Coordination under threshold uncertainty in a public good game

Astrid Dannenberg[a], Andreas Löschel[a], Gabriele Paolacci[b], Christiane Reif[a], and Alessandro Tavoni[c]

[a] Centre for European Economic Research (ZEW), Mannheim, Germany

[b] Ca' Foscari University of Venice, Italy

[c] Grantham Research Institute on Climate Change and the Environment, LSE, London, UK

July 2011

Very preliminary draft – do not cite.

Abstract

We explored in a laboratory experiment how threshold uncertainty affected coordination success in a threshold public good game. Whereas all groups succeeded in providing the public good when the exact value of the threshold was known, uncertainty was generally detrimental for the public good provision. The negative effect of threshold uncertainty on the efficient coordination of efforts was particularly severe when it took the form of ambiguity, i.e. players were not only unaware of the value of the threshold but also of its probability distribution. Early signaling of willingness to contribute and sharing the burden equitably helped groups in coping with threshold uncertainty.

1 Introduction

Many natural resources involve threshold effects. Using these resources beyond a tipping point can have disastrous consequences for the environment and human well-being (Lenton et al. 2008). The most prominent examples are related to climate change, such as the dieback of the Amazon rainforest (Malhi et al. 2009), the collapse of the Atlantic Thermohaline Circulation (Marotzke 2000, Zickfeld et al. 2007) or the decay of the Greenland ice sheet (Notz 2009). The prospect of dangerous climatic changes has led to a political consensus about the urge of containing the global temperature rise below two degrees Celsius. However, catastrophes may occur even if we keep the temperature rise below two degrees or they may not occur even if we go beyond. Thus, high uncertainty is entrenched in these natural tipping points (Kriegler et al. 2009, Alley et al. 2003, Scheffer et al. 2001), and it is pressing to understand how such uncertainty affects people's willingness to cooperate in order to prevent catastrophes (Barrett 2011).

In this work, we explored the effect of uncertainty on agents' ability to coordinate their cooperative efforts in order to prevent a collective damage. To this end, we conducted a laboratory experiment involving a threshold public good game. In a typical threshold public good game, each player in a group receives an endowment and decides how much of it to contribute to a public good. If the group contribution exceeds a certain threshold, then the public good is provided and each player receives a fixed amount of money, no matter how much she contributed to the public good. If the threshold is not reached, contributions are not returned to the players.[1]

Threshold public good games have been studied theoretically for a long time, and in particular it is known that differently from continuous public good games, Pareto-optimal outcomes are supportable as Nash equilibria (Bagnoli and Lipman 1989, Palfrey and Rosenthal 1984). Uncertain thresholds, however, can lead to free-riding and ultimately to inefficient equilibria (Nitzan and Romano 1990, Suleiman 1997). McBride (2006) considered changes in the probability distribution of the threshold under various public good values. He found that voluntary contributions do not relate monotonically to uncertainty. In particular, increasing uncertainty through a mean-preserving spread leads to higher contributions if the value of the public good is sufficiently high. On the other hand, an increase in uncertainty leads to lower

[1] There are also threshold public good games with refunding if the provision point is not met (e.g. Spencer et al. 2009, Rondeau et al. 2005) or a rebate beyond the provision point (e.g. Isaac et al. 1985). For an overview see Croson and Marks (2000).

contributions if the public good value is relatively low. Barrett (2010) showed that threshold uncertainty changes the nature of the cooperation problem in a climate change game. Provided that the climate change damage is large (compared to the costs of avoiding it) and the threshold is certain, the challenge requires only coordination of efforts because preventing the damage is both collectively optimal and implementable as a Nash equilibrium. With threshold uncertainty, in contrast, cooperation is needed and difficult to enforce because the social optimum is not supportable as Nash equilibrium. Increasing uncertainty by thickening the tails of the probability density function makes little difference in this model.

Some experimental studies tried to shed further light on how uncertainty affects cooperative outcomes. McBride (2010) found that threshold uncertainty hampers cooperation when the value of the public good is relatively low, although the opposite can happen for higher public good values. It has also been shown that the effect of threshold uncertainty can depend on the mean of the threshold distribution, such that uncertainty helps (hinders) cooperation when the mean is high (low) (Suleiman et al. 2001). Whereas Kotani et al. (2010) confirmed that high levels of threshold uncertainty hamper cooperation, their evidence suggests that moderate levels of uncertainty can be beneficial. Environmental uncertainty has also been explored by researchers in resource dilemmas, who generally found that uncertainty is detrimental for collective outcomes. The more uncertain people are regarding the size of the available resource, the more likely they are to overharvest from that resource (Budescu et al. 1992 and 1995, Gustafsson et al. 1998, Rapoport et al. 1992; see Wit and Wilke 1998 for a comparison between threshold public good games and resource dilemmas).

Given the fair amount of experimental research on the effects of threshold uncertainty on public good provision, the implementation of uncertainty so far has been surprisingly unsophisticated. Previous studies manipulated uncertainty solely by widening the threshold interval (or the resource size), thus ignoring the potential peculiarities of different kinds of threshold distribution. Moreover, to the best of our knowledge, there has been no investigation of the effect of threshold *ambiguity*: How are collective outcomes in a threshold public good game affected if the probability distribution of the threshold is unknown to the players?

The distinction between risk (known probability distribution) and ambiguity (unknown probability distribution) has a long theoretical tradition (Knight 1921, Savage 1954). Starting from the Ellsberg paradox (Ellsberg 1961) researchers have begun to explore extensively individuals' attitudes and behavioral responses toward ambiguity, typically revealing aversion to situations in which probabilities are unknown (e.g., Chow and Sarin 2002, Slovic and Tversky 1974; see Camerer and Weber 1992 for a review). Some authors explored how behavior in games changes when players' perception of others' decisions is ambiguous (Bailey, Eichberger, and Kelsey 2005, Eichberger and Kelsey 2002, Eichberger, Kelsey, and Schipper 2008), and found that players cope with strategic ambiguity by choosing more secure actions. However, we found no evidence on the role of environmental ambiguity, e.g. how ignoring the probability distribution of the threshold affects players' behavior in a public good game.

In our laboratory experiment we compare how coordination success in a threshold public good game is affected by whether the threshold is known or not. In particular, we employ four different forms of threshold uncertainty. Whereas two experimental treatments involve *risk*, as the threshold is a random variable with known probability distribution, two other treatments involve *ambiguity*, as the probability distribution of the threshold is unknown.

A prominent goal of our study is to reproduce those real-world setups in which agents such as individuals or communities need to coordinate their cooperative efforts in order to prevent an undesirable event. Accordingly, our setup deviates from traditional threshold public good games in three important ways. First, players contribute to the common account not to realize a gain but to avoid a loss. This means that if the group contribution does not reach a certain amount of money, all members will lose almost all of their remaining endowments. Second, the provision of the public good is sequential, as the assessment of the group effectiveness in preventing the public bad is carried out only after multiple stages of contributions. This allows for the examination of how players in a group react to the fellow members' behavior under different uncertainty configurations. Third, we implement the possibility to communicate, as players can suggest non-binding proposals for the group's targeted contribution (Tavoni et al. 2011).

Our experimental data indicate that threshold uncertainty was detrimental for the provision of the public good. Whereas all our experimental groups succeeded in preventing the public bad when the threshold was known, this result was not replicated in the presence of threshold uncertainty. Although the contribution pattern differed depending on how uncertainty was configured, contributions were generally lower when players did not know ex-ante the exact threshold value. Critically, contributions were lower in the treatments involving ambiguity than in the treatments involving risk. We also found that early signaling of willingness to contribute and sharing the burden equitably made groups more likely to reach a high public good provision level.

The paper is organized as follows: Section 2 describes in detail our public good game and the experimental design and procedures. Section 3 discusses the equilibria of the game. Section 4 presents our results. Section 5 concludes by offering some remarks.

2 The Game

Our game shares certain features with the decision setup developed by Milinski et al. (2008) and extended by Tavoni et al. (2011). At the beginning of the experiment, subjects were endowed with €40 and randomly assigned to groups of six anonymous players. The groups remained unchanged throughout the session. The experiment was composed of 10 rounds. In each round, players decided how much of their private endowment to contribute to a common account between €0, €2, and €4. Players knew that if the group contribution at the end of the 10 rounds failed to reach some threshold, each player would lose 90% of her remaining endowment. This means that failing to reach the threshold would leave players with only 10% of their private savings as opposed to 100%. After each round players were informed about the contributions of all individuals and of the group, both in the current round and cumulated. At round 1 and round 6, players could make non-binding suggestions to the group regarding the collective contribution to reach, which were also notified to the group.

Subjects in our experiment were assigned to one of five different treatments. In a control treatment ("*Baseline*") the contribution threshold was certain. Players knew that if the group failed to contribute €120 or more after 10 rounds, all members would be paid only 10% of their remaining private endowments. In the treatments with uncertainty, in contrast, players did not know in advance the threshold that had to be reached in order to prevent the public bad, i.e. to keep their private savings. Unlike previous experiments on threshold uncertainty, we kept the threshold interval constant across treatments. In particular, threshold probability functions were described over 13 potential thresholds ranging from €0 to €240 in €20 increments. Although such probability density functions were obviously discrete, they were designed as to resemble continuous distributions that are typically used to model uncertainty in climate tipping points (Kriegler et al. 2009, Zickfeld et al. 2009). Note that the [€0, €240] interval implied both that the public bad might be avoided with zero contributions and that the public bad might occur even if all six players contribute their entire €40 endowment (thus becoming indifferent to the occurrence of the public bad). At the end of the experiment, the threshold was determined through a ball picking task: A participant volunteered to publicly pick one small plastic ball out of many, which determined the threshold value. Subjects were paid either 100% or 10% of their remaining endowments, depending on whether their group reached the threshold contribution or not.

We implemented four treatments with threshold uncertainty. Figure 1 illustrates the frequency distribution of the balls. There were two treatments involving *risk*, which had the same expected value of the threshold (€120) but different probability distributions. One treatment ("*Normal*") resembled a normal distribution, with a symmetric triangle-shaped probability density function clustered around the single mode of €120. The other treatment involving risk ("*Uniform*") was based on a flat uniform distribution, meaning that all potential threshold values were equally likely.

We also implemented two treatments in which subjects faced *ambiguity*. That is, not only players could not know the threshold with certainty, they were also ignorant about the probability distribution of the threshold. Such treatments were seemingly related to the risk treatments in that we added "noise" to our implementations of the normal and uniform distributions. However, we also wanted to vary how confident people would likely feel about the ultimate probability distribution of the threshold, arguably capturing different "levels of ambiguity". In one such treatment ("*AmbNormal*"), the 12 subjects who entered the lab were asked to choose one out of 13 colors on a paper sheet. Knowing that all individuals had made this decision (but not knowing the others' decisions), subjects were subsequently informed that each choice identified the color of an additional ball to be added to a triangle-shaped frequency of balls similar to the one in the *Normal* treatment. In the second ambiguity treatment ("*AmbUniform*"), one randomly selected subject was asked to go into another room in order to complete a brief task and wait until the end of the session. The task was to distribute 50 balls over a blank matrix on a paper sheet (without knowing the purpose). The student was explicitly informed that he or she had complete freedom of choice and that the balls could be distributed in any way, e.g. symmetric or asymmetric. The resulting distribution determined the probability distribution of the threshold. The remaining participants were informed about this procedure and thus played the game without knowing the threshold probability distribution.

Table 1 summarizes the experimental design. It is fair to say that the €120 threshold is a natural focal point of the game. It is the certain threshold in the *Baseline* treatment and it is the expected value of the threshold in the two risk treatments. But it is also a focal point in the two ambiguity treatments as €120 is the mean (and the median) of the [€0, €240] interval and it is the collective outcome if all the players choose the intermediate €2/round strategy. Note that there was no information asymmetry between experimenters and subjects, meaning that the formers were also ignorant about the probability distribution determined via the tasks. This is an important feature of our design for two different reasons. First, decision makers perceive ambiguity differently when there is somebody else (e.g. the experimenter) who has more information or not (Chow and Sarin 2002). Moreover, the environmental uncertainty that revolves around tipping points is typically one of the "unknowable" type, as nobody has nor could have more information than decision makers. Validity concerns thus imposed to implement a procedure in which subjects and experimenters had the same information regarding threshold distribution.

The experiment was conducted in a computer lab at the University of Magdeburg, Germany. In total, 300 subjects participated in the experiment, recruited from the general student population (recruitment software ORSEE, Greiner 2004). Subjects earned €13.08 on average including a show-up fee of €2.00. Sixty subjects participated in each treatment. Subjects in each experimental session were assigned to the same treatment. Each subject was seated at linked computer terminals that were used to transmit all decisions and payoff information (game software Z-tree, Fischbacher 2007). Once subjects were seated, a set of written instructions was handed out. Experimental instructions (see Appendix) included numerical examples and control questions in order to ensure that subjects understood the game. An oral presentation highlighted the key features of the game and provided further numerical examples before the game started. After the final round, subjects completed a short questionnaire that elicited, among other things, their motivation during the game (see Table S3 in the Appendix).

3 The Equilibria

The game can be analyzed in the framework of expected payoff maximization, as follows. All players $N = \{1, \dots, n\}$ have symmetrical strategy sets C_i and make simultaneous contribution choices in each round belonging to $R = \{1, \dots, r\}$. The contribution threshold T needed to provide the public good (after the final round has been played and r successive contributions c_i^t have been made in each round $t \in R$ by the n players, yielding $I = \sum_{t=1}^{r} \sum_{j=1}^{n} c_j^t$), comes from a distribution function $F_T(I)$. Given a profile c of contributions in the entire game, player i's expected payoff is $\pi_i(c) = F_T(I)(w - \sum_{t=1}^{r} c_i^t) + (1 - F_T(I))(w - \sum_{t=1}^{r} c_i^t)d$, where w is players' endowment and d is the percentage of private moneys that a player keeps if the threshold is not reached.

In the game we tested, $n = 6$, $C_i = \{0, 2, 4\}$ in each round ($r = 10$), $w = 40$ and $d = 10\%$. Whereas in *Baseline* $T = 120$ with certainty, in *Normal* and *Uniform* T is a discrete random variable with $E(T) = 120$ and increasing dispersion around the first moment.[2] Recalling that, with the exception of *Baseline*, the requirement to provide the public good is no longer to reach a fixed sum of €120 but rather to tackle a probabilistic threshold given different sets of information, one can reason in terms of the investment I^* that maximizes the group's expected value. Figure 2 gives a graphical representation of the provision probability for each threshold in *Baseline*, *Normal* and *Uniform.* We do not discuss the two ambiguity treatments in this section, due to the inherent difficulty in expected payoff reasoning in the face of ambiguity. Expected utility theory cannot be of much guidance in the ambiguity treatments since subjects are not given sufficient information to form a prior. Therefore, rather than testing a theory, their purpose is more explorative and empirical.

A salient feature of this game is that the value of the public good decreases with contributions. When players have already contributed a substantial share of their endowments, the public good is of low value because the players have little left in their private accounts, and thus little to lose. Therefore, the right tail of the distribution does not matter as much as the left tail, where players have much to lose. This is why *Uniform* is characterized by lower optimal contributions $I^* = 100$ than the other treatments as highlighted in Figure 3 and Table 2.

[2] Note that, while in *Baseline* $F_T(I) = 0, if\ I < 120$ and $F_T(I) = 1, if\ I \geq 120$, in the risky treatments $F_T(I) > 0$ for each investment level (i.e. there is a positive provision probability even for I=0). On the other end of the spectrum, only I=240 guarantees provision in the *Normal* and *Uniform*, which would leave each player with $w - \sum_{t=1}^{r} c_i^t = 0$. The coordination problem is therefore much more complex in the risky treatments.

Let us restrict attention to the two risk treatments with uncertain threshold but known probability (center and right panels in Figure 3) for now. When the group collectively increases contributions I to target a higher threshold, the benefits from the investment increase (red curves), as the likelihood that the ex-post drawn threshold is reached ($T \leq$ I) increases. However, also the ensuing costs increase (blue curves), more steeply on the right side of the figures. The leftmost panel in Figure 3 concerns the *Baseline* treatment. In it, because of the certainty of the threshold (T = 120), group benefits (red curve) sharply jump from €24 when the threshold is not reached (given the 90% loss) to €240 when it is reached. Again, investments are initially relatively less costly (blue curve, angular coefficient = 0.1), and become steeper from I^*=120 onwards (angular coefficient = 1).

Comparing the expected costs and benefits, it is apparent why the coordination challenge becomes harder with increasing dispersion around the mean, i.e. from *Baseline* to *Normal* to *Uniform*. First of all, while in *Baseline* there are only two pure strategy Nash equilibria around which groups can coordinate (I = 0 and I = 120, with the latter payoff-dominating the former), there are many under threshold uncertainty. Moreover, the expected payoff does not change as abruptly when moving from one value of I to another one in *Normal* and *Uniform* (i.e. the net benefits of choosing I = 120 over I = 0 or any other value of I are less marked than in *Baseline*). Lastly, the maximum group payoff (which is given by the vertical distance between the curves) drops from €120 in *Baseline* to €74 in *Normal*, both achieved at $I^* = 120$ (implying a probability of provision of 1 and 0.57, respectively). In *Uniform*, the maximum expected payoff is €72, when $I^* = 100$ and the probability of provision is 0.46.

Let us now focus on individual players' strategies. The game is characterized by a multiplicity of equilibria, so we restrict attention to those in pure strategies. In *Baseline*, in addition to the zero contribution equilibrium, there exists one where the group as a whole invests $I = 120$ (provided that each player contributes less than €36). The latter may be symmetric, when each subject invests €20, or asymmetric. In the treatments with probabilistic threshold, such value is somewhat less focal, since it is no longer the case that any contributions below or above €120 are wasted. In particular, each of the seven thresholds between 0 and 120 inclusive are Nash equilibria. Moreover, in *Normal*, provided that in the first nine rounds investments have amassed to €128, c = €2 is the dominant strategy in round 10. So 140 may be also a Nash equilibrium under these conditions. This is not the case in *Uniform*, as exemplified in Table S1 and Table S2 in the Appendix.

Note that in the risk treatments, the zero contribution strategy $I = 0$ is also a (payoff-dominated) Nash equilibrium, since unilateral deviations lower a player's expected payoff. To illustrate this, consider the treatment with normally distributed thresholds; when all players engage in zero contributions, their expected payoff is €4.7. If one player were to switch, say in the first round, to a different strategy, she could only hope to improve his or her expectations targeting either $\widehat{T}$=20 or $\widehat{T}$=40, which means carrying the entirety of the burden and providing c = €2/round or c = €4/round, respectively. Computation of the expected payoff shows, however, that the resulting amount will be €3.1 or €0. Thus this person is better off sticking to the zero contribution strategy.

Table 2 summarizes the above findings, by reporting the payoffs from following a (pure) symmetric strategy as well as from following the optimal symmetric contribution, i.e. the one leading the group to reach I^*. In sum, we have established that groups are best off with positive contributions of either €2/round, or slightly less in *Uniform.* (But note that the expected payoff from contributing €2/round, €11.7, is close to the maximal attainable value €12.0). However, expected utility theory does not provide precise predictions with respect to the effect of threshold ambiguity on the provision of this discrete public good. Due to the limited guidance of the theory, assessing its effect on coordination is ultimately an empirical matter.

4 Results

Table 3 presents the summary statistics of the experimental data averaged across groups per treatment. The contributions to the public good decreased from the certainty (*Baseline*) to risk (*Normal*, *Uniform*) and from risk to ambiguity (*AmbNormal*, *AmbUniform*). A series of Wilcoxon rank-sum tests confirms that subjects in *Baseline* contributed significantly more than those in the other treatments ($p<0.01$ for each treatment, see Table 4).[3] Therefore threshold uncertainty hampered cooperative efforts in our public good game.

The average proposals for the group target, shown in the first and second column of Table 3, confirm that €120 is a focal point of the game. Both the first and the second proposals were close to €120 and do not significantly differ between treatments (Wilcoxon rank-sum test $p>0.1$ for each treatment and both proposals). The second proposals were generally very close

[3] Statistical tests are based on group averages as units of observation. If not stated otherwise, the reported tests are two-sided throughout the paper.

to the first proposals except for the two ambiguity treatments where the second proposal was somewhat lower than the first one. In all treatments except for *Baseline*, that is whenever uncertainty was involved, contributions were markedly lower than proposals. Under uncertainty, subjects contributed significantly less than what they had proposed before (Wilcoxon Signed-Rank test $p<0.01$ for each treatment and both proposals). This may suggest that although players had a similar approach to the game, uncertainty ultimately affected their behavioral responses.

The experiment was designed in order to examine the effects of uncertainty on subjects' ability to coordinate their efforts to avoid a collective damage. However, the groups' *actual* effectiveness in avoiding the damage depended on the single drawing in the experimental sessions: A group that was successful in its own session might have been unsuccessful in another session, and vice versa. In order to elaborate on groups' comparative performance, Table 5 shows the percentages of groups that would have succeeded in avoiding the damage at different *hypothetical* thresholds given their contributed amounts in the experiment. The results indicate that all groups would have succeeded at a threshold of €20 and none would have succeeded at €160 in all treatments. Between these two values there are remarkable treatment differences. Let us first consider the focal €120 threshold. In *Baseline*, all groups reached the threshold successfully, with 7/10 groups contributing exactly €120. In the risk treatments, *Normal* and *Uniform*, only 2/10 groups would have succeeded at a threshold of €120. In *AmbNormal* 1/10 group would have succeeded while no group would have reached this threshold in *AmbUniform*. Compared to the 100% success rate in *Baseline*, these differences in percentages of successful groups are highly significant (one-sided Fisher's exact probability test $p<0.01$ for each treatment). At a hypothetical threshold of €100, 4/10 groups would have succeeded in *Normal*, 6/10 groups in *Uniform*, 2/10 groups in *AmbNormal*, and 4/10 in *AmbUniform*. Presuming the threshold to be €80, we observe that almost all groups (9/10) would have succeeded in *Normal* and *Uniform* while only 5/10 groups in *AmbNormal* and 6/10 groups in *AmbUniform* would have avoided the collective damage.

The players' investment to reach a certain threshold was very robust with respect to specific group characteristics such as the presence of free-riders or the distribution of contributions over time. In fact, *all* groups reached the threshold under certainty. In contrast, the group performance varied widely under uncertainty. The dispersion of the group contributions increased from certainty to risk and from risk to ambiguity (see Table 3). What did determine the group performance in these treatments? Let us first consider the players' proposals for the group target. Table 3 shows that under uncertainty the average contributions always fell short of the average proposals. Only 1/40 group (in the *AmbNormal* treatment) managed to collect the amount proposed by the group members prior to the game. Still, proposals might have helped the subjects to coordinate their efforts insofar as higher proposals might have led to higher contributions even if the latter did not reach the former. Figure 4 shows the correlation between the average proposal and the group's total investment. It indicates that the correlation depends on the treatment. While the gap between proposal and actual investment was generally small in the two risk treatments, it was larger in the two ambiguity treatments, especially when looking at the first proposal. A series of Pearson correlation tests confirms a significant positive correlation between the average first proposal by a group and its investment for *Normal* (r=0.88, p=0.001) and *Uniform* (r=0.58, p=0.076) but reveals no significant correlation for *AmbNormal* (r=-0.07, p=0.843) and *AmbUniform* (r=0.24, p=0.510).[4] The same is true for individual proposals. The individual first proposals and individual contributions to the public good are significantly correlated in *Normal* (r=0.55, p=0.000) and *Uniform* (r=0.25, p=0.057) while there is no significant correlation in *AmbNormal* (r=0.02, p=0.906) and *AmbUniform* (r=0.13, p=0.322). Figure 4 shows furthermore that the gap between the average proposal and actual contributions became smaller for the second proposal, indicating that the subjects adjusted their proposals downwards to what proved to be feasible after the first half of the game.

If subjects *ex-ante* made similar contribution plans across treatments, why did they actually invest less when faced with uncertainty? To answer this question we consider the first round of the game. This round shows players' decision without any feedback about their co-players' actions, and therefore is informative regarding players' general willingness to contribute. Indeed, in all treatments with uncertainty there is a significant correlation between a player's first round contribution and the subsequent contributions in the remaining rounds (r>0.30, p<0.03 for each treatment). Figure 5 shows the correlation between early action, defined here as the average group contribution undertaken in the first round, and the contributions provided in all the subsequent rounds. The correlation depends, again, on the treatment. While there is no significant correlation in *Normal* (r=0.21, p=0.552), early action and subsequent

[4] All the results on the correlation between variables do also hold if we employ the Spearman's rank correlation test.

contributions are positively and significantly correlated in *Uniform* (r=0.72, p=0.019), *AmbNormal* (r=0.69, p=0.026), and *AmbUniform* (r=0.78, p=0.008). This finding suggests that, when players were confronted with a high degree of uncertainty, they reacted very sensitively to their co-players' behavior at the beginning of the game. Whereas in *Baseline* and *Normal* a low first round investment did not necessarily lead to poor overall performance, this was more likely to be the case in *Uniform* and in the two ambiguity treatments.[5]

This observation leads to the next salient question: How likely was a low first round investment in the different treatments? The average group contribution in the first round is 11.8 in *Baseline*, 11.6 in *Normal*, 11.6 in *Uniform*, 9.8 in *AmbNormal*, and 10.6 in *AmbUniform*. Thus, the groups faced with ambiguity started the game with slightly lower contributions than the groups under certainty or risk. The combination of little early action and players' sensitivity to the first round behavior explains the poor performance of some groups in these treatments. To illustrate this, consider the group that provided the smallest amount (€26) of all groups taking part in the *AmbUniform* treatment (and of all groups taking part in the experiment). This group started in the first round with only €6 allocated to the public good with three players giving €2 and the other three players giving nothing. In contrast, the group with largest investment after ten rounds in *AmbUniform* (€118) provided €14 in the first round with five players giving €2 and one giving €4. Put differently, the difference in contributions between these two groups increased in the course of the game from €8 in the first round to €92 in the last round. In the *AmbNormal* treatment, the group with the lowest overall investment (€36) provided only €6 in the first round, while the one with highest overall investment (€120) contributed €12 in the first round. Thus, the difference between these two groups increased from €6 at the beginning to €84 at the end of the game. On the other hand, the *Uniform* treatment, characterized by higher overall investment, owed much of it to many groups starting the game with relatively high contributions (see Figure 6). Since the players in *Normal* were less sensitive to first round behavior, early action was of less importance for the performance in these treatments.

The minimum first round contribution across all groups taking part in the experiment was €6, the maximum was €14. Although the difference is substantial for a single round, the groups with a low first round contribution could have easily made up for that during the nine

---

[5] In the *Baseline* treatment, the correlation between early action and subsequent contributions is also highly significant but negative (r=-0.84, p=0.002), reflecting the presence of groups that had a bad start but ultimately strived and managed to reach the threshold.

remaining rounds. Still, this did not happen. Most groups taking early action, as defined in Figure 6 by investing at least €12 in the first round, did so because all of their members invested at least €2. About one-third of these groups (11/31) contained exactly one free-rider who gave nothing and was compensated by its co-players' contributions. None of these groups contained more than one free-rider. Thus, most of these groups started the game with a high contribution level *and* with an equally shared burden. The latter, in particular, might have helped to keep the group's motivation up for the remaining rounds. To test this hypothesis we calculate the normalized Gini coefficient for the first round as well as the average normalized Gini coefficient across all rounds.[6] Both coefficients are positively correlated (r=0.64, p=0.000), indicating that an equal burden sharing in the first round increased the likelihood of an overall equal burden sharing. The average normalized Gini coefficient across all rounds is 0.09 for *Baseline*, 0.16 for *Normal*, 0.18 for *Uniform*, and 0.22 for both ambiguity treatments. That is, inequality within groups tended to be higher under uncertainty. Figure 7 presents the correlation between inequality, i.e. the average normalized Gini coefficient across all rounds, and total investment. As could be expected from the above discussion, the correlation depends on the treatment. It is negative and highly significant in *Uniform* (r=-0.94, p=0.000), *AmbNormal* (r=-0.93, p=0.000), and *AmbUniform* (r=-0.87, p=0.001) while it is not significant in *Baseline* (r=0.03, p=0.945) and *Normal* (r=-0.44, p=0.206).

In an econometric regression analysis, we further explore the effects of uncertainty, early action, and inequality while simultaneously controlling for other variables collected in the ex-post questionnaire. The regression models include the questions about the players' motivation for their proposal for the group target, the motivation for their investment decisions, and the question about fairness consideration (see Table S3 in the Appendix). All the other variables taken from the questionnaire, for example risk aversion, trust, and analytical skills, have been excluded from the final regression models shown below because the pre-regression analysis has shown that these characteristics did not significantly affect the players' behavior.

[6] The average Gini coefficient was calculated by

$$G^+ = \left(\frac{2k\sum_{j=1}^{n}\sum_{t=1}^{r}c_j^t}{n\sum_{t=1}^{r}\sum_{j=1}^{n}c_j^t} - \frac{(n+1)}{n}\right)\frac{n}{(n-1)}$$

with k being the rank if individual contributions are ranked in an ascending order within a group.

Table 6 presents a series of linear regressions of the cumulative group investment. Columns 1 and 2 capture the investment over the entire game, while Columns 3 and 4 capture the rounds 2-10 only, because these models include the first round investment as regressor. Columns 2 and 4 exclude the *Baseline* treatment in order to highlight the effects of the independent variables under uncertainty. All independent variables as well as the dependent variable are defined at group level. The results qualify the relationship we have identified between uncertainty and group investment: The groups in *Baseline* contributed more to the public good than those in all the other treatments, and the difference in contributions is highly significant between *Baseline* and *Uniform* and between *Baseline* and the two ambiguity treatments (Column 1). In addition, the groups in *Normal* contributed more than those in the ambiguity treatments (Column 2). Contributions were significantly larger when the groups had made a larger second proposal. This effect is not observed for the average first proposal, which confirms that this did not serve as a good signal for group performance.

Recall that after the game players stated the motivations for their decisions in a questionnaire (see Table S3 in the Appendix). The regression analysis indicates that groups contributed more to the public good when they included a high number of players whose investment decisions were motivated by their own or the average proposals. Thus, while the proposal itself was not a good predictor of group performance, a high number of members motivated by the proposal did help. In order to show the effect of early action, two regression models include the first round investment as regressor. These models confirm that a high first round investment was only important for the groups facing uncertainty (Columns 3 and 4). Since we already know that an equal burden sharing was helpful, another interesting question is whether fairness considerations affected group performance. 37% of the players reported in the questionnaire that fairness did not play a role in their investment decision. For the other players, the impact of fairness was at least twofold; people either increased their contributions when they had observed a high investment level within their group (6%) or, more likely, they decreased their contributions when they had observed a low investment level (31%) (see Table S3 in the Appendix). The regression analysis indicates that the group performance suffered from a high number of members who reduced their contributions due to fairness considerations. This finding, in combination with the fact that fairness considerations were more likely to decrease contributions rather than to increase them (31% vs. 6%), suggests that an unequal burden sharing was detrimental for players' willingness to cooperate and ultimately for the game's outcome.

Table 7 presents the results from a series of linear regressions of the cumulative individual contributions to the public good. The model in Column 2 excludes the *Baseline* treatment. The regression results basically confirm the key findings presented so far. First of all, the results confirm that uncertainty was detrimental for the willingness to cooperate. The subjects in *Baseline* contributed significantly more than the subjects in all the other treatments (Column 1). The results confirm furthermore that a high first round contribution of the other fellow group members increased the individual investment. This effect is larger if the analysis is restricted to the uncertain treatments (Column 2). The players who had made a larger second proposal chose somewhat larger contributions afterwards. This effect is not observed for the first proposal. On the other hand, the regression models show that players' *motivation* for their first proposals played an important role. The subjects who stated safety as most important motive for their proposal invested significantly more than those who stated risk assessment. The players whose proposals were subject to strategic considerations invested less. These differences explain why the first proposals and actual contributions did not necessarily go hand in hand. The motivation for the second proposal did not significantly affect the individual contributions, which is why this variable has been excluded from this regression model.

5 Conclusions

Science tells us that climate change involves tipping points, beyond which potentially catastrophic and irreversible consequences to our planet may ensue. However, climate tipping points and the efforts required to avoid triggering them are highly uncertain. Although there is widespread political consensus about the need to avoid potentially dangerous climate change, countries' willingness to contribute to this collective goal may be seriously affected by environmental uncertainty. We conducted an experiment involving a threshold public good game and compared how coordination success is affected by whether the threshold is known or not. The challenge for players was always one of coordinating their contributions to the public good because the social optimum, that maximizes the expected joint payoff, is supportable as Nash equilibrium in all treatments. However, coordination is clearly harder under uncertainty because the number of equilibria is much higher than under certainty and they are often very close to each other in terms of expected payoffs.

The experimental results show that threshold uncertainty negatively affected the provision of the public good. Whereas all our experimental groups succeeded in preventing the public bad when the threshold was known, this result was not replicated in presence of threshold uncertainty. Contributions were generally lower when players did not know the threshold precisely. Moreover, contributions were lower when players faced ambiguity than when they faced risk.

The players' proposals for the targeted collective contribution indicate that *ex-ante* the players had planned more or less the same in all treatments. However, in the presence of uncertainty (and in particular of ambiguity), contributions were markedly lower than proposals, arguably because players were more sensitive to others' behavior. This sensitivity would not matter so much if the players got off on a good start of the game. However, there was also a tendency among the players facing ambiguity to start the game "carefully" with rather low first round contributions. The combination of both, the sensitivity and the bad start, eventually led to a very poor performance of some groups in these treatments. On the other hand, when a group happened to start the game with high and equally distributed first round contributions, it was likely to reach an overall high contribution level and to ultimately avert the collective damage. As a consequence the group performance varied widely under uncertainty. The first key result of our experiment therefore is that early action and fairness become very important in the presence of uncertainty.

The finding that people who do not know the target with precision orientate their behavior on other people in their peer group may help to explain the prominent role of equity and fairness in climate negotiations (Lange et al. 2007). Countries often make conditional pledges, meaning they are willing to reduce their greenhouse gas emissions provided that other countries contribute equitably. However, unlike in our game, the equitable distribution of efforts is not obvious as countries do not only differ in their contributions to climate protection but also in many other aspects. For this reason, it is difficult to compare countries' domestic climate protection efforts and their pledges. In addition to this comparability problem, countries' fairness perceptions are often subject to a self-serving bias so that they prefer the fairness principle that would generate least costs for them (Lange et al. 2010). Therefore, if a fair distribution is decisive for success but at the same time difficult to implement, a practical implication may be to reframe the negotiations in a way that makes the comparison easier (Barrett 2011).

Another key result of the experiment is the 100% success rate in the Baseline treatment and its robustness with respect to the distribution of efforts among players and over time. It suggests that, if the climate change effects were truly catastrophic and the tipping points were known with precision, countries could be expected to tackle the problem. The large uncertainty involved in the climate system, however, may worsen the chances considerably. The experimental results suggest that the coordination problem gets increasingly easier from ambiguity to risk to certainty. Therefore any future climate policy should aim at reducing uncertainty.

References

Alley, R. B., J. Marotzke, W. D. Nordhaus, J. T. Overpeck, D. M. Peteet, R. A. Pielke Jr., R. T. Pierrehumbert, P. B. Rhines, T. F. Stocker, L. D. Talley, and J. M. Wallace (2003), Abrupt Climate Change, *Science* 299 (5615), 2005-2010.

Bagnoli, M. and B. L. Lipman (1989), Provision of Public Goods: Fully Implementing the Core through Private Contributions, *The Review of Economic Studies* 56 (4), 583-601.

Bailey, R., J. Eichberger, and D. Kelsey (2005), Ambiguity and Public Good Provision in Large Societies, *Journal of Public Economic Theory* 7, 741-759.

Barrett, S. (2010), Climate Treaties and Approaching Catastrophes, Columbia University.

Barrett, S. (2011), Avoiding disastrous climate change is possible but not inevitable, *Proceedings of the National Academy of Sciences* 108 (29), 11733-11734.

Budescu, D.V., A. Rapoport, and R. Suleiman (1992), Simultaneous vs. sequential requests in resource dilemmas with incomplete information, *Acta Psychologica* 80, 297-310.

Budescu, D.V., R. Suleiman, and A. Rapoport (1995), Positional order and group size effects in resource dilemmas with uncertain resources, *Organizational Behavior and Human Decision Processes* 61, 225- 238.

Camerer, C. and M. Weber (1992), Recent developments in modeling preferences: Uncertainty and ambiguity, *Journal of Risk and Uncertainty* 5 (4), 325-370.

Chua Chow, C. and R. K. Sarin (2002), Known, Unknown, and Unknowable Uncertainties, *Theory and Decision* 52 (2), 127-138.

Croson, R. and M. Marks (2000), Step Returns in Threshold Public Goods: A Meta- and Experimental Analysis, *Experimental Economics* 2 (3), 239-259.

Eichberger J. and D. Kelsey (2002), Strategic Complements, Substitutes and Ambiguity: The Implications for Public Goods, *Journal of Economic Theory* 106, 436-466.

Eichberger, J., D. Kelsey, and B. Schipper (2008), Granny versus Game Theorist: Ambiguity in Experimental Games, *Theory and Decision* 64, 333-362.

Ellsberg, D. (1961), Risk, Ambiguity, and the Savage Axioms, *The Quarterly Journal of Economics* 75 (4), 643-669.

Fischbacher, U. (2007), Z-Tree: Zurich Toolbox for Ready-made Economic Experiments, *Experimental Economics* 10 (2), 171-178.

Greiner, B. (2004), An Online Recruitment System for Economic Experiments, in: Kremer K. and V. Macho (Eds.), *Forschung und wissenschaftliches Rechnen*, GWDG Bericht 63, Gesellschaft für Wissenschaftliche Datenverarbeitung Göttingen, 79-93.

Gustafsson, M., A. Biel, and T. Gärling (1999), Overharvesting of resources of unknown size, *Acta Psychologica* 103 (1-2), 47-64.

Isaac, R. M., K. F. McCue, C. R. Plott (1985), Public Goods Provision in an Experimental Environment, *Journal of Public Economics* 26, 51-74.

Knight, F. H. (1921), Risk, Uncertainty, and Profit, Hart, Schaffner & Marx, Houghton Mifflin Co., 1st Edition, Boston, MA.

Kontani, K., K. Tanaka, and S. Managi (2010), Cooperative choice and its framing effect under threshold uncertainty in a provision point mechanism, available at: http://ssrn.com/abstract=1616065

Kriegler, E., J. W. Hall, H. Hermann, R. Dawson, and H. J. Schellnhuber (2009), Imprecise probability assessment of tipping points in the climate system, *Proceedings of the National Academy of Sciences* 106 (13), 5041-5046.

Lange, A., C. Vogt, and A. Ziegler (2007), On the Importance of Equity in International Climate Policy: An Empirical Analysis, *Energy Economics* 29 (3), 545-562.

Lange, A., A. Löschel, C. Vogt, and A. Ziegler (2010), On the Self-Interested Use of Equity in International Climate Negotiations, *European Economic Review* 54 (3), 359-375.

Lenton, T. M., H. Held, E. Kriegler, J. W. Hall, W. Lucht, S. Rahmstorf, and H. J. Schellnhuber (2008), Tipping elements in the Earth's climate system, *Proceedings of the National Academy of Sciences* 105 (6), 1786-1793.

Malhi, Y., L. E. O. C. Aragão, D. Galbraith, C. Huntingford, R. Fisher, P. Zelazowski, S. Sitch, C. McSweeney, and P. Meir (2009), Exploring the likelihood and mechanism of a climate-change-induced dieback of the Amazon rainforest, *Proceedings of the National Academy of Sciences*.

Marotzke, J. (2000), Abrupt climate change and thermohaline circulation: Mechanisms and predictability, *Proceedings of the National Academy of Sciences* 97 (4), 1347-1350.

McBride, M. (2006), Discrete public goods under threshold uncertainty, *Journal of Public Economics* 90, 1181– 1199.

McBride, M. (2010), Threshold uncertainty in discrete public good games: an experimental study, *Economics of Governance* 11 (1), 77-99.

Milinski, M., R. D. Sommerfeld, H.-J. Krambeck, F. A. Reed, and J. Marotzke (2008), The collective-risk social dilemma and the prevention of simulated dangerous climate change, *Proceedings of the National Academy of Sciences* 105 (7), 2291-2294.

Nitzan, S. and R. E. Romano (1990), Private provision of a discrete public good with uncertain cost, *Journal of Public Economics* 42 (3), 357-370.

Notz, D. (2009), The future ice sheets and se ice: Between reversible retreat and unstoppable loss, *Proceedings of the National Academy of Sciences* 106 (49).

Palfrey T.R. and H. Rosenthal (1984), Participation and the Provision of Public Goods: A Strategic Analysis, *Journal of Public Economics* 24, 171-193.

Rapoport, A., D.V. Budescu, R. Suleiman, and E. Weg (1992), Social dilemmas with uniformly distributed resources, in W.B.G. Liebrand et al. (Eds), *Social dilemmas: Theoretical issues and research findings*, Oxford, Pergamon Press, 43-57.

Rondeau, D., G. L. Poe, and W. D. Schulze (2005), VCM or PPM? A comparison of the performance of two voluntary public goods mechanisms, *Journal of Public Economics* 89 (8), 1581-1592.

Savage, L.J. (1954), The Foundations of Statistics, New York, Wiley.

Scheffer, M., S. Carpenter, J. A. Foley, C. Folke, and B. Walker (2001), Catastrophic shifts in ecosystems *Nature*, 413 (6856), 591-596.

Slovic, P. and A. Tversky (1974), Who Accepts Savage's Axiom?, *Behavioral Science*, 19, 368-373.

Spencer, M. A., S. K. Swallow, J. F. Shogren, and J. A. List (2009), Rebate rules in threshold public good provision, *Journal of Public Economics* 93 (5-6), 798-806.

Suleiman, R. (1997), Provision of Step-Level Public Goods under Uncertainty a Theoretical Analysis, *Rationality and Society* 9 (2), 163-187.

Suleiman, R., D. V. Budescu, and A. Rapoport (2001), Provision of Step-Level Public Goods with Uncertain Provision Threshold and Continuous Contribution, *Group Decision and Negotiation* 10 (3), 253-274.

Tavoni, A., A. Dannenberg, G. Kallis, and A. Löschel (2011), Inequality, communication and the avoidance of disastrous climate change in a public good game, *Proceedings of the National Academy of Sciences* 108 (29), 11825-11829.

Wit, A. and H. Wilke (1998), Public good provision under environmental and social uncertainty, *European Journal of Social Psychology* 28 (2), 249-256.

Zickfeld, K., A. Levermann, M. Morgan, T. Kuhlbrodt, S. Rahmstorf, and D. Keith (2007), Expert judgements on the response of the Atlantic meridional overturning circulation to climate change, *Climatic Change* 82 (3), 235-265.

Zickfeld, K., M. Eby, H. D. Matthews, and A.J. Weaver (2009), Setting Cumulative Emissions Targets to Reduce the Risk of Dangerous Climate Change, *Proceedings of the National Academies* 106(38), 16129-16134.

Table 1: Experimental design

Treatment	Uncertainty	Interval	Threshold	Probability	No. of subjects
Baseline	None	[€0, €240]	T=120	Known (=1)	60
Normal	Risk	[€0, €240]	E(T)=120	Known	60
Uniform	Risk	[€0, €240]	E(T)=120	Known	60
AmbNormal	Ambiguity	[€0, €240]		Unknown	60
AmbUniform	Ambiguity	[€0, €240]		Unknown	60

Table 2: Expected payoffs

Treatment	EV(c=€0/rd) (I=0)	EV(c=€2/rd) (I=120)	EV(c=€4/rd) (I=240)	c*	EV(c*)	I(c*)
Baseline	4.0	20.0	0	€2/rd	20.0	120
Normal	4.7	12.3	0	€2/rd	12.3	120
Uniform	6.8	11.7	0	€1.7/rd	12.0	100

Note: Player's expected payoffs from following a symmetric strategy and from the collectively optimal investment c*. If all players contribute an equal share of the burden (€2/rd), this corresponds to an expected payoff of €20 in *Baseline* and €12.3 in *Normal*. In *Uniform*, players are best off when each provides about €1.7/rd, which is not possible given that in each round the strategy set is c={0, 2, 4}. Of course players could still coordinate on I=100, but that necessarily requires asymmetric contributions.

Table 3: Summary statistics

Treatment	First proposal	Second proposal	Group contribution	Min / max group contribution
Baseline	121.8 (8.7)	121.9 (4.2)	121.2 (2.1)	120 / 126
Normal	120.4 (18.5)	122.9 (18.9)	99.4 (19.5)	78 /140
Uniform	124.1 (10.1)	123.2 (11.9)	101.4 (18.6)	58 / 122
AmbNormal	127.0 (7.2)	120.3 (9.4)	84.0 (23.5)	36 /120
AmbUniform	122.9 (12.2)	115.2 (16.1)	83.0 (29.4)	26 / 118

Note: Average values by treatment; standard deviations in parentheses; last column shows the minimum and maximum group contributions.

Table 4: Significance of treatment differences

Normal	0.0043			
Uniform	0.0023	0.4717		
AmbNormal	0.0003	0.1032	0.0819	
AmbUniform	0.0001	0.2727	0.1854	0.8501
	Baseline	*Normal*	*Uniform*	*AmbNormal*

Note: p-values from a Wilcoxon rank-sum test of the differences in average contributions to the public good between the treatments.

Table 5: Success rate at given hypothetical thresholds

Threshold	*Baseline*	*Normal*	*Uniform*	*AmbNormal*	*AmbUniform*
20		100%	100%	100%	100%
40		100%	100%	90%	90%
60		100%	90%	90%	80%
80		90%	90%	50%	60%
100		40%	60%	20%	40%
120	100%	20%	20%	10%	0%
140		10%	0%	0%	0%
160		0%	0%	0%	0%

Note: Percentage of groups which would have reached hypothetical thresholds given the actual amounts contributed in the game.

Table 6: Linear regression of group investment

Variables	(1) Rd.1-10	(2) Rd.1-10	(3) Rd.2-10	(4) Rd.2-10
Treatment				
(*Baseline* or *Normal* omitted)				
Normal	-9.158		-6.665	
	(6.695)		(6.496)	
Uniform	-16.39***	-6.943	-13.14**	-6.499
	(4.821)	(5.638)	(5.140)	(4.663)
AmbNormal	-21.19***	-11.38**	-15.22**	-6.948
	(7.250)	(5.517)	(6.702)	(4.262)
AmbUniform	-24.22***	-13.38**	-19.06***	-10.21*
	(6.196)	(5.788)	(6.470)	(5.403)
Average 1st proposal	0.0848	0.0665	0.120	0.268
	(0.176)	(0.234)	(0.171)	(0.207)
Average 2nd proposal	0.764***	0.764***	0.637***	0.466**
	(0.198)	(0.230)	(0.163)	(0.192)
Group investment rd.1			1.160	2.127**
			(0.839)	(0.939)
Motivation investment				
(no. of group members, risk assessment omitted)				
Own proposal	4.075***	4.968**	2.712*	2.933
	(1.366)	(2.100)	(1.397)	(2.087)
Average proposal	8.968***	9.082***	6.293***	5.759***
	(2.025)	(2.192)	(1.953)	(1.894)
Safeness	2.771	4.598	3.040	7.109**
	(1.908)	(3.229)	(1.958)	(3.436)
Fairness				
(no. of group members, no fairness omitted)				
Positive	-0.112	0.619	0.111	1.719
	(1.365)	(1.976)	(1.192)	(1.706)
Negative	-5.270**	-5.122*	-5.532***	-5.249**
	(2.368)	(2.571)	(2.009)	(2.181)
Constant	-1.499	-12.76	-12.02	-31.74
	(21.10)	(25.26)	(19.61)	(25.21)
No. of observations	50	40	50	40
R^2	0.856	0.825	0.862	0.846

Linear regression of group investment in rd.1-10 (columns 1 and 2) and in rd.2-10 (columns 3 and 4); columns 2and 4 exclude the *Baseline* treatment; robust standard errors in parentheses; significance: *** p<0.01, ** p<0.05, * p<0.10.

Table 7: Linear regression of individual investment

Variables	(1) Rd.1-10	(2) Rd.1-10
Treatment		
(*Baseline* or *Normal* omitted)		
Normal	-2.256***	
	(0.662)	
Uniform	-2.032***	0.226
	(0.627)	(0.667)
AmbNormal	-3.777***	-1.400
	(0.953)	(0.840)
AmbUniform	-3.672***	-1.306
	(0.926)	(0.874)
1st proposal	0.00904	0.0221
	(0.0138)	(0.0135)
2nd proposal	0.0760***	0.0627***
	(0.0140)	(0.0146)
Others average rd.1	1.842**	2.228**
	(0.800)	(0.829)
Motivation 1st proposal		
(risk assessment omitted)		
Safety	1.005*	1.406**
	(0.511)	(0.682)
Strategic	-1.726**	-1.964**
	(0.722)	(0.851)
Motivation investment		
(risk assessment omitted)		
Own proposal	3.974***	4.449***
	(0.599)	(0.649)
Average proposal	3.848***	4.279***
	(0.724)	(0.779)
Safety	3.590***	4.898***
	(0.838)	(1.333)
Fairness		
(no fairness omitted)		
Positive	2.536***	3.377***
	(0.672)	(0.851)
Negative	-0.0622	0.0316
	(0.753)	(0.815)
Constant	1.887	-1.736
	(2.309)	(2.315)
No. of observations		
R^2		

Linear regression of individual investment in rd.1-10; column (2) excludes the *Baseline* treatment; robust standard errors in parentheses (clustered at group level); significance: *** p<0.01, ** p<0.05, * p<0.10.

Figure 1: The distribution of balls used to determine the threshold

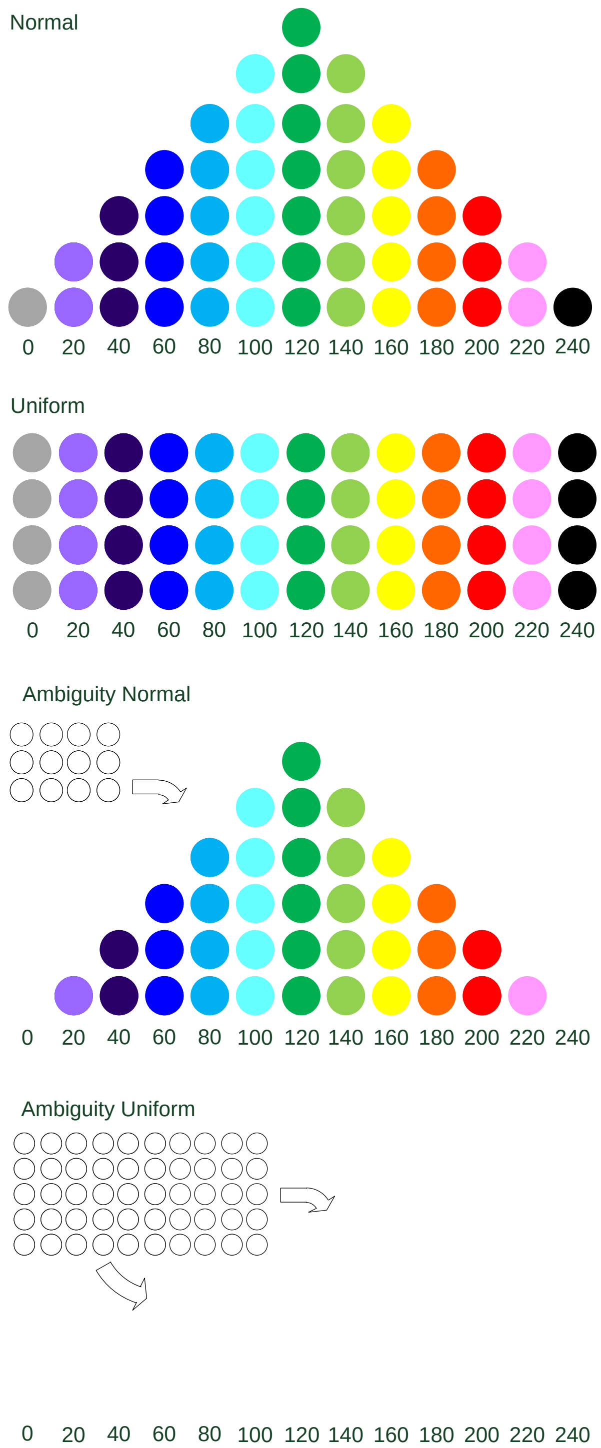


Figure 2: The provision probability for each threshold, in *Baseline*, *Normal* and *Uniform*.

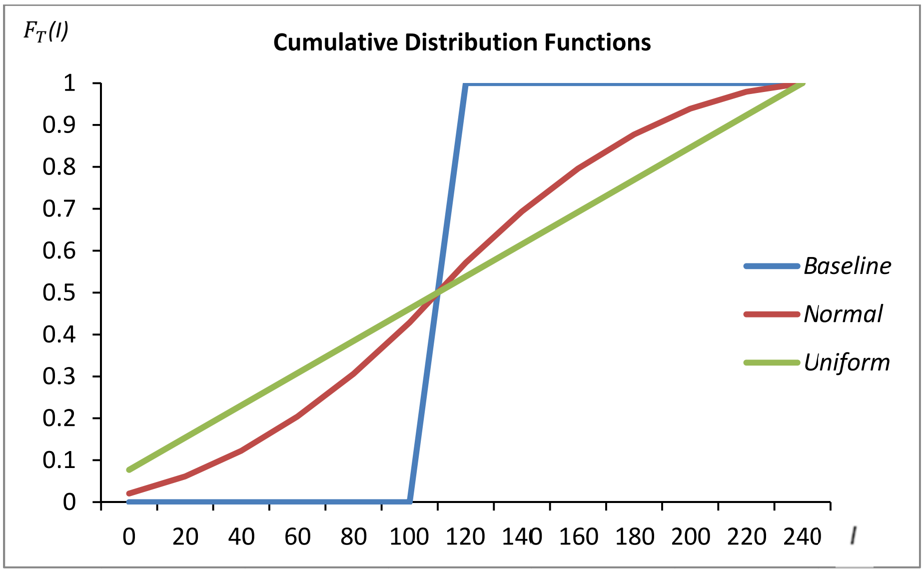


Figure 3: Costs (in blue) and benefits (in red) from contributing to the public good, in *Baseline*, *Normal* and *Uniform* respectively. The vertical segments indicate the maximum expected payoff achievable by a group for a given investment *I*.

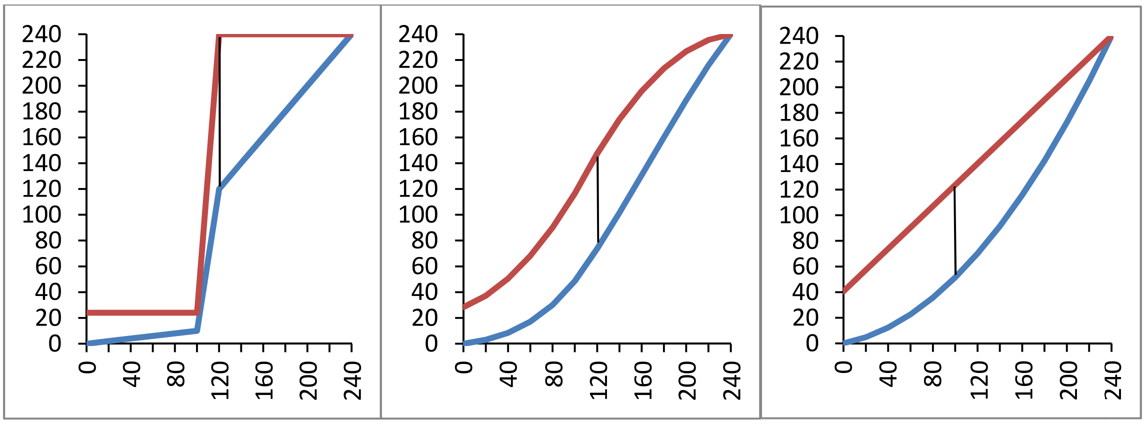
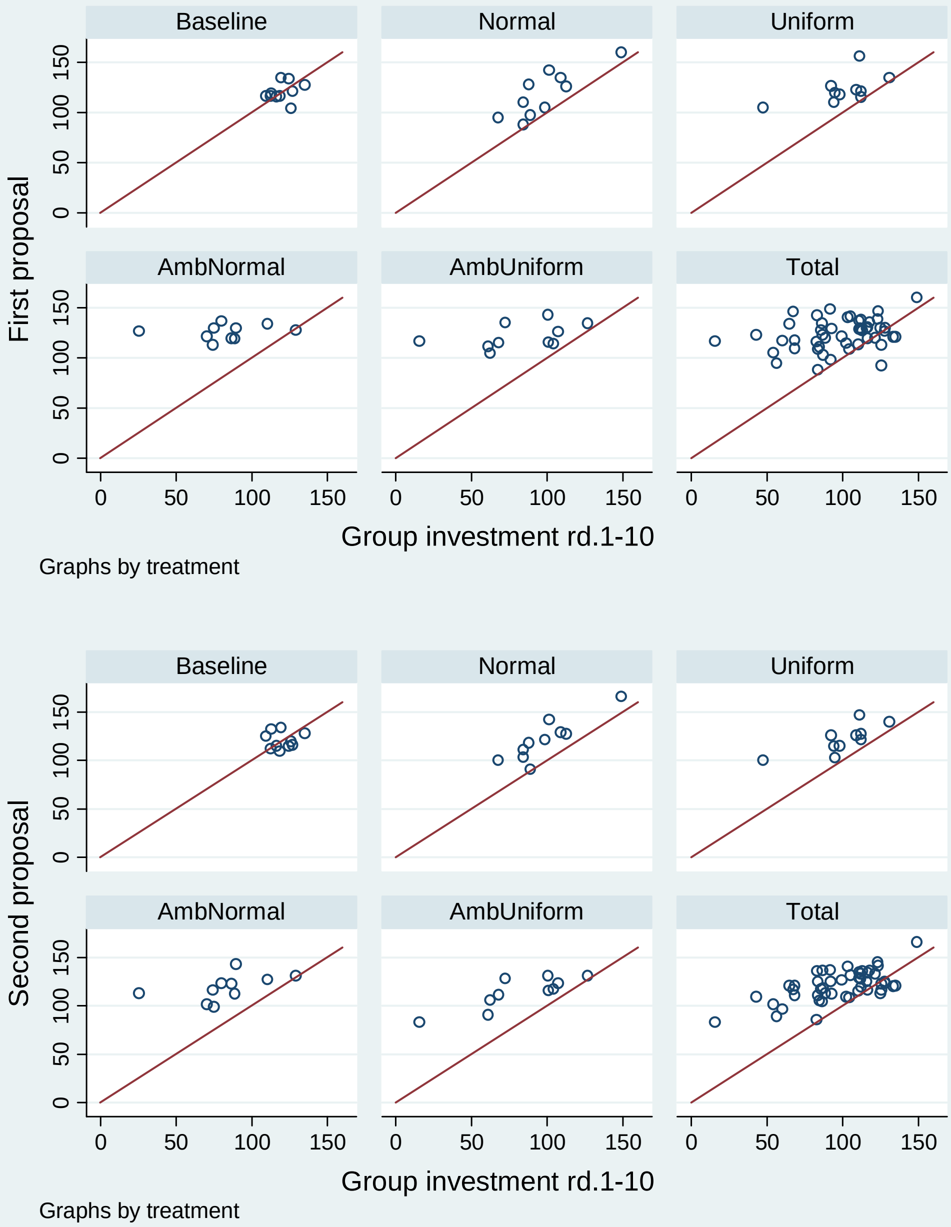


Figure 4

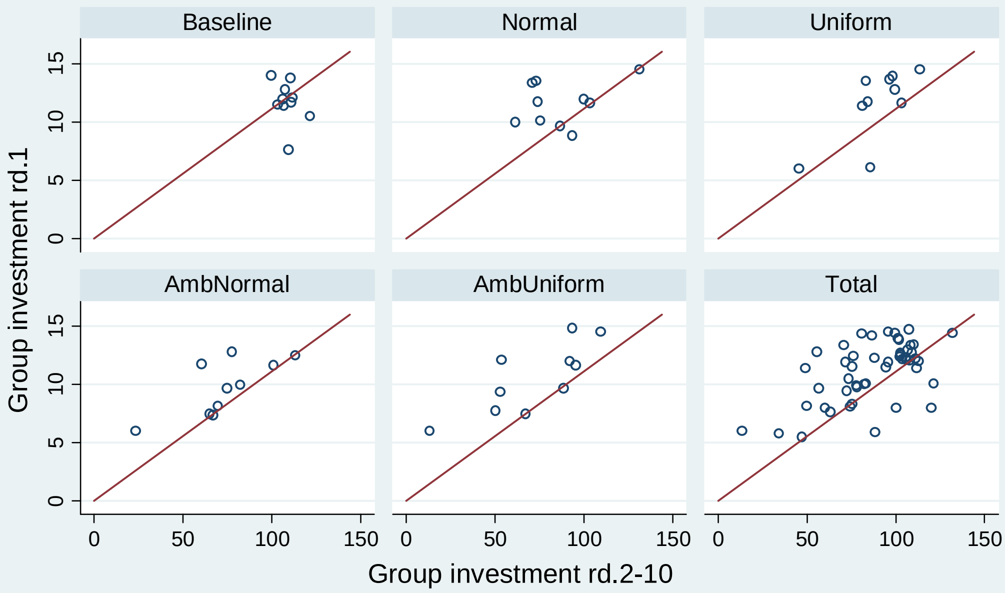
Proposals and contributions



Correlation between average proposals and investment

Figure 5

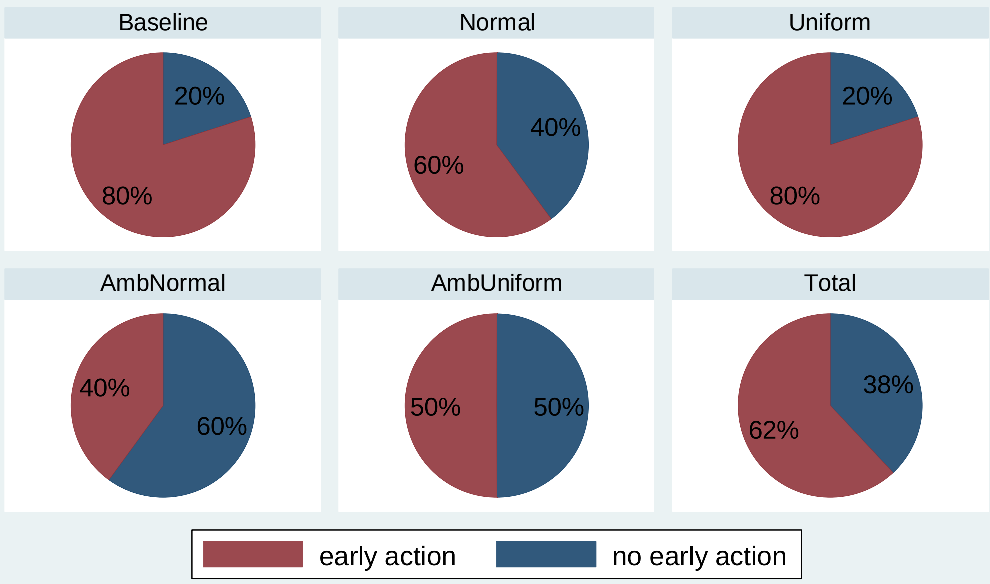
Early action and contributions



Correlation between group investment in rd.1 and in rd.2-10.

Figure 6

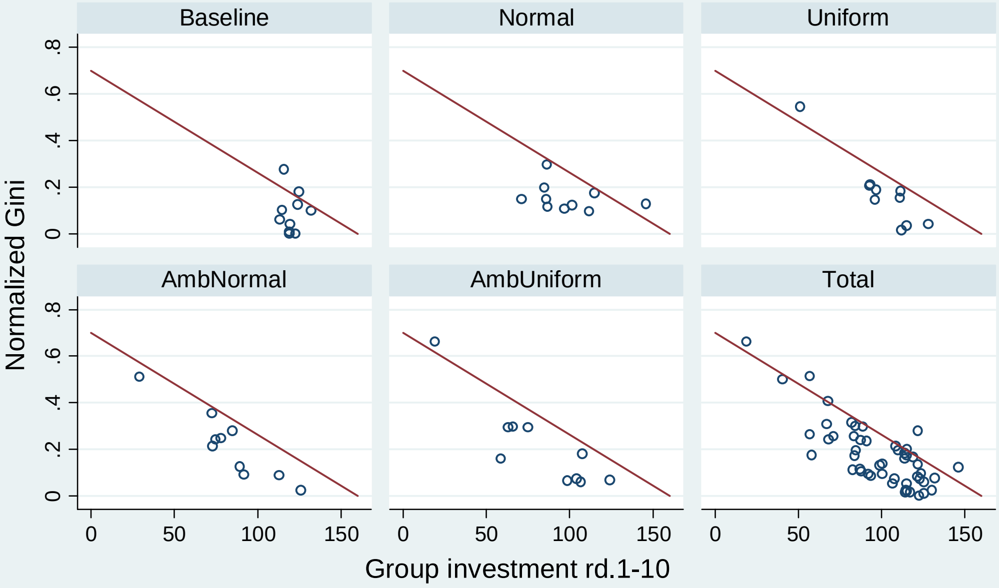
Percentage of groups taking early action



Early action defined as group investment in the first round being €12 or higher.

Figure 7

Inequality and contributions



Correlation between normalized Gini and total group investment.

Appendix

Table S1: Example I

Round	P1	P2	P3	P4	P5	P6	
1	2	2	2	2	2	2	
2	2	2	2	2	2	2	
3	2	2	2	2	2	2	
4	2	2	2	2	2	2	
5	2	2	2	2	2	2	
6	2	2	2	2	2	2	
7	2	2	2	2	2	2	
8	2	2	2	2	2	2	
9	2	2	2	2	2	2	sum=108
10	2	2	2	2	2	2	sum=120

Note: An hypothetical example of symmetrical play of the c= €2 strategy in *Uniform*; I=120 is a Nash equilibrium, as switching to c=0€ in the last round diminishes the EV.

Table S2: Example II

Round	P1	P2	P3	P4	P5	P6	
1	4	4	4	4	4	4	
2	4	4	4	4	2	2	
3	2	2	2	2	2	2	
4	2	2	2	2	2	2	
5	2	2	2	2	2	2	
6	2	2	2	2	2	2	
7	2	2	2	2	2	2	
8	2	2	2	2	2	2	
9	2	2	2	2	2	2	sum=128
10	2	2	2	2	2	2	sum=140

Note: An hypothetical example showing that I=140 is not supportable as a Nash equilibrium in *Uniform*; switching to c=0€ in the last round is a profitable deviation.

Tables S1 and S2 present hypothetical examples for the *Uniform* treatment. The example in Table S1 shows how, given the symmetric intermediate-contribution strategies followed by all players in rounds 1-9, no one has an incentive to deviate in the final round. By sticking to c=€2, players expect €11.7, while if a single player switches to c=€0, the expected payoff from T=100 is €11.3.[7] Having established that T=120 is (under reasonable symmetrical

[7] Note that, should a player (irrationally) deviate in round 10 and choose c=€0, the remaining players would be best-off by following suit, as EV(c=€4)=€10.5<EV(c=€0)=11.3. That is, it is not advantageous for other players to compensate the free-rider, so T=120 will not be provided. Put differently, the set of strategies requiring all an investment of €2/round is a Nash equilibrium, but is not evolutionarily stable. By contrast, T=0 (which doesn't

contributions conditions) preferred to T=100, we show in Table S2 that T=140 is not preferred to T=120. Assume that players 1-4 have each invested €22 in the first 9 rounds, while players 5-6 have each invested €20. This means they have collectively contributed €128 to the climate account, before the last round begins: are they better off by all choosing c=€2 in round 10 and reaching T=140? Players 5 and 6 would, as the ensuing expected pay is €11.8, while switching to c=€0 implies an expected pay of €11.7. However, this not a Nash equilibrium, as players 1-4 are (marginally) better off when switching: EV(c=€2)=€10.46<EV(c=€0)=10.52.

require coordination) is always stable, so a deviating player will find it optimal to revert back to c=€0 in successive rounds.

Table S3: Ex-post questionnaire and responses

Question	Answer	No.	%
(1) What was the motivation for your first proposal for the group target? Please tick one answer.	Safeness	81	27.00
	Risk assessment	140	46.67
	Strategic considerations	58	19.33
	Other	21	7.00
(2) What was the motivation for your second proposal for the group target? Please tick one answer.	Safeness	64	21.33
	Risk assessment	127	42.33
	Strategic considerations	82	27.33
	Other	27	9.00
(3) Please recall your investment decisions during the game. What was the motivation for your investment? Please tick one answer.	Own proposal for group target	86	28.67
	Average proposal for group target	68	22.67
	Safeness	28	9.33
	Risk assessment	79	26.33
	Other	39	13.00
(4) Did fairness play a role in your investment decisions and if so, in which respect? Please tick one answer.	Fairness did not play a role	112	37.33
	I invested more than initially planned because my co-players invested a lot	17	5.67
	I invested less than initially planned because my co-players invested little	92	30.67
	Other fairness consideration	79	26.33
(5) How do you see yourself: Are you generally a person who is fully prepared to take risk or do you try to avoid taking risk? Please tick a box on the scale, where the value 1 means: "fully prepared to take risk" and the value 6 means: "risk averse". You can use the values in between to make your estimate.	1 (fully prepared to take risk)	2	0.67
	2	32	10.67
	3	111	37.00
	4	109	36.33
	5	43	14.33
	6 (risk averse)	3	1
(6) How good are you at working with fractions (e.g. “one fifth of something”) or percentages (e.g. “20% of something”)? Please tick a box on the scale, where the value 1 means: "not good at all" and the value 6 means: "extremely good". You can use the values in between to make your estimate.	1 (not good at all)	1	0.33
	2	10	3.33
	3	21	7.00
	4	50	16.67
	5	123	41.00
	6 (extremely good)	95	31.67
(7) Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people? Please tick a box on the scale, where the value 1 means: "most people can be trusted" and the value 6 means: "need to be very careful". You can use the values in between to make your estimate.	1 (most people can be trusted)	4	1.33
	2	28	9.33
	3	86	28.67
	4	94	31.33
	5	63	21.00
	6 (need to be very careful)	25	8.33
(8) Do you trust your fellow students completely, somewhat, not very much or not at all? Please tick one answer.	Completely	27	9.00
	Somewhat	202	67.33
	Not very much	63	21.00
	Not at all	8	2.67
	∑	300	100.00