to damage everyone; in other words, the threshold is the "point of no return". The public good that we consider therefore exists, in a limited measure, even though the sum of contributions falls below the threshold. Second, prior to any contribution decision, each group member receives a signal informing him either vaguely or reliably about the point of no return, specified as the sum of all members' signals. Finally, similar to standard VCMs, the agents' payoff function is linear in contribution levels both above and below the threshold with a constant marginal per capita return from the public good. However, differently from standard VCMs, the payoff function is discontinuous at the threshold: if the sum of the contributions falls short of the threshold, all subjects' payoffs are reduced by a commonly known factor. Thus, the "point of no return" is just a dramatic description of an "edgeproblem" where "falling from the edge" has more or less dramatic payoff effects.

We vary two characteristics of our set-up in order to investigate their impact on contribution levels. Specifically, we modify (i) the payoff reduction factor, which can be either small or large, and (ii) the received signal, which can be either homogeneous (all group members receive the same signal) or heterogeneous (each group member's signal is independently drawn from the same discrete distribution). The common signal case appears to be an ideal scenario where all countries agree on how to evaluate the empirical evidence, e.g., by letting a committee of international experts, possibly appointed by the United Nations, be responsible for the signal generation. The private signal case represents a more realistic scenario where actors hold independent and different views on what needs to be done to reach the target.[5]

By this design, we aim to engage the following research questions:

[3] In the literature, the rules that apply when the total contribution level exceeds the required threshold are called "rebate rules". Marks and Croson (1998) and Spencer et al. (2009) investigate the effects of alternative rebate rules on voluntary contributions.

[4] Cadsby and Maynes (1999) compare experimentally the money-back case to the non-money-back case.

[5] For instance, different countries have different opinions about the necessity to ratify the Kyoto protocol. The most notable country opposing the protocol is the United States. This may be due to a self-serving bias or to who should bear the burden of the mitigation costs. Here, we do not allow for self-serving generation of signals, but only for self-serving behavior in the sense that a party can undercontribute its signal.

(i) Does the risk of making everyone suffer by falling below the threshold inspire more voluntary cooperation, e.g., by contributing at least one's own signal, irrespective of whether or not "contributing the signal" is an equilibrium?

(ii) Does the heterogeneity of actors in the treatment with private signals undermine cooperation even though, (game) theoretically, behavior should be the same as in the corresponding homogeneous case?

(iii) How does the strength of the possible damage affect the probability of meeting the threshold?

Our focus on the effects of the threat of the "point of no return" on willingness to contribute connects our work to that of Milinski et al. (2008), who introduce the concept of "collective-risk social dilemma". Milinski and coauthors set up a climate change game in which participants, in groups of six, have to invest a certain amount of their endowment in a "climate account" with the objective of collectively reaching a certain target. If they succeed, every group member keeps any leftover money. If they fail, there is a chance that they lose everything (both the collective fund and their personal money). The results show that, even faced with the possibility of near-certain doom, only half of the groups collect enough funds. Differently from us, Milinski et al. do not provide the participants with a coordination device like the signal and do not include any kind of linearity in the payoff function (they implement an all-or-nothing scenario).

The investigation of behavior under heterogeneous signals links our paper to a (small) strand of literature which examines the effects of heterogeneity on voluntary contributions in PPMs. Rapoport and Suleiman (1993) find that heterogeneity in endowment negatively affects successful provision of threshold public goods. They also find (in line with van Dijk and Grodzka 1992) that people contribute the same percentage of their endowment regardless of its magnitude. Croson and Marks (1999) compare heterogeneous and homogeneous valuations for the public good, and show that heterogeneity does not undermine average contributions or the rate of successful provision, but increases the variance in contributions.[6] Additionally, since participants in our heterogeneous treatment decide on their contributions being unaware of the others' signal, and thus of the accurate position of the point of no

[6] Bagnoli and McKee (1991) consider as well homogeneous and heterogeneous valuations. However, they have only one homogeneous baseline session, which makes it difficult to reach firm conclusions about the impact of this kind of heterogeneity on behavior. Rondeau et al. (1999) use a one-shot PPM with heterogeneous valuations to test whether this mechanism is demand revealing.

return, our experiment provides evidence of how incomplete information about the threshold affects behavior.[7]

In Section 2, we lay out the game (2.1), derive some predictions (2.2), and describe the experimental procedures (2.3). In Section 3, we detail the results. In Section 4, we conclude.

2. The experiment design

2.1 The game

We consider a four-person threshold public good game with linearity above and below the threshold. Each player is endowed with 10 points which can be either consumed privately or contributed to a public good. Before making his contribution choice, each player *i* receives a signal, s_i, about the level of contributions *T* that must be reached by the group as a whole. The threshold *T* is the sum of all group members' signals: $T = \sum_{j=1}^{4} s_j$. If the group's total contribution reaches this level, each member earns:

$$\pi_i^0 = 10 - g_i + 0.4\sum_{j=1}^{4} g_j , \qquad (1)$$

where g_i is player *i*'s contribution to the public good. Otherwise, each member's earnings are reduced by the factor $\gamma \in (0,1)$. Thus, player *i*'s payoff equals

$$\pi_i = \begin{cases} \pi_i^0 \ \text{ if} \sum_{j=1}^{4} g_j \geq \sum_{j=1}^{4} s_j \\ \gamma\pi_i^0 \ \text{ if} \sum_{j=1}^{4} g_j < \sum_{j=1}^{4} s_j \end{cases} \qquad (2)$$

Within this basic setup, we manipulate two dimensions in a factorial design (the experiment therefore involves four different treatments). The first treatment dimension concerns the reduction factor *γ*. In the low cost treatments, we set $\gamma = 0.91$, i.e. everyone's earnings are reduced by 9% if the group's contribution does not reach the threshold. In the high cost treatments, we set $\gamma = 0.50$, implying a reduction in each member's earnings by 50% in case the threshold is not met. The second treatment dimension refers to the signal that each subject receives about the threshold. In the case of a common signal, all group members receive the same signal so that the threshold is commonly known. In the case of a private signal, the group members' signals are drawn independently from a uniform distribution and each member just knows his own signal. Thus, subjects can at best probabilistically predict

[7] Previous PPMs with incomplete information are Marks and Croson (1999) and Rondeau et al. (1999).

the threshold. Regardless of the treatment, the signals are drawn with equal probability from the set {3, 4, 5, 6, 7, 8}. Hence, the lowest threshold is 12 and the highest is 32.

2.2 Predictions

First, we present the game-theoretic predictions based on self-regarding motives. Then, we assess the implications of conditional cooperation, which can be thought of as a consequence of a preference for fairness (Fischbacher et al. 2001).

If the sum of contributions is higher than the threshold *T*, the incentives are like in the standard linear public goods game: keeping one point yields a private marginal return of 1, whereas contributing the point yields only 0.4. The same is true if the sum of contributions is lower than the threshold. In this case, keeping one point yields a private marginal return of γ, whereas contributing the point yields $\gamma \cdot 0.4$. Due to the freeriding incentives above and below *T*, the only candidates for equilibria are the contribution vectors $\boldsymbol{g}^* = (0, 0, 0, 0)$, i.e., general freeriding, and $\boldsymbol{g}^t = (g_1^t, g_2^t, g_3^t, g_4^t)$ with $\sum_{j=1}^{4} g_j^t = T$.

In all treatments, there is a strict equilibrium in which everybody contributes zero. Since the lowest threshold equals 12, no participant can unilaterally reach the threshold, thereby avoiding the "point of no return". The existence of the equilibrium $\boldsymbol{g}^t$ depends on whether a player has an incentive to deviate from this outcome by contributing zero (the most profitable deviation).

If the signal is common, i.e. $s_i = s$ for $i = 1, \ldots, 4$, the game is one with complete information. For $\boldsymbol{g}^t$ to be an equilibrium, we must have $10 - g_i^t + 0.4T \geq \gamma[10 + 0.4(T - g_i^t)]$ or

$$\frac{1-\gamma}{1-0.4\gamma}(10 + 0.4T) \geq g_i^t \qquad \text{for all } i. \qquad (3)$$

In the high cost common signal treatment, there exist many contribution vectors satisfying this condition, among which the most salient and focal one is the vector where everyone contributes the common signal amount *s*. If $g_i^t = s$ for all *i*, condition (3) becomes

$$\frac{1-\gamma}{1-0.4\gamma}(10 + 0.4 \times 4s) \geq s$$

or

$$\frac{10}{0.6s} \geq \frac{2\gamma - 1}{1-\gamma}. \qquad (4)$$

If $\gamma = 0.5$, the right-hand side of (4) is zero and thus the condition is satisfied for any value of the signal.[8] Although there exist other equilibria in which the contributions of those who contribute too little are offset by the contributions of others, such equilibria demand more coordination and are less salient compared to the equilibrium in which each player contributes the signal.

Turning to the low cost common signal treatment, when $\gamma = 0.91$ there are no equilibria in which the players collectively contribute exactly enough to achieve the threshold. To illustrate this, consider the lowest possible signal $s = 3$ (implying $T = 12$). The left-hand side of condition (3) then equals 2.094 so that only contributions of 0, 1, and 2 could guarantee (3). Thus the threshold cannot be reached and the individually rational contribution level is zero. Furthermore, the coefficient of T in (3) equals 0.057, i.e., it is smaller than 1. This proves that also for larger values of T, condition (3) cannot be satisfied.

If s_i is player i's private information (for $i = 1, \dots, 4$), the game is one with incomplete information. While $\boldsymbol{g}^* = (0, 0, 0, 0)$ remains an equilibrium outcome, we need to find the condition under which the outcome where the group contributes exactly the threshold can be an equilibrium. Suppose that the other players follow their signal and all together contribute $S_{-i} = \sum_{j \neq i} s_j$. Assume first that player i knows S_{-i}. Then, if player i follows his signal, his payoff equals $U_i(s_i) = 10 - s_i + 0.4[s_i + S_{-i}]$. Again, the best deviation is to contribute zero, which would yield $U_i(0) = \gamma[10 + 0.4S_{-i}]$. This deviation is not profitable if

$$\frac{1-\gamma}{0.6}(10 + 0.4S_{-i}) \geq s_i . \qquad (5)$$

In the high cost private signal treatment ($\gamma = 0.50$), condition (5) is satisfied for all possible signal values because the left-hand side equals at least 11.33 (if $S_{-i} = 9$), which is higher than any possible signal. Instead, in the low cost private signal treatment ($\gamma = 0.91$), the left-hand side of (5) equals at most 2.94 (if $S_{-i} = 24$), which is below any possible signal. This result holds for any possible S_{-i}. Thus, also if player i does not know S_{-i}, he has an incentive to follow the signal in the high cost private signal treatment, and to contribute zero in the low cost private signal treatment. Of course, in the former treatment there exist many other equilibria in which undercontributions with respect to the signal are compensated by overcontributions.

[8] Suppose that $s = 8$ and that the vector of contributions is $\boldsymbol{g}^T = (8, 8, 8, 8)$. No player has an incentive to deviate by contributing 0. If he does so, the threshold would not be met and he would earn 9.8 points, less than his payoff in case of no deviation (14.8 points).

Thus, according to standard game theory, only general freeriding is an equilibrium outcome in the low cost treatments, for both the private and common signals. Conversely, general freeriding as well as the outcome where everyone contributes his signal are equilibria in the high cost treatments, whatever the type of signal. This analysis suggests that the following can be expected.

Hypothesis 1: Contributions are higher in the high cost treatments than in the low cost treatments.

Hypothesis 2: In the low cost treatments, contributions are negligible.

Hypothesis 3: In the high cost treatments, players follow their signal.

The above hypotheses do not differentiate between the private and the common signal treatments. Usually, private signals make coordination much more difficult because players do not know the others' signal. However, in our experiment, if participants want to coordinate and reach the threshold, they have a natural way to do so: following their signal. Thus, based on standard assumptions, there is no reason why coordination should differ between the two treatments.

This prediction changes if we assume that players have a preference for fairness, for example in the form of inequity aversion as modeled in Fehr and Schmidt (1999) or Bolton and Ockenfels (2000). Since these models imply conditional cooperation, people are willing to contribute both below and above the threshold provided others contribute as well. As a result, higher contribution levels than those suggested by the standard model can be observed in both the high cost and the low cost treatments (see, e.g., Fehr and Schmidt 1999). However, in the high cost private signal treatment, conditional cooperation can also entail that people contribute less than the cooperative equilibrium amount (equal to the threshold level). Indeed, if a player has a high signal, he may believe that some of his fellow members have received a lower signal, and therefore they should contribute less and earn more. Aversion to inequity may hence cause players with a high signal to contribute less in the private signal case than in the common signal case. The vice-versa holds for inequity averse players with a low signal, who might be willing to contribute more in the private signal case than in the common signal case. But following the strategy of not contributing the signal renders coordination almost impossible. If people are aware of this problem, they could relinquish the attempt to coordinate on the cooperative equilibrium.

In the low cost treatments, which have only the zero-contribution equilibrium, inequity averse individuals may contribute positive amounts using the signal as a coordination device.

Yet, coordination should work better in the common signal case than in the private signal case for the reasons given above. So we expect positive but lower contribution rates when signals are private.

These considerations give rise to the following hypotheses.

Hypothesis 4. In the high cost treatments, subjects respond less to the private signal than to the common signal.

Hypothesis 5. In the low cost common signal treatment, contributions are correlated with the signal.

Hypothesis 6. In the low cost treatments, subjects contribute less in the private signal case than in the common signal case.

In a nutshell, we can summarize our hypotheses as follows. Standard theory predicts higher contributions in the high cost treatments than in the low cost treatments; conditional cooperation predicts higher contributions in the treatments with common signal than in those with private signals.

2.3 Experimental procedures

Each treatment consisted of two phases. In the first phase, the game was repeated ten times using a stranger matching, i.e., subjects were randomly rematched in every period. In this phase each point was converted into €0.07. In the second phase, the subjects were again rematched, played the game only once, and were paid using a conversion rate of €0.70 per point. In both phases, we used the strategy method, i.e., subjects decided how much to contribute for each of the 6 possible signals.

All experiments were programmed in z-Tree (Fischbacher 2007) and conducted in the experimental laboratory of the Max Planck Institute of Economics (Jena, Germany). The subjects were undergraduate students from the Friedrich-Schiller University of Jena. They were recruited using the ORSEE software (Greiner 2004). Upon entering the laboratory, the subjects were randomly assigned to visually isolated computer terminals. The instructions were distributed and then read aloud to establish public knowledge. Before starting the experiment, subjects had to answer a control questionnaire which tested their comprehension of the rules.

We conducted 12 sessions (three per treatment). In each session we had 32 participants (for a total of 384 participants) and used two matching groups. Hence, we have 6 independent observations per treatment. Each session lasted roughly 90 minutes. Average earnings per subject were € 20.30, including a show-up fee of € 3.00.

3. Results

Figure 1 shows the temporal patterns of average contributions for all signals in each of our four treatments. In order to analyze the phase 1 data in a statistical way, we use OLS regressions with individual contributions as dependent variable and signal, period, and treatment dummies as independent variables. To capture the dynamics of play which strongly interacts with the treatment, we use models with Period-1 and Period-10 as regressors. Similarly, we use Signal-3 and Signal-8 in order to estimate time trends for high and low signals. In all regressions, we interact the corresponding period and signal terms.

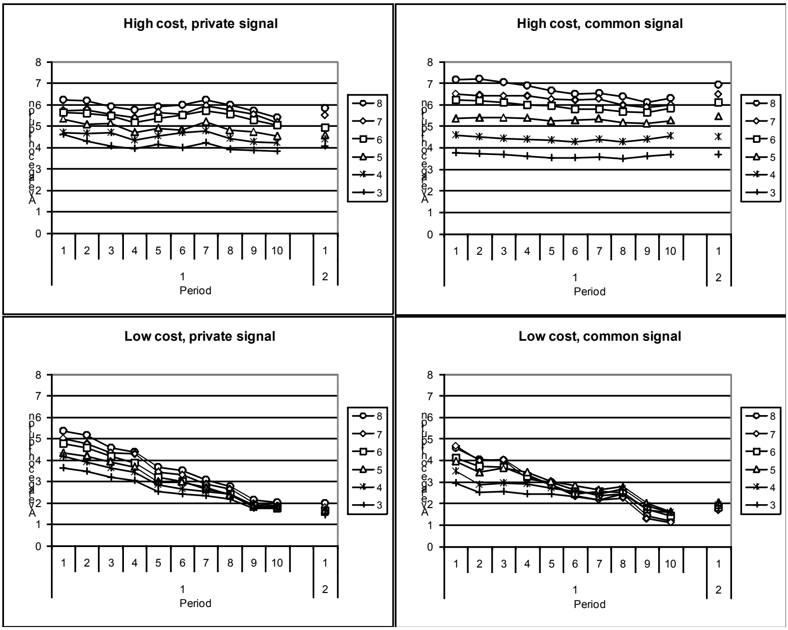

Figure 1: Time path of average contributions for all signals, separately for each treatment.

The results of these regressions are reported in the first four columns of Table 1. For example, the row "signal | period 10" (reading "the signal coefficient conditional on period 10") is the coefficient of Signal-3 if the other regressors are Period-10 and (Period-

10)(Signal-3), and the coefficient of Signal-8 if the other regressors are Period-10 and (Period-10)(Signal-8). It can be interpreted as the approximated effect of the signal in period 10. The constants are defined in an analogous way. For example, "const | s3,p1" is the constant of a regression with Signal-3, Period-1 and (Signal-3)(Period-1) as regressors. In columns 5–8, we report the differences in the estimated coefficients, derived from regressions with the combined datasets, including interaction terms. Using the data from Figure 1 and Table 1, we organize the discussion of the results along the hypotheses derived in Section 2.2.

Table 1: OLS regressions with contribution as dependent variable (data from phase 1).

Data	low cost private signal	low cost common signal	high cost private signal	high cost common signal	low cost	high cost	private signal	common signal
Comparison					common - private	common - private	high cost - low cost	high cost - low cost
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
signal | period 1	0.351***	0.343***	0.352***	0.704***	-0.008	0.352***	0.001	0.361***
	(0.059)	(0.045)	(0.045)	(0.049)	(0.07)	(0.063)	(0.07)	(0.063)
signal | period 10	0.042	-0.153	0.387***	0.517***	-0.194*	0.131	0.345***	0.670***
	(0.059)	(0.077)	(0.085)	(0.08)	(0.093)	(0.111)	(0.098)	(0.106)
period | signal 3	-0.232***	-0.119***	-0.055**	0.002	0.112***	0.058*	0.176***	0.122***
	(0.021)	(0.019)	(0.019)	(0.022)	(0.027)	(0.028)	(0.027)	(0.028)
period | signal 8	-0.403***	-0.394***	-0.036	-0.101***	0.009	-0.065	0.367***	0.293***
	(0.036)	(0.055)	(0.045)	(0.02)	(0.062)	(0.047)	(0.055)	(0.055)
signal * period	-0.034***	-0.055***	0.004	-0.021**	-0.021	-0.025**	0.038***	0.034**
	(0.007)	(0.011)	(0.009)	(0.008)	(0.012)	(0.011)	(0.011)	(0.013)
const | s3,p1	3.712***	3.028***	4.403***	3.823***	-0.684**	-0.580**	0.691**	0.795***
	(0.262)	(0.074)	(0.194)	(0.161)	(0.259)	(0.241)	(0.311)	(0.17)
const | s3,p10	1.628***	1.956***	3.904***	3.845***	0.328	-0.059	2.276***	1.889***
	(0.291)	(0.136)	(0.109)	(0.262)	(0.307)	(0.27)	(0.296)	(0.281)
const | s8,p1	5.466***	4.743***	6.162***	7.342***	-0.723*	1.180***	0.696*	2.599***
	(0.298)	(0.225)	(0.233)	(0.283)	(0.356)	(0.35)	(0.36)	(0.345)
const | s8,p10	1.836**	1.193**	5.837***	6.432***	-0.643	0.596	4.001***	5.239***
	(0.459)	(0.363)	(0.321)	(0.304)	(0.558)	(0.421)	(0.534)	(0.451)
Observations	5760	5760	5760	5760	11520	11520	11520	11520
R-squared	0.107	0.076	0.064	0.158	0.097	0.116	0.186	0.274

Notes: Robust standard errors in parentheses, matching groups as clusters.

* Significant at 10%; ** significant at 5%; *** significant at 1%

Result 1. The contribution level is higher in the high cost treatments than in the low cost treatments.

Support. The constants (last four rows in Table 1) provide us with estimates of contributions for the border cases: period 1 and period 10 as well as signal 3 and signal 8. Comparing column (3) with column (1) and column (4) with column (2) shows that contributions are, on average, always higher in the high cost treatments than in the corresponding low cost treatments. The difference between high and low cost treatments is always positive and significant (see the last four rows of columns (7) and (8)). This difference is larger at the end of the experiment than at the beginning because, as shown by Figure 1, contributions are fairly stable in the high cost treatments, whereas they decline substantially over time in the low cost treatments.

Result 2. The low cost treatments replicate standard findings: contributions start at a medium level and follow a downward trend. At the beginning contributions are correlated with the signal, but this relation disappears over time.

Support. In columns (1) and (2) the constants for signal 3 in period 1 are above 3, i.e., initial average contributions are significantly above 3 for signal 3, and those for signal 8 in period 1 are 5.466 and 4.743 under private signal and common signal, respectively. However, the constants in period 10 are all below 2. Furthermore, the signal coefficients are significantly positive in period 1 (see row "signal | period 1" of columns (1) and (2)), meaning that at the beginning of the experiment the signal serves as an anchor, but they are not significant in period 10 (see row "signal | period 10" of columns (1) and (2)), implying that contributions do not increase with the signals at the end of the experiment.

Result 3. In the high cost treatments subjects' contributions are significantly correlated with the signal throughout the experiment. Yet while low signals are always followed, high signals are not.

Support. In columns (3) and (4) the signal coefficients are positive and significant in period 1 as well as in period 10, suggesting that participants always contribute their signal. The constants for signal 3 are above 3 in both period 1 and period 10, but the constants for signal 8 are below 8 in both periods. This decline in contributions is, however, significantly weaker than in the low cost treatments. Additionally, the interaction between period and signal is higher when the cost of not reaching the threshold is high than when it is low, meaning that the relation between signal and contribution is more robust in the high cost treatments.

Result 4. In the high cost treatments subjects respond less to the private signal than to the common signal, in particular at the beginning of the experiment.

Support. The coefficients of the signal variable are higher when the signal is common (column (4)) than when it is private (column (3)) in period 1 as well as in period 10. However, the difference is only significant in period 1 (see first two rows of column (6)).

Result 5. In the low cost common signal treatment, contributions are only at the beginning correlated with the signal.

Support. Column (2) reveals that the coefficient of "signal | period 1" is significantly positive, whereas the coefficient of "signal | period 10" is not only insignificant but also negative.

Result 6. In the low cost treatments subjects do not contribute less in the private signal case than in the common signal case.

Support. A comparison between the constants in column (1) and the constants in column (2) shows that actually average contributions are sometimes even larger in the private signal case. The last four rows of column (5) indicate that this difference is significant at the beginning but not at the end.

Our results qualitatively support the standard game-theoretic predictions. The cost dimension has a strong and stable influence on contributions and our first three hypotheses could be confirmed. The hypotheses based on conditional cooperation receive less support. The type of signal seems to have a weaker impact on contributions than the cost. We saw, though, that subjects respond less to the signal when it is private. This suggests that success rates will be lower in the private signal case, especially (in light of Result 3) for high signals.

In order to investigate how often the threshold is reached (and the point of no return is avoided) in the various treatments, we calculate the success rates based on the strategies, conditional on the realization of the signal. For the common signal treatments, we report the expected success for a particular signal. For the private signal treatments, we report the expected success when a subject gets a certain signal, averaging all possible cases for the signal of the other subjects. Furthermore, we also analyze the counterfactual situations: the expected success rate in the private signal treatments if all signals were equal, and the expected success rate in the common signal treatments assuming private signals. All calculations are done for the actual groups in the experiment, but taking the average of all possible signals (not only of the signals actually realized). Figure 2 depicts the results separately for each of the four treatments and for each of the two phases.

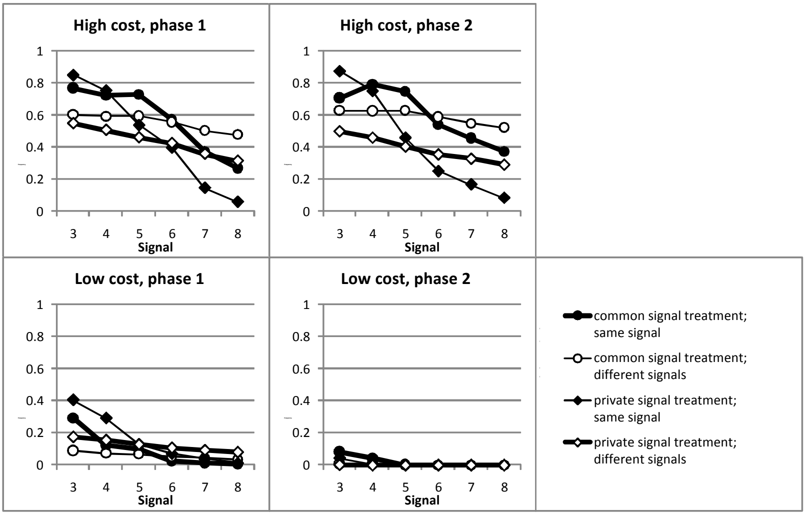

Figure 2: Theoretical probability to reach the threshold conditional on the signal, based on strategy decisions. The "same signal" graphs refer to the cases (actual for the common signal and counterfactual for the private signal) in which all group members get the same signal. The "different signals" graphs correspond to the cases (actual for the private signal and counterfactual for the common signal) in which all signals occur with the same probability.

The figure shows three things. First, the likelihood of success is much higher in the high cost treatments than in the low cost treatments (significant for all situations and for all signals, using OLS regressions with matching group clusters, $p < 0.01$). Second, the subjects in the low cost treatments are less successful in phase 2 (where success rates are close to 0%) than in phase 1. This is due to the decline of cooperation over time. We do not observe such a decline in the high cost treatments. Third, while in the low cost treatments the success rates do not depend on the type of signal (private vs. common), in the high cost treatments common signals lead to more success than private ones (OLS regressions with matching group clusters, $p < 0.05$). Such a difference is driven by low signal-values for it shrinks as the value of the signal increases. The result that the difference between common and private signals tends to decrease with increasing values of the signal may appear surprising. Yet, it may be explained as follows. In the common signal treatment, when the signal is high, all players have to provide a high contribution in order to reach the threshold. Instead, in the private signal treatment, when someone has a high signal, others might have a low signal, which makes reaching the threshold easier. The counterfactual situations reveal that this intuition is correct. If we compare the same situation (the actual in one treatment and the counterfactual in the other treatment), we see that the subjects' decisions in the private signal treatment lead always to lower contributions for higher signals.

In the high cost treatments, the success rate has strong implications on the expected payoff. Figure 3 presents the average expected payoffs conditional on the signal, for each treatment and phase. In the low cost treatments, the expected payoff is, on average, independent of the signal; neither the size nor the type of signal affects the payoff. The impact of the cost on the payoff is not obvious. On the one hand, higher costs create an incentive to cooperate; on the other hand, if the threshold is not reached, the payoff is really low. The results reflect this ambiguity. In the high cost private signal treatment, the expected payoff decreases, on average, with increasing signals because (as indicated by Result 3) high signals are not followed. In the high cost common signal treatment, the average expected payoff depends on the signal in a non-monotonous way: for low signals it increases with the size of the signal because the threshold is likely to be reached; for signals higher than 5 failure to reach the threshold increases and therefore the average expected payoff decreases.

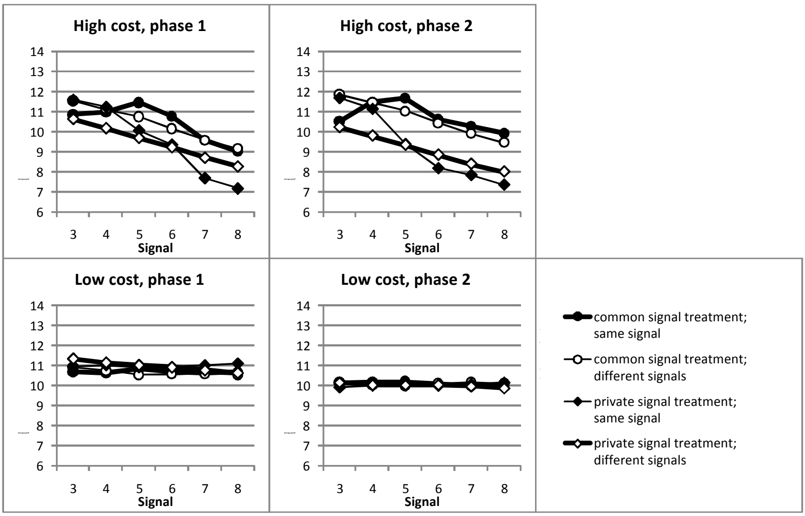

Figure 3: Average expected payoffs conditional on the signal, based on strategy decision. The labels have the same meaning as in Figure 2.

Finally, we look at the strategies people choose. We classify strategies into five types. The first type, the "zero" type, is the strategy in which contributions equal zero for all possible signal values. The second type, called the "signal" type, is the strategy to follow the signal perfectly. The third type consists of the strategies where positive contributions are made, but they are never above the signal. We call this the "low" type. The "high" type consists of the strategies in which contributions equal or exceed the signal. The remaining strategies are in the "mixed" type. In these strategies, contributions are sometimes higher and sometimes lower than the signal. Figure 4 depicts the distribution of strategy types over time, for each treatment and phase. Table 2 shows the share of the strategy types for the four treatments and reports probit regressions for the probability to be of a specific type (column (6) is the sum of columns (1) and (2) and column (7) is the sum of columns (4) and (5)).

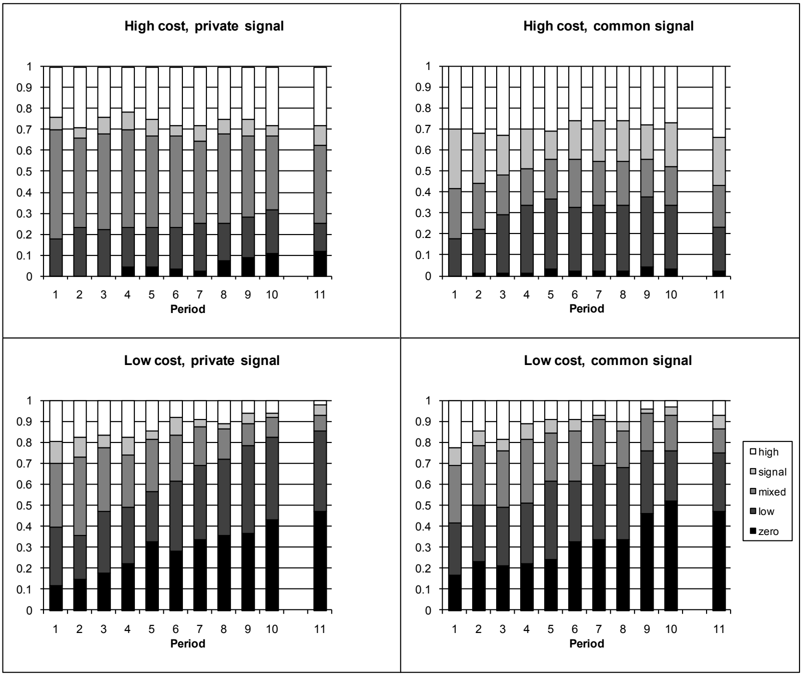

Figure 4: Types of strategies over time in the four treatments. Period 11 corresponds to the decision in the second phase.

This data confirms what we observed above. In the low cost treatments, contributions decline because the signal type is almost nonexistent and the high type is also rare. Surprisingly, the "following the signal"-strategy is infrequent in the high cost treatments as well. In particular, in the high cost private signal treatment the share of the signal type (7 percent) is only slightly higher than in the low cost treatments. Thus, although the standard predictions make good comparative static predictions, the salient equilibrium – choosing the signal – is rarely chosen (except for the high cost common signal treatment where the share of the signal type is 20%). Comparing the private and common signal cases under high cost gives us a further confirmation of Hypothesis 4, which assumes that participants in the high cost treatments respond less to the private signal than to the common signal. In line with this hypothesis, we find that the share of signal types is 20% in the high cost common signal treatment and 7% in the high cost private signal treatment. Actually, we get an even stronger result. In the high cost private signal treatment, the mixed type is the most frequent strategy and, within the mixed type, 87 percent of the contributions are above the signal if this is low and below the signal if this is high, as conjectured by conditionally cooperative play

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	zero	low	mixed	signal	high	zero and low	signal and high
LC private	29%	32%	21%	6%	12%	61%	18%
LC common	32%	30%	22%	5%	11%	62%	16%
HC private	5%	20%	43%	7%	26%	24%	33%
HC common	2%	28%	20%	20%	30%	30%	50%
common signal	0.076	-0.067	0.045	-0.050	-0.054	0.007	-0.064
	(0.142)	(0.156)	(0.112)	(0.247)	(0.129)	(0.092)	(0.132)
high cost	-1.132***	-0.397***	0.623***	0.104	0.541***	-0.990***	0.493***
	(0.131)	(0.093)	(0.095)	(0.258)	(0.110)	(0.069)	(0.124)
common signal*high cost	-0.451	0.347*	-0.695***	0.676**	0.159	0.173	0.490***
	(0.285)	(0.191)	(0.170)	(0.323)	(0.165)	(0.138)	(0.185)
Constant	-0.549***	-0.462***	-0.809***	-1.56***6	-1.183***	0.289***	-0.927***
	(0.115)	(0.071)	(0.076)	(0.197)	(0.100)	(0.046)	(0.097)
Observations	4224	4224	4224	4224	4224	4224	4224

Robust standard errors in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%

Table 2: Percentage of choices in accordance with each type, and probit estimates of the probability of being of a particular type.

4. Conclusions

We found that subjects take the threat of the "point of no return" seriously when zero-contribution is not a dominant strategy. While in the low cost treatments the signal works as an anchor only in early periods and contributions do not much differ from standard public goods games, in the high cost treatments people are willing to contribute and to follow the signal. As a consequence, the rates of successfully reaching the threshold are higher under the high cost treatments. Our results also show that when the failure to reach the threshold has dramatic consequences, people must be informed.

Although our experimental scenario is too simplistic, it captures some crucial aspects of the present debate about global warming and other environmental problems. For instance, our assumption that failure to reach the threshold implies an abrupt reduction in people's payoff may appear rather artificial. Yet, Hansen (2006) refers to a point of no return as a situation beyond which begins an irreversible process, and Lever-Tracy (2008) writes: "*if any of the scenarios of probable serious effects ... or runaway climate change materialize beyond a point of no return, then global society as a whole, its structure, culture and trajectory, will surely be completely changed, as will the nature and relations of states to society and to each other*". Our experimental results indicate that if such a point of no return wants to be avoided, people must believe that not meeting the threshold implies extremely high costs. Moreover, the information about the point of no return should be as accurate and reliable as possible, and people should at least suppose that everyone has received the same signal and will make the same contribution. In this sense, our experiment supports the view of Scott Barrett (2009), a natural resource economist at Columbia University in New York, who – referring to the target in CO_2 emissions that several European countries pledged, but failed, to meet by 2005 – maintains "*no one's willing to go very far unless the others are*".

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