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Experimental evidence of common pool resource use in the presence of uncertainty ☆

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ABSTRACT

Tipping points can occur in many complex environmental systems and often produce abrupt and irreversible change. Thresholds associated with tipping points are difficult to predict in many cases, leading to considerable challenges associated with the management of natural resources. We use a common pool resource (CPR) framework to investigate the impact of different types of threshold uncertainty on CPR use and the efficacy of coordination among group members. Participants in an economic laboratory experiment made decisions on the use of a CPR under three types of threshold treatments – a known threshold (certainty), an uncertain threshold with a known probability distribution of possible thresholds (risk), and an uncertain threshold with an unknown probability distribution (ambiguity). We also tested the effect of communication on coordination among participants in each treatment. We find that while threshold uncertainty (both risk and ambiguity) tends to increase CPR use, communication reduces the use of shared resources and increases social efficiency. Communication reduces the incidence of coordination failure in the presence of both types of threshold uncertainty. A takeaway from our results is that encouraging communication is likely to improve CPR management, while improving information about the probability of specific thresholds may only be useful if thresholds can be identified with certainty.

1. Introduction

Many shared natural resources involve threshold effects such that aggregate resource use beyond a tipping point can have disastrous consequences for the environment and human well-being. The challenge is amplified when tipping point thresholds are uncertain both in terms of their level and distribution. Critical examples where threshold uncertainty is present in the commons include climate change, biodiversity loss, depletion of fish stocks, ocean acidification, saltwater intrusion into aquifers, and overuse of antibiotics (Maas et al., 2017; Guilfoos et al., 2019; Dannenberg et al., 2014; Barrett and Dannenberg, 2014; Aflaki, 2013; Rockstrom et al., 2009; Barnosky et al., 2012; Barrett, 2013). The presence of threshold uncertainties coupled with heterogeneous attitudes toward uncertainty make coordination difficult, yet coordination among

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resource users is required to improve management of the commons (Chandrashekhar et al., 2018). Research is needed to understand how uncertainty related to critical environmental thresholds affects behavior in common pool resource (CPR) settings and whether coordination improves when individuals communicate.

The existing literature does not fully examine how different types of uncertainty affect behavior. Most studies compare behavior in decision-making environments with and without uncertainty; however, uncertainty is more nuanced in terms of the type and quality of information that exists. Two types of threshold uncertainties need consideration – the range of potential threshold levels and the likelihood of those threshold levels occurring (which can be communicated via probability distributions). Past studies have reported that the presence of threshold uncertainty with known probability distributions leads to collective action failures in many contexts (Wit and Wike, 1998; McBride, 2010, 2006; Anderies et al., 2013; Aflaki, 2013; Dannenberg et al., 2011; Guilfoos et al., 2019; Budescu et al., 1990; Kidwai and de Oliveira, 2020). Recent research has also examined how ambiguity impacts contributions to public goods, finding only limited evidence that ambiguity influences cooperative behavior (Levati and Morone, 2013; Bjork et al., 2016; Butera et al., 2020). We know of no studies, however, that examine CPR use when threshold probability distributions are ambiguous. The differentiation between the effect of risk and ambiguity has important policy implications (Barham et al., 2014). For instance, credit and insurance can serve as a risk-reducing policy instruments, while provision of appropriate information might be a suitable ambiguity-reducing strategy.

Extant literature suggests that communication, a key component in many economic transactions, plays a beneficial role in supporting socially-preferred outcomes in coordination games (Guilfoos et al., 2019; Cooper et al., 1992; Russell et al., 1992; Crawford, 1998; Charness et al., 2013; Charness and Grosskopf, 2004; Duffy and Feltovich, 2006; Blume and Ortmann, 2007; Devetag and Ortmann, 2007; Ellingsen and Ostling, 2010; Li et al., 2016). Communication enables individuals to identify and implement better strategies and deal with non-conforming group members (Ostrom and Walker, 1991). Fershtman and Segal (2018) theoretically show that interaction among decision-makers, even if they are strangers, can influence individuals' choices in a group setting. Information sharing through communication and risk pooling across individuals within a group may increase in cases involving threshold uncertainty (Abbott and Wilen, 2010; Holland, 2018; Holland and Jannot, 2012). With communication, the effect of risk and ambiguity on individual decisions depends on the behavior of both the individual and other group members (Bougheas et al., 2013; Keck et al., 2014; Brunette et al., 2015). Communication, as a result, may have considerable impacts on behavior in CPR settings when there is uncertainty about critical resource thresholds.

In this paper, we use a laboratory experiment to explore the effects of threshold uncertainty and communication on individual resource use behavior and group coordination in a CPR setting. Specifically, we observe individual CPR use and coordination behavior in the presence of two types of threshold uncertainty – one in which the probability distribution of potential thresholds is known (risk treatment), and the other in which it is unknown (ambiguity treatment) – and we compare them with coordination behavior in these two treatments with behavior when the threshold is known (certainty treatment). Understanding behavior under uncertainty involves examining the influence of risk preferences (Barsky et al., 1997; Noussair et al., 2014), and a growing body of research points to the need to also study ambiguity preferences (Dimmnock et al., 2016; Halevy, 2007; Sarin and Weber, 1993; Sarin and Winkler, 1992). In the first stage of our experiment, participants reveal their attitudes toward uncertainty (both risk and ambiguity) in a modified Holt-Laury type exercise. Participants then make CPR use decisions in a series of one-shot decision rounds under varying levels of threshold uncertainty. In order to examine opportunities for improving coordination, a communication treatment is introduced.

We find that, in the presence of threshold uncertainty, CPR use is higher, earnings are lower, and groups exhibit a higher incidence of resource collapse relative to a setting in which the threshold is known with certainty. There are no significant differences between the risk and uncertainty treatments in terms of CPR use or earnings. In addition, individuals' risk aversion and ambiguity aversion levels are generally not significantly correlated with CPR use. Finally, communication improves coordination by reducing CPR use in both the risk and ambiguity treatments, resulting in a lower incidence of resource collapse.

2. Theoretical framework and hypotheses

2.1. Basic setup

The basic model that underlies the experiment builds on Rapoport and Suleiman (1992) and Budescu et al. (1995), which was further developed in recent literature (Aflaki, 2013; Maas et al., 2017). Our model shares similarities with group mechanisms for reducing ambient pollution (Spraggon, 2002; Vossler et al., 2006; Suter et al., 2010; Spraggon, 2013) and those reflecting discrete public good provision in the presence of uncertainty (Dannenberg et al., 2015).

Consider a CPR game with threshold uncertainty $\Gamma_R = (n,\ u_i,\ F_{\tilde{R}}, h)$, defined as a group of n individuals who make decisions about how to use a shared resource that will deteriorate or collapse completely if collective resource use exceeds threshold $\tilde{R}$. Individual risk preferences are represented by von Neumann-Morgenstern (vNM) utility functions u_i that are functions of payoffs π_i generated by the resource. Each player is assumed to choose a level of resource use r_i to maximize her utility. Since there are $n-1$ other players competing for the same resource stock, player i's payoff depends on four factors: the amount of own use r_i, total group resource claims $R = \Sigma_{i=1}^{n} r_i$, the realization of the resource threshold $\tilde{R}$, which is uncertain when resource use decisions are made, and the resulting $h(R,\ \tilde{R}) \in [0,\ 1]$ that represents the threshold risk function (TRF). The realization of R and $\tilde{R}$ determines the value of h that represents the share of r_i that is received as the payoff for each player, such that $h(R \le \tilde{R}) = 1$ and $0 \le h(R > \tilde{R}) < 1$. The TRF captures both deterioration and collapse of the resource when $R > \tilde{R}$. For sensitive resources, $h = 0$ implies that the resource collapses and each person in the group receives nothing when $R > \tilde{R}$. Player i's payoff is

$$\pi_i = r_i h\left(R, \tilde{R}\right). \tag{1}$$

The probability distribution of $\tilde{R}$, represented by $F(\cdot)$, may be known or unknown. When the distribution is unknown, $\ddot{F}_i$ represents individual i's subjective belief about the distribution of the threshold, which reflects the ambiguity about the size of the threshold.[1] We assume that the parameters and rules of the game are common knowledge to all players.

In addition to the own choice of r_i, an individual's payoff depends on two types of uncertainties – *strategic uncertainty* about the total claims by other group members R_{-i}, and *structural uncertainty* about the group threshold $\tilde{R}$. This means beliefs about others' decisions and the group threshold affect each participant's decision process. There are always uncertainties in predicting the thresholds of certain resources, usage beyond which will lead to deterioration or collapse. For example, the level of groundwater withdrawals beyond which pumping will lead to saltwater intrusion in an aquifer or the amount of fishing effort beyond which the fishery will collapse. In general, we know that increasing (decreasing) group claims increases (decreases) the likelihood of incurring resource deterioration or collapse. Higher (lower) thresholds, on the other hand, reduces (raises) the likelihood of incurring resource deterioration or collapse.

2.2. Participants' optimal claims when the threshold distribution is known

Consider the case in which $\tilde{R}$ has a finite support over the range $[\alpha,\ \beta]$ for $\alpha < \beta$ with a uniform distribution over the interval, and assume $h(R \le \tilde{R}) = 1$ and $h(R > \tilde{R}) = 0$. This implies that if total use of the resource is below the threshold, $R < \tilde{R}$, each of the i users receives utility as a function of the total units each claims. If group resource use exceeds $\tilde{R}$, then each individual user receives zero utility. Given the set-up of the CPR game, expected utility can be expressed by a step function

$$E[u_i] = \{ \begin{array}{c} u_i(r_i)\ if\ R \le \alpha, \\ u_i(r_i) * prob\left(R \le \tilde{R}\right)\ if\ \alpha < R \le \beta, \\ 0\ if\ R > \beta. \end{array} \tag{2}$$

According to Eq. (2), each individual's choice determines whether the group is in one of the three zones – the safe zone when $R \le \alpha$, the risky zone when $\alpha < R \le \beta$, and the resource collapse zone when $R > \beta$. The claim required to stay within the safe zone where $R \le \alpha$ is achieved when,

$$r_i^* = \frac{\alpha}{n}. \tag{3}$$

In the resource collapse zone where $R > \beta$, the payoff is always zero.

The literature mostly focuses on continuous possible thresholds over an interval, implying that the possible number of thresholds within the support $[\alpha,\ \beta]$ are infinite. In contrast, we model a case with discrete thresholds. The discrete nature of the threshold is meant to resemble a resource that experiences collapse once resource use exceeds a specific level, such as use of a groundwater aquifer above a level that causes saline intrusion to take place. The use of discrete thresholds is also intended to facilitate participants' understanding of the probabilistic nature of resource destruction in the experiment. Consider a case with three possible discrete thresholds $\alpha,\ \gamma$, and β where $0 < \alpha < \gamma < \beta$ with the corresponding probabilities $p_1,\ p_2$ and p_3 such that $p_1 +\ p_2 + p_3 = 1$. Given individual i's attitude toward risk ρ, their best response depends on strategies by the remaining participants in the group represented by R_{-i}.

The possible scenarios for participant i's best response strategy are as follows:

(1) $R_{-i} \le \alpha$: in this scenario, individual i's best response strategy depends on which of three claims ($r_i = \alpha - R_{-i}$,. $r_i = \gamma - R_{-i}$, or $r_i = \beta - R_{-i}$) generates the highest expected utility based on i's risk preferences and the probabilities of each threshold occurring.
(2) $\alpha < R_{-i} \le \gamma$: in this scenario, individual i's best response strategy will be to select the claim that generates the highest expected utility among two possible responses ($r_i = \gamma - R_{-i}$ or $r_i = \beta - R_{-i}$).
(3) $\gamma < R_{-i} \le \beta$: in this scenario, $r_i = \beta - R_{-i}$ yields more utility than any other claim because a larger claim will lead everyone to earn zero payoff with certainty.
(4) $R_{-i} > \beta$: in this case, group claims are above the threshold with certainty and participant i's best response strategy is to claim any amount $r_i \ge 0$ as her payoff will be zero for any claim.

2.3. Effects of ambiguity

The literature has established that individuals often exhibit ambiguity aversion in cases of uncertain prospects with unknown probability distributions (Trautmann and Kuilen, 2015). Emanating from (Ellsberg, 1961), this implies that individuals

[1] Threshold uncertainty associated with the unknown probability distribution is heterogeneous. That is, the subjective beliefs about the probability distribution of the unknown threshold can differ across individuals. This type of uncertainty is termed 'ambiguity' in the literature.

prefer uncertain prospects with known probability (risk) to an equivalent uncertain prospect with unknown probability (ambiguity). There is a small but growing literature relating such attitudes toward uncertainty (risk and/or ambiguity) to individual behavior (Vieider et al., 2019, 2018, 2014; Brick and Visser, 2015; Barham et al., 2014). Aflaki (2013) shows that a decision maker in a CPR game under ambiguity reduces consumption compared to a case with known probabilities. The intuition behind such claim is that in case of increased ambiguity, ambiguity averse participants tend to assume a probability distribution that is associated with higher (probabilistically) marginal damages due to each participant's claim. Hence, given the uncertainty about the threshold, participants' ambiguity aversion is predicted to be associated with lower resource use, as ambiguity averse participants perceive a distribution that puts higher weight on the lower threshold and lower weight on the higher ones.[2] See Appendix A for a formal presentation of this result.

2.4. Socially optimal claims

Socially optimal claims maximize the utility associated with payoffs across all group members. In the case where the resource threshold $\tilde{R}$ is known with certainty, the socially optimal claim by each member of the group is simply $r_i = \tilde{R}/n$, such that total group claims are exactly equal to the threshold. When the resource threshold is not certain and the probability of specific thresholds is known, then socially optimal claims depend on both the magnitude of the thresholds and their associated probabilities. Consider again the case with three discrete thresholds $\alpha,\ \gamma$, and β $(0 < \alpha < \gamma < \beta)$ with corresponding probabilities $p_1,\ p_2$ and p_3 $(p_1 +\ p_2 + p_3 = 1)$. The socially optimal claims, assuming symmetry, are determined by a comparison of the expected utility associated with the payoffs from exactly meeting each of the three thresholds (α, $(p_2 + p_3)\gamma$, and $p_3\beta$, respectively). Importantly, socially optimal claims can diverge from individually (privately) optimal claims because individuals do not account for the increase in the probability of exceeding the threshold that they impose on all other group members with a marginal increase in their own claim. The social optimum is not affected by ambiguity in the threshold probabilities.

2.5. Communication

Communication is an important factor in many economic transactions and is expected to reduce strategic uncertainty (Messick et al., 1988; Guilfoos et al., 2019). In addition, communication is predicted to reduce coordination problems and support socially desired outcomes (Ostrom and Walker, 1991). Messick et al. (1988) points out that there are three potential outcomes that communication among participants leads to – (*i*) superior coordination; (*ii*) fewer sub-optimal choices; and (*iii*) more conservative behavior and reduced claims due to increased trust, group risk concerns, group cooperation expectations, and pressure to conform to social norms (Keck et al., 2014; Gong et al., 2013). Communication within groups may also alter individual preferences regarding uncertainty; however, the direction of the effect differs across studies. For example, when communication among group members is possible, Keck et al. (2014) find that participants making decisions in groups are more likely to display ambiguity neutrality relative to their decisions when acting individually, whereas Bougheas et al. (2013) find that groups take more risk than individuals and Harrison et al. (2013) suggest that participants are more risk averse when making decisions in a social setting in which they know the risk preferences of group members.

Once two-way (unrestricted) communication is introduced, individuals get signals about others' resource claim behavior through communication. That is, initially, resource users make choices with a given set of beliefs about other users in the group, which is expected to change after communicating. Communication can change one's pre-existing beliefs about others' resource claims and strategic uncertainty. Such information and beliefs might change after communicating with others in the group, leading to potential changes in individual claims as well.

2.6. Hypotheses

Based on the theoretical framework, we test the following hypotheses using data from our experiment.

H1: Uncertainty about the threshold will lead to higher token claims, lower efficiency, and a higher incidence of resource collapse compared to threshold certainty.

H2: Risk averse participants will claim fewer tokens when the threshold is uncertain relative to their claims when the threshold is certain.

H3: Ambiguity averse participants will claim fewer tokens when the threshold is ambiguous relative to when the probability distribution of thresholds is known.

H4: Communication will result in fewer token claims, higher efficiency and a lower incidence of resource collapse in all threshold conditions (certainty, risk, and ambiguity).

[2] Aflaki (2013) showed this result in the case of a continuous distribution of potential thresholds, but the finding also applies to our case in which there are discrete thresholds.

3. Experimental design

Identifying the effect of uncertainty on CPR behavior has implications for the design of policies and programs to improve resource management, but it is often difficult to isolate the role uncertainty plays with studies that rely on observational data. Laboratory experiments are a valuable tool to test economic theory, analyze behavior that is affected by factors that are beyond the researcher's control outside of the laboratory and are often not observed, and to test program and policy designs prior to implementing them in the field (Rosch et al., 2021). We designed a laboratory experiment to test the impact of different types of uncertainty on CPR use behavior with and without communication. In this section, we describe the experiment design and setup, and in the following section, we present the theoretical predictions and testable hypotheses based on the model described above.

Our experiment consisted of two stages. The first stage elicited participants' risk and ambiguity preferences. The second stage was a CPR game where groups of 6 participants made resource use decisions in settings where the resource threshold was either known (certainty treatment), unknown with a known probability distribution (risk treatment) or unknown without information about the distribution (ambiguity treatment). Experiment participants were university students. A benefit of laboratory experiments with students is that researchers can carefully test theoretically-derived hypotheses about behavior by introducing treatments with high levels of control (Cason and Wu, 2019), and studies have found that basic insights about decision-making generally do not differ between student and non-student samples (Fréchette, 2015).

3.1. Stage 1: eliciting attitudes toward uncertainty

To elicit risk and ambiguity preferences, each participant completed two tasks, one related to risk preferences and the other related to ambiguity preferences. The order of the two tasks was randomized. For a given task, participants made 20 paired-choices between a lottery with a fixed prize and a sure payout that increased in 5 USD increments with each subsequent choice. The probability distribution of the lottery was known for the risk elicitation tasks, while it remained unknown for the ambiguity elicitation task. Our approach corresponds to that of Akay et al. (2012), which is a modified version of Holt and Laury's (2002) multiple-price list (MPL) approach and later adapted by Barham et al. (2014). Instead of keeping the same sure payout and varying the expected payoff of uncertain prospects across different choices as in Barham et al. (2014), we kept the prizes and expected payoff of the risky choice fixed (expected value of 50 USD) while we varied the sure payout across choices. Specifically, the sure payout increased by 5 USD starting from 5 USD in the first-choice pair to 100 USD in the 20th choice. Appendix Fig. B1 provides a snapshot of the choice scenario subjects faced in the risk elicitation task.[3]

The risky prospect allowed each participant to bet on the color of a ball drawn from a virtual bag containing 10 orange and 10 white balls, which provided a 50% chance to win the prize (see Fig. B1 in Appendix B). The ambiguous prospect, on the other hand, allowed each participant to bet on the color of a ball drawn from a virtual bag containing 20 balls in it, but the proportion of white versus orange balls was unknown thus making the probability of winning also unknown.

In order to make the tasks incentive compatible, one person in each session was randomly selected to implement their choices in Stage 1 of the experiment.[4] Specifically, the computer randomly selected one subject in each session for real play. Then one of the risk or ambiguity tasks was randomly chosen for that individual. Finally, one of twenty choices of the chosen task was randomly selected for real play. For example, suppose for the selected person, the task eliciting the person's risk preference was randomly chosen, and the 8th choice in the corresponding choice list was selected for real play. If the person chose to take the sure payout (selected option B) in the 8th choice, the person was given $40 as her earnings from this stage of the experiment. If, on the other hand, the person's choice was to play the lottery (option A) in the 8th choice, the computer drew a ball from a virtual bag with 10 white and 10 orange balls. The person won and was paid $100 if the drawn ball was orange, the person won $0 from this stage of the experiment if the drawn ball was white. In the ambiguity task, the computer drew a ball from the virtual bag where the probability distribution was unknown to the participants.[5] Note that only one participant in each session was randomly selected for real play in stage 1, and their earnings in stage 1 were announced at the end of the session and added to earnings in stage 2.

The choice list in the risk and ambiguity elicitation tasks are used to elicit each participant's certainty equivalent (CE) at switching points for the two prospects. The elicited CEs can then be used to measure the coefficients of relative risk aversion and ambiguity aversion for each subject (Eggert and Lokina, 2007; and Akay et al., 2012). The CE measures participants' constant relative risk aversion (CRRA) with the power utility function $u(r) = r^{\rho}$ where ρ is the participant's coefficient of risk aversion with $\rho = 1$ indicating risk neutrality in which case the utility function is linear, $\rho > 1$ indicating risk loving, and $\rho < 1$ indicating risk averse.[6] The CEs in both risk and ambiguity tasks are then used to calculate each participant's

[3] The screen for the ambiguity attitude elicitation task is the same as that in Fig. B1, except that the probability associated with white and orange balls is unknown.

[4] Randomly picking a certain number of participants for payment has been found to deliver very similar results to the alternative procedure of paying each subject (Laury, 2006).

[5] The actual probability distribution was the same as that in the risk elicitation task (1/2 for each of the lottery prizes), but this was unknown to the participants.

[6] See Wakker (2008) for a discussion of the power (CRRA) utility family.

Table 1
Experimental design.

Stage 1: Eliciting risk and ambiguity attitudes			
Task	Within/between subject	Order	Probability of lottery prize
Risk eliciting task	Within	Random	0.5
Ambiguity eliciting task	Within	Random	Unknown

Stage 2: CPR game				
Treatment (between)	Treatment (within)	Threshold	Range	Probability
Certainty	Communication: 8 rounds	Known: 100		Known (=1)
Risk	Communication: 8 rounds	Unknown	[50, 100, 150]	Known (1/3)
Ambiguity	Communication: 8 rounds	Unknown	[50, 100, 150]	Unknown

ambiguity aversion coefficient using the following formula (Akay et al., 2012):

$$\theta = \frac{CE_r - CE_a}{CE_r + CE_a} \tag{4}$$

where subscripts r and a in Eq. (4) indicate CE in risk and ambiguity experiments, respectively. Positive values of θ indicate ambiguity aversion, negative values indicate ambiguity loving, and $\theta = 1$ represents ambiguity neutrality.

3.2. Stage 2: the CPR game

The second stage of the experiment investigates CPR use behavior and includes treatments where the threshold beyond which resource destruction occurs is uncertain and where threshold distributions are either known or unknown. We also investigate if communication improves coordination in using the CPR. At the beginning of the CPR game, each participant was randomly assigned to a group of 6 members. The experimental design includes three between-subject uncertainty treatments (see Table 1) – (1) certainty about the threshold (baseline); (2) threshold uncertainty with known probability distribution about the threshold (risk treatment); and (3) threshold uncertainty with unknown probability distribution (ambiguity treatment).

In each round, a threshold level of token claims was determined for each group, which was unknown to the participants in the risk and ambiguity treatments before they made the token claim decision, and participants made token claims from the group account. If total claims by all participants in a group for that round fell below the threshold, each participant received the claim they requested. If the total group claims exceeded the threshold, each participant received zero earnings in that round. Groups first played three uncompensated practice rounds. After the three practice rounds, groups were randomized and participants played eight rounds that were compensated. Participants were informed that each decision was completely anonymous. After the first 8 compensated rounds of the CPR game, groups were randomly reassigned, and another 8 rounds were played. Communication among the corresponding group members was allowed in the first 8 rounds in some of the sessions and in rounds 9–16 of other sessions. When allowed, communication took place during a 1.5 min communication period prior to making the individual token claim decision in each round. During the communication period in each round, participants could write public text messages that were seen by all members of their group. In some sessions, participants made token claims in all 16 rounds without communication. Total earnings from this stage of the experiment were reported as the sum of tokens earned in all compensated rounds, which were converted to U.S. dollars using the exchange rate: 1 USD = 6 tokens. Payments were made at the end of the session.

The threshold for the certainty treatment, which was known to all participants, was 100. Each participant's choice space for token claims in the certainty treatment was 0–100. The thresholds in the uncertainty (risk and ambiguity) treatments were unknown to the participants. At the time of decision-making in each round, participants were informed in the decision screen that the threshold was one of 50, 100, and 150, which was drawn by the computer and revealed at the end of the round. In the risk treatment, the probability of each threshold occurring was 1/3, which was known by participants. In the ambiguity treatment, participants did not know the probability distribution of the three thresholds. For the latter case, the computer drew one of the thresholds using a uniform distribution of the thresholds – attaching an equal 1/3 probability to each of 50, 100, and 150. In both uncertainty treatments, each participant's choice space for token claims was 0–150.[7] Each participant completed a socio-economic survey at the end of the experiment, after which they were paid in cash based on their total earnings in the experiment. On average, individuals received approximately $35 for sessions that lasted 60 min.

[7] Even though the choice space was different in the certainty and uncertainty treatments, the participants' strategies should be unaffected as any claim greater than 100 would exceed the threshold with certainty, which is analogous to any claim greater than 150 in the uncertainty treatments. As a result, such difference in choice space does not affect the equilibrium claims.

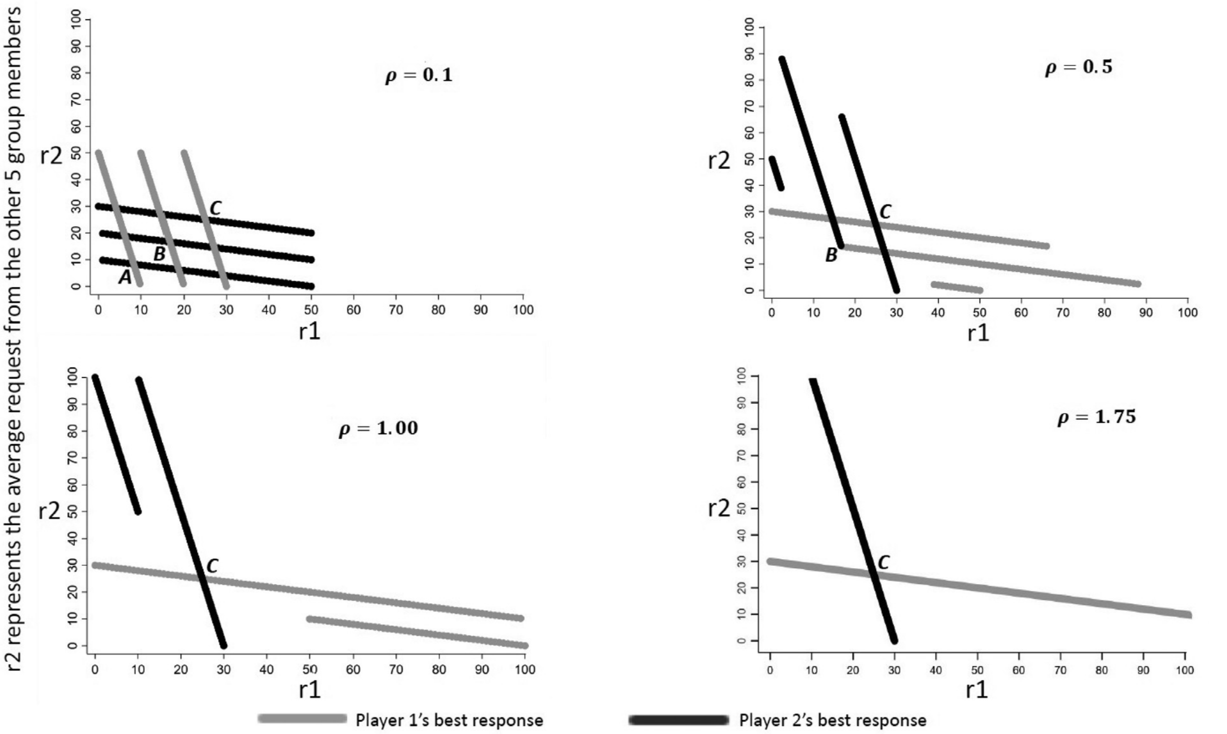

Fig. 1. Best response functions for individuals that are very risk averse ($\rho = 0.1$), moderately risk averse ($\rho = 0.5$), risk neutral ($\rho = 1.00$), and risk loving ($\rho = 1.75$). A player's best response is to make a token claim (r_i) that results in the highest expected payoff based on the probabilities associated with each threshold and average request from other 5 group members R_{-i} (represented by r2 in the figure). In our experiment, each threshold is equally likely to occur, i.e., prob($\tilde{R}$= 50)=prob($\tilde{R}$=100) = prob($\tilde{R}$=150) = 1/3. Intersections of best responses at *A*, *B*, and *C* indicate SNE of 8.33, 16.67, and 25, respectively.

4. Theoretical predictions

In the experiment, the payoff function, based on Eq. (1), is $\pi_i = r_i h(R, \tilde{R})$ where $h(R \le \tilde{R}) = 1$ and $h(R > \tilde{R}) = 0$. In the certainty treatment, $\tilde{R} = 100$. In both uncertainty treatments (risk and ambiguity), there are three possible threshold values, $\tilde{R} \in \{\alpha = 50,\ \gamma = 100,\ \beta = 150\}$. In the risk treatment, participants are told that the probability of each threshold is $p_\alpha = p_\gamma = p_\beta = \frac{1}{3}$; however, participants in the ambiguity treatment are not informed of the probability of each threshold. Based on this experiment setup and assuming risk preferences are reflected by the utility function $u(r) = r^\rho$, we evaluate the predicted token claims in each of the three treatments.

In the *certainty treatment*, the privately optimal token claim is $r_i = \frac{\gamma}{n} = \frac{100}{6} = 16.67$, regardless of the participant's risk preferences.[8] No one has an incentive to deviate from this claim because doing so would make them worse off.

Depending on individual risk preferences, multiple equilibrium choices in the *risk treatment* are possible. Due to the discrete nature of the three thresholds and the associated probabilities, we know that any symmetric Nash equilibrium (SNE) must involve total claims being equal to one of the three thresholds. If this were not the case, an individual could increase their claim slightly and be better off. Therefore, we consider whether the following three claims hold as a SNE: $r_i = \frac{\alpha}{n} = \frac{50}{6} = 8.33$, $r_i = \frac{\gamma}{n} = \frac{100}{6} = 16.67$, and $r_i = \frac{\beta}{n} = \frac{150}{6} = 25$. A claim will only be a SNE if none of the participants have an incentive to deviate from that claim (i.e., that claim is the best response to the claims of the other five participants).

We predict the best response strategies by participant *i*, based on the discussion in Section 2, that depend on the strategies taken by others in the group (R_{-i}), uncertainty about the threshold ($\tilde{R}$), and the individual's risk attitude represented by ρ. Fig. 1 illustrates the best response functions for participants with different risk attitudes – from highly risk averse (upper left panel) to highly risk-loving (lower right panel). It shows that all three SNEs can be supported depending on ρ. Comparing expected utilities that depend on the strategies of others in the group R_{-i}, and corresponding threshold probabilities (p_i), the range of risk preferences, ρ, for which there may be different best responses can be calculated, assuming a power utility function. For risk averse individuals with $\rho < 0.238$, there are three possible best responses: $\alpha - R_{-i}$, $\gamma - R_{-i}$, and $\beta - R_{-i}$ leading to three possible SNEs ($r^* = 8.33$, $r^* = 16.67$ and $r^* = 25$). However, as ρ rises, the strategy profile $\alpha - R_{-i}$

[8] Even though 100/6 = 16.67, the set-up in our experiment allows only integer valued choices. As a result, the maximum symmetric amount of token claim by each participant is 16 tokens.

is no longer a best response for $0.238 < \rho < 0.585$, leading to two SNEs ($r^* = 16.67$ and $r^* = 25$) in the range. Finally, for $\rho > 0.585$, $r^* = 25$ is a unique SNE.

In the case of risk neutral individuals, there is a unique SNE with $r_i = 25$ that is portrayed in Fig. 1 (lower left panel: $\rho = 1.00$). When the average claim by other group members is less than 25, it is in a participant's best interest to increase their claim above the average. The following two cases illustrate the decision framework that leads to this result. First, consider a participant who thinks that the other five participants will each claim $r_{-i} = 8.33$ such that $R_{-i} = 41.67$. In that case, the individual will decide whether to also claim 8.33 or to increase their claim to 58.33 or 108.33, which would allow them to meet thresholds of 100 or 150. To make this decision, they will calculate their expected payoff from each strategy. Since $58.35(2/3) = 38.9 > 8.33$, it is in the individual's best interest to increase their claim; therefore, r_i =8.33 is not a SNE. The same logic holds when evaluating $r_i = 16.67$ as a potential SNE. The best response to assuming the five other members will claim 16.67 is to increase the claim to 66.67 to reach the threshold of 150. The expected utility of that claim is $66.67(1/3) = 22.22$ which is greater than $16.67(2/3) = 11.11$. For this reason, $r_i = 16.67$ is not an SNE. The only SNE in this discrete setting with risk neutral individuals is $r_i = 25$ because no individual can deviate from this claim and improve their expected payoff of $25(1/3) = 8.33$. Following a similar argument, it can be shown the SNE for individuals with risk-loving attitude is unique as shown in the lower-right panel of Fig. 1.

In the *ambiguity treatment*, everyone is assumed to choose r_i to maximize their expected utility; however, they must make this assessment without information about the probabilities of different threshold levels. Past research suggests that participants likely overweight bad outcomes in the case of ambiguity in the relevant issues such as investment decisions (Huang and Tzeng, 2017; Gollier, 2011; Taboga, 2005). In our experiment, this would result in assuming higher probabilities of lower thresholds, which would reduce the size of privately optimal claims.

The socially optimal token claim in the *certainty treatment* is $r_i = \frac{\gamma}{n} = \frac{100}{6} = 16.67$, leading to total token claims by the group equal to γ. This result does not depend on risk preferences. If group claims are $nr_i < \gamma$, then claims can be increased without risk of exceeding the threshold, however, if $nr_i > \gamma$ then the group receives a payoff of zero.

The socially optimal claim in the *risk and ambiguity treatments* is also $r_i = 16.67$ under risk neutrality. There is a 2/3 probability that the threshold will be less than or equal to 100, and therefore the expected group payoff is $2/3 * 100 = 66.67$ when total group claims are equal to 6×16.67=100. By comparison, if group claims are equal to 50, the group payoff is equal to 50 with certainty. Finally, if group claims are equal to 150, there is only a 1/3 probability that the threshold will be less than or equal to this amount and therefore the expected group payoff is $1/3 \times 150 = 50$. Given the probabilistic nature of the threshold in the risk and ambiguity treatments, the lower threshold value can be socially optimal if the group is sufficiently risk averse. For example, if participants have a symmetric risk preference parameter (ρ) less than 0.585, then the certain payoff of 50 yields higher utility than the probabilistic group payoff associated with the threshold of 100. Similarly, if participants are risk seeking, with $\rho > 1.71$, then total group claims equal to the high threshold of 150 yield the highest utility to the group and can therefore be supported as a social optimum.

5. Data and results

A total of 318 students participated in 18 experiment sessions conducted at the University of Delaware's Center for Experimental and Applied Economics (CEAE) laboratory.[9] The log of experiment sessions is presented in Table 2. The sessions took place in the Spring, Summer, and Fall semesters of 2019 using the SoPHIELabs platform (Achim, 2012). The lower panel of Table 2 shows the number of participants and the total number of individual decisions made in each treatment cell. Because communication was not introduced in all sessions, the number of participants differs among treatment cells.

5.1. Risk and ambiguity preferences

The first stage of the experiment was used to elicit participants' attitudes toward risk and ambiguity. Fig. 2 exhibits the cumulative distribution of the measured attitudes of the participants elicited through the choices made in the first stage.[10] The majority (78%) of participants are risk averse or risk neutral (median $\rho = 0.93$). Participants are also found to have neutral attitudes related to ambiguity (median $\theta = 0.05$) with the majority of participants revealing ambiguity neutral (21%) or ambiguity averse (52%) attitudes. As shown in Fig. 3, the observed relationship between the two behavioral attributes reveals that for risk neutral and risk averse participants, ambiguity aversion is positively correlated with their degree of risk aversion (correlation coefficient = 0.38). However, there is no correlation between the two attributes for risk-loving participants (correlation coefficient = −0.005).

[9] Due to a programming issue, the risk and ambiguity preferences of 10 participants were not recorded. When analyzing individual token claim decisions, these 10 individuals are dropped from the analysis.

[10] The measured coefficient of risk aversion (ρ) ranges from 0.19 to 27.38 but approximately 95% of them fall below 3. Fig. 3 only considers participants with risk attitudes $\rho \leq 3$.

Table 2
Experiment sessions log and participant totals by treatment.

Session number	Treatment	Communication sequence	Number of participants
1	Certainty	None	18
2	Risk	None	18
3	Ambiguity	None	24
4	Certainty	None	12
5	Risk	None	24
6	Ambiguity	None	18
7	Certainty	9–16 rounds	12
8	Risk	9–16 rounds	18
9	Ambiguity	9–16 rounds	18
10	Certainty	9–16 rounds	12
11	Risk	9–16 rounds	18
12	Ambiguity	9–16 rounds	12
13	Certainty	1–8 rounds	24
14	Risk	1–8 rounds	18
15	Ambiguity	1–8 rounds	24
16	Certainty	1–8 rounds	12
17	Risk	1–8 rounds	18
18	Ambiguity	1–8 rounds	18
Summary	**Uncertainty treatment**	**Communication treatment**	**Total number of individual decisions**
By treatment cell	Certainty	No Comm	960
		Comm	480
	Risk	No Comm	1248
		Comm	576
	Ambiguity	No Comm	1248
		Comm	576

Notes: All sessions took place in the same room.

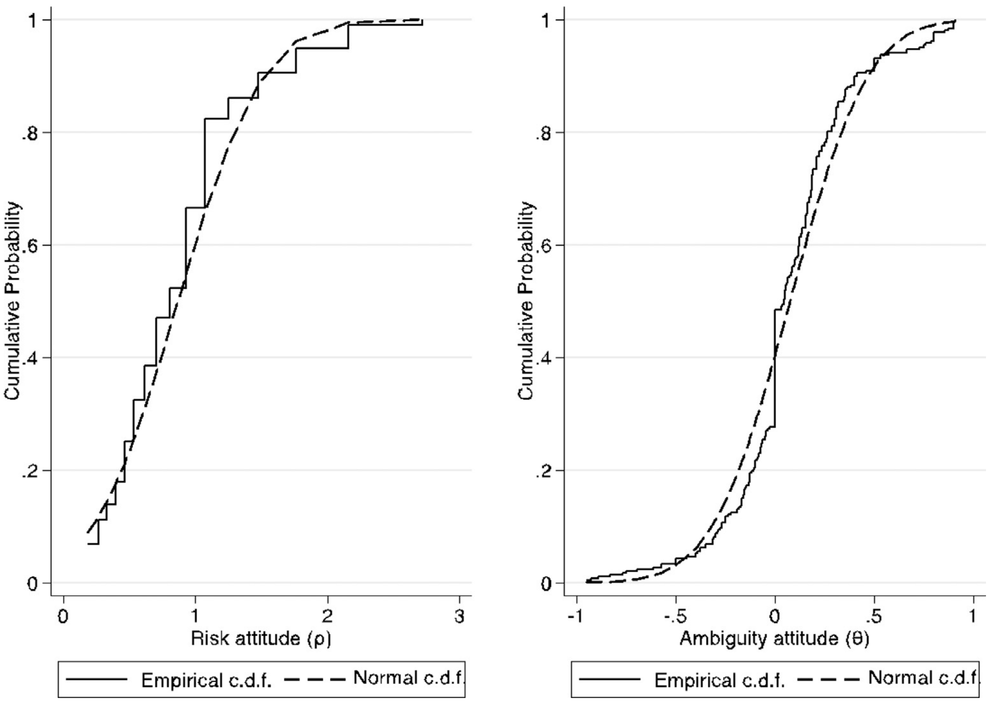

Fig. 2. Cumulative distributions of attitudes toward uncertainty.

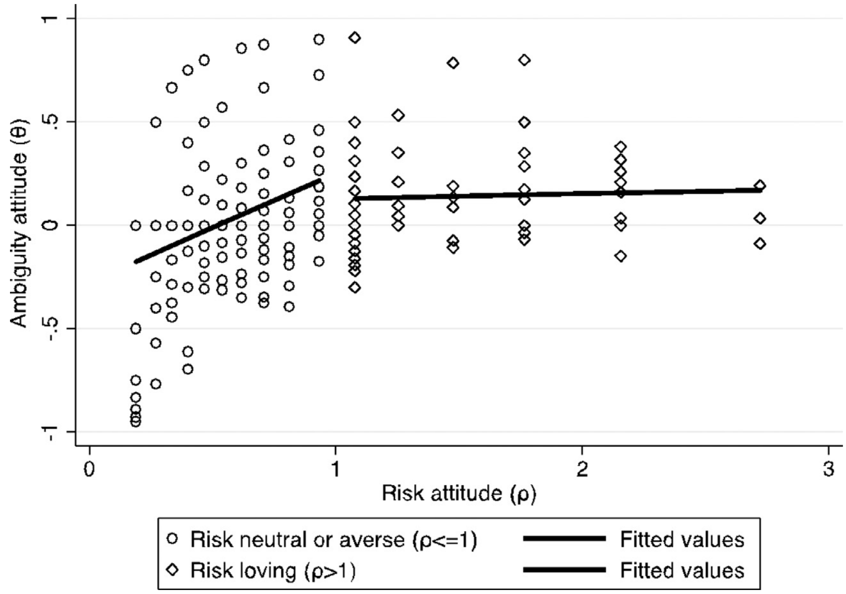

Fig. 3. Relationship between risk (ρ) and ambiguity (θ) attitudes.

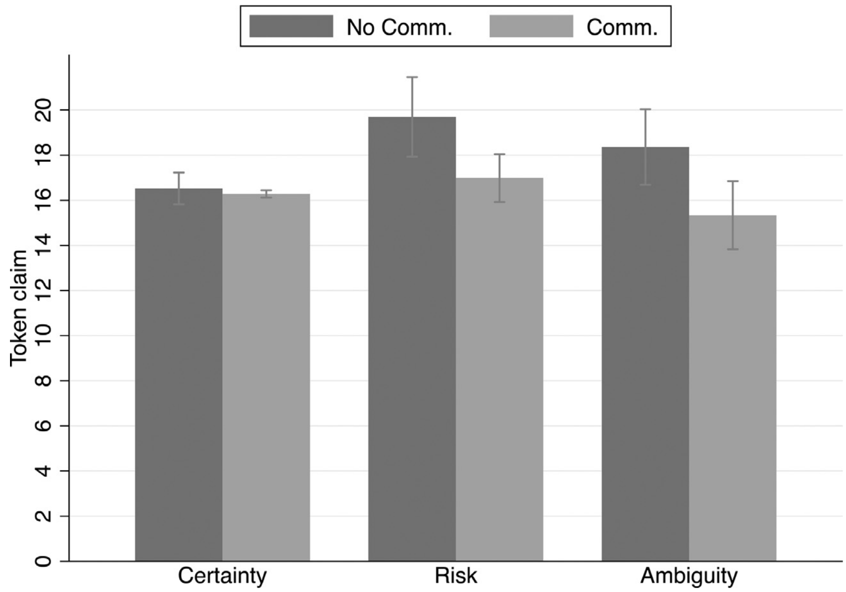

Fig. 4. Average individual token claims across treatments and communication.

5.2. CPR use under threshold uncertainty

A primary objective of the study is to investigate CPR use behavior under varying degrees of threshold uncertainty. Table 3 reports the summary statistics of CPR use (measured by token claims) for each treatment. Overall, token claims are on average higher with uncertain threshold levels (18.75 and 17.29 tokens for Risk and Ambiguity treatments, respectively) compared to when the threshold is known with certainty (16.42 tokens). Comparing the two uncertainty treatments, token claims are 7.8% lower, on average, in the ambiguity treatment (17.29 tokens) compared to the risk treatment (18.75 tokens). When communication is not allowed, average token claims are lowest (16.49 tokens) when the threshold level is certain and highest (19.54 tokens) in the risk treatment in which the threshold is uncertain, but the probability distribution of potential thresholds is known (Fig. 4). The difference in average token claims between the certainty and uncertainty treatments,

Table 3
CPR use with and without communication.

Communication status	Outcome	Certainty		Risk		Ambiguity	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
All decision rounds (full dataset)	Earnings	13.36	6.57	7.34	10.02	8.16	10.07
	Individual claim	16.42§	3.61	18.75§§	10.16	17.29§§§	9.98
	Exceeded realized threshold	0.17^{p}	0.38	0.57^{pp}	0.50	0.49^{ppp}	0.50
	Exceeded 100 token threshold	0.17^{p}	0.38	0.61^{pp}	0.49	0.53^{ppp}	0.50
No communication	Earnings	12.35	7.41	6.64	10.16	7.79	10.69
	Individual claim	16.49$^{\zeta,\ \S}$	4.38	19.54$^{\zeta,\ \S\S}$	11.30	18.22$^{\zeta,\S,\S\S}$	10.33
	Exceeded realized threshold [a]	0.23^{p}	0.42	0.62^{pp}	0.48	0.55^{pp}	0.50
	Exceeded 100 token threshold [b]	0.23$^{i,\ p}$	0.42	0.73$^{i,\ pp}$	0.44	0.64$^{i,\ pp}$	0.48
Communication	Earnings	15.40	3.69	8.88	9.54	8.94	8.58
	Individual claim	16.28$^{\zeta,\ \S}$	0.91	17.01$^{\zeta\zeta,\ \S,\ \S\S}$	6.75	15.34$^{\zeta\zeta,,\S,\ \S\S\S}$	8.91
	Exceeded realized threshold [a]	0.05^{p}	0.22	0.45^{pp}	0.50	0.36^{pp}	0.48
	Exceeded 100 token threshold [b]	0.05^{p}	0.22	0.35^{pp}	0.48	0.30^{pp}	0.46
Difference in means: (Mean with communication – mean without communication)[c]							
	Earnings	3.05***	34.85	2.24***	22.59	1.15***	6.14
	Individual claim	−0.21	0.17	−2.53***	32.33	−2.88***	42.90
	Exceeded realized threshold [a]	0.18***	40.37	0.17***	51.09	0.18***	62.31
	Exceeded 100 token threshold [b]	0.18***	50.71	0.38***	287.16	0.34***	225.93

Notes: [a]Exceeded threshold=1 if the group request in the corresponding round exceeded group threshold; 0 otherwise.
[b] Exceeded threshold=1 if the group request in the corresponding round exceeded 100; 0 otherwise.
[c] Numbers in mean columns are mean difference calculated as: Mean with communication – Mean without communication, and the numbers in Std. Dev. Columns are the test statistics of the corresponding test of mean difference used to test for the equality of means of two cases.
^{p}, ^{pp}, ^{ppp}: same superscript across columns indicates they are not statistically different at 5 percent level.
§, §§, §§§: same superscript across columns indicates they are not statistically different at 5 percent level. ζ, $\zeta\zeta$, $\zeta\zeta\zeta$: same superscript across columns indicates they are not statistically different at 5 percent level.
***, **, and * indicate statistically significant at 1%, 5%, and 10%, respectively in testing the quality of means with and without communication across treatments.

and the difference between token claims in the risk and ambiguity treatments are statistically significant[11] ($p < 0.05$). However, when communication is allowed, the difference in token claims is not statistically significant between the certainty and uncertainty treatments (Table 3). Lower individual claims in the ambiguity treatment in all cases may be related to conservative subjective beliefs about the possible thresholds, thus overweighting the lower threshold relative to the higher one; however, the difference in token claims between the uncertainty treatments is not statistically significant.

Fig. 5 provides evidence related to the occurrence of resource collapse. The consequence of aggregate token claims exceeding the threshold is less common when the threshold is certain (17%), and more common in the threshold uncertainty cases (57% in the risk treatment and 49% in the ambiguity treatment). Resource collapse rates under threshold uncertainty are compared to that of the certainty case by evaluating groups' total claims with both the realized thresholds (Fig. 5a) and with a threshold of 100 (Fig. 5b). 100 is the threshold used in the certainty treatment and is also the socially efficient outcome in each treatment. Without communication, the resource collapse rates (using both the realized thresholds and 100 as the threshold for all treatments) for each treatment are certainty (23%), risk (63, 73%), and ambiguity (55%, 63%), where the numbers in the parentheses correspond to the resource collapse rate using the realized thresholds and the common threshold of 100 units, respectively. Tests of equality of means confirm that resource collapse rates are statistically different between the certainty treatment and the threshold uncertainty treatments – risk treatment: t-statistic $= -7.45$; p-value < 0.01, and ambiguity treatment: t-statistic $= -6.27$; p-value < 0.01.[12] The difference in the incidence of resource collapse between risk and ambiguity treatments is not statistically significant (t-statistic $= 1.55$; p-value $= 0.37$ for realized threshold, and t-statistic $= 1.07$; p-value $= 0.86$ for threshold of 100 units). With communication, the incidence of resource collapse declines in all treatments and the incidence of exceeding the threshold in the certainty treatment is again statistically different and smaller from that in the risk treatment (t-statistic $= 5.59$; p-value < 0.01) and ambiguity treatment (t-statistic $= 4.09$; p-value < 0.01).[13]

[11] When applicable, we have made the Bonferroni type adjustment in p-values when comparing multiple treatments.
[12] Corresponding test statistics for the threshold of 100 units are: t-statistic $= 3.21$; p-value<0.01 for certainty vs. risk treatment, and t-statistic $= 2.60$; p-value<0.05 for certainty vs. ambiguity treatment.
[13] To implement two-way clustering, we use the user-written Stata command 'vcemway' that permits two-way clustering with a random effects specification (Gu and Yoo, 2019).

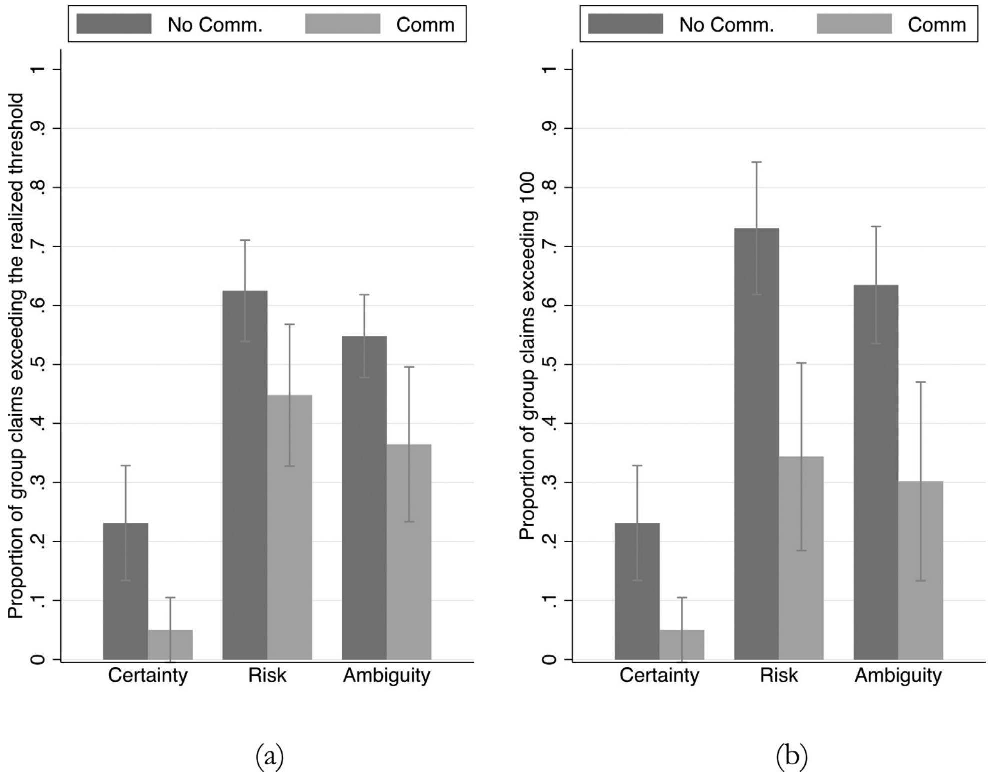

Fig. 5. Proportion of groups exceeding the (a) realized threshold and (b) 100 token threshold across treatments and communication.

To more formally analyze the effects of threshold uncertainty and communication on token claims, we estimate the following regression

$$r_{it} = \alpha_0 + \sum_{k=1}^{2} \alpha_k T_{k,\ it} + \sum_{k=0}^{2} \gamma_k \left(T_{k,\ it} \times S\right) + \sum_{k=0}^{2} \phi_k \left(T_{k,\ it} \times C_{it}\right) + \sum_{k=0}^{2} \beta_k (T_k \times O) + \sum_{m=1}^{2} \omega_m A_{m,\mathrm{i}} + \sum_{k=1}^{2}\sum_{m=1}^{2} \tau_{mk} \left(T_{k,\ it} \times A_{m,it}\right) + \psi B_{\mathrm{t}} + \sum_{k=0}^{2} \theta_k (T_k \times B_t) + \eta_i + \epsilon_{it} \tag{5}$$

where r_{it} is the token claim by participant i in round t, T_k is an indicator variable for treatments $k = 0$, 1, 2, and C indicates communication (1 if communication was allowed; 0 otherwise); S indicates the stage of the game (1 if first 8 rounds; 0 otherwise), O indicates the order/timing of communication (1 if communication took place in the first 8 rounds; 0 otherwise); A_m is the participant's attitude toward uncertainty (where $m = 1$ reflects the constant relative risk aversion coefficient (ρ) and $m = 2$ reflects ambiguity aversion (θ)); and B is a continuous round variable that takes values between 1 and 8. η_i is an individual specific random effect that is normally distributed, i.e., $\eta_i \sim N(0,\ \sigma_\eta^2)$ and ϵ_{it} represents the idiosyncratic errors with standard normal distribution $\epsilon_{it} \sim N(0,\ \sigma^2)$. We estimate Eq. (5) employing a random effect regression with errors clustered at the group level using two-way clustering to account for membership of two groups during the experiment session.[14]

We also estimate a model with individual earnings as the dependent variable and the same right-hand side variables as in Eq. (5). This model is intended to provide insight on how the treatment conditions impact social efficiency. Given that participants in the experiment are assumed to be the only beneficiaries of resource use (e.g., there are no external benefits from resource use or conservation), the realized earnings by participants in the experiment provide a measure of social efficiency. Treating earnings as a social efficiency measure assumes risk neutral preferences. Alternatively, the individual risk preference parameters (ρ), estimated from the first stage of the experiment, could be used in conjunction with the power utility function and the realized earnings to generate a measure of individual utility obtained in each round. Econometric results that use individual utility as a dependent variable instead of earnings are provided in the appendix (Table A2).

Table 4
Regression results of the effects of threshold uncertainty on token claims.

Variable	Coefficients[a]
Treatment:	
Risk	2.55**
	(1.26)
Ambiguity	0.57
	(0.67)
First 8 round dummy[b] × *treatment:*	
Certainty	0.16**
	(0.07)
Risk	0.52
	(0.73)
Ambiguity	0.07
	(0.44)
Treatment × *communication*[c]*:*	
Certainty	−0.18***
	(0.06)
Risk	−1.90*
	(1.00)
Ambiguity	−2.99***
	(0.41)
Interaction of treatment with communication timing dummy[d]*:*	
Certainty	−0.16
	(0.15)
Risk	−1.92**
	(0.77)
Ambiguity	−1.09
	(1.12)
Attitudes toward uncertainty:	
Risk preferences (ρ)	−0.007
	(0.02)
Ambiguity preferences ((θ))	−0.81
	(0.97)
Attitudes interaction with treatment:	
$\rho\times$ Risk	−0.12*
	(0.07)
$\rho\times$ Ambiguity	0.09
	(0.1)
$\theta\times$ Risk	1.71
	(1.61)
$\theta\times$ Ambiguity	0.60
	(1.90)
Round effect interaction with treatment:	
Round	−0.06
	(0.07)
Round × Risk	0.16
	(0.16)
Round × Ambiguity	0.30***
	(0.10)
Constant	16.81***
	(0.42)
N	4928

Notes: [a]: Numbers in parentheses are robust standard errors clustered at the group level.
[b]: 1 if the first 8 round, 0 otherwise;
[c]: 1 if the communication took place prior to making choices in that round, 0 otherwise;
[d]: 1 if the communication was in the first 8 round, 0 otherwise;
***, **, * indicate statistically significant at 1, 5, and 10 percent, respectively.

The regression results for specifications with token claims and earnings as dependent variables are reported in Tables 4 and 5, respectively. Results from the individual token claim regression suggest that threshold uncertainty with known probability (risk treatment) is significantly different from zero and raises token claims (by 2.55 tokens, 15%) compared to the certainty treatment (Table 4). Statistical tests indicate that the token claims in the certainty treatment are not significantly different from the SNE of 16.67 ($\chi^2_{(1)} = 0.10$; p-value $= 1.00$), and a test of the hypothesis that token claims in the risk and ambiguity treatments are jointly different from the certainty treatment confirms that the participants' token claims with

[14] Despite the differences in game structure and the communication protocol between Dannenberg et al. (2015) and our study, we refer to Dannenberg et al. (2015) as it investigates the effects of both risk and ambiguity in thresholds in a single study.

Table 5
Regression results of the effects of threshold uncertainty on efficiency in token claims.

Variable	Coefficients[a]
Treatment:	
Risk	−2.07
	(2.25)
Ambiguity	−2.35
	(2.13)
First 8 round dummy[b] × treatment:	
Certainty	−0.71
	(0.69)
Risk	−0.01
	(1.34)
Ambiguity	−0.19
	(0.87)
Treatment × communication[c]:	
Certainty	1.76***
	(0.52)
Risk	1.09
	(1.58)
Ambiguity	1.11
	(0.96)
Interaction of treatment with communication timing dummy[d]:	
Certainty	3.21***
	(0.88)
Risk	2.67**
	(1.12)
Ambiguity	0.39
	(0.93)
Attitudes toward uncertainty:	
Risk preferences (ρ)	−0.00
	(0.03)
Ambiguity preferences ((θ))	0.13
	(1.03)
Attitudes interaction with treatment:	
$\rho\times$ Risk	0.11**
	(0.05)
$\rho\times$ Ambiguity	−0.11**
	(0.04)
$\theta\times$ Risk	−0.57
	(1.27)
$\theta\times$ Ambiguity	−0.47
	(1.25)
Round effect interaction with treatment:	
Round	0.45**
	(0.20)
Round × Risk	−0.83***
	(0.31)
Round × Ambiguity	0.34
	(0.30)
Constant	9.82***
	(0.42)
N	4928

Notes: [a]: Numbers in parentheses are robust standard errors clustered at the group level.
[b]: 1 if the first 8 round, 0 otherwise;
[c]: 1 if the communication took place prior to making choices in that round, 0 otherwise;
[d]: 1 if the communication was in the first 8 round, 0 otherwise;
***, **, * indicate statistically significant at 1, 5, and 10 percent, respectively.

threshold uncertainty are different from the certainty treatment ($\chi^2_{(2)} = 6.98$; p-value=0.06). Attitudes toward uncertainty (both risk and ambiguity preferences) are found to have no significant effect on token claims, which is consistent with previous findings (Guilfoos et al., 2019; Bochet et al., 2019). While neither of the attitudes toward uncertainty are statistically significant, interaction of the attitude variables with treatments suggests that risk averse participants in the risk treatment increase token claims compared to participants in the certainty treatment with similar risk attitudes. A closer look at token claims for individuals with different risk attitudes suggests that such trend might be due to higher average token claims (21.13) by moderately risk averse individuals (30% of participants) ($\rho \in [0.70,\ 0.94]$) in the risk treatment compared to that (16.93) by participants in the certainty treatment with similar risk attitude. Finally, there is no round effect on average token claims, but the interaction of round with treatments reveals that participants in the ambiguity treatment increase

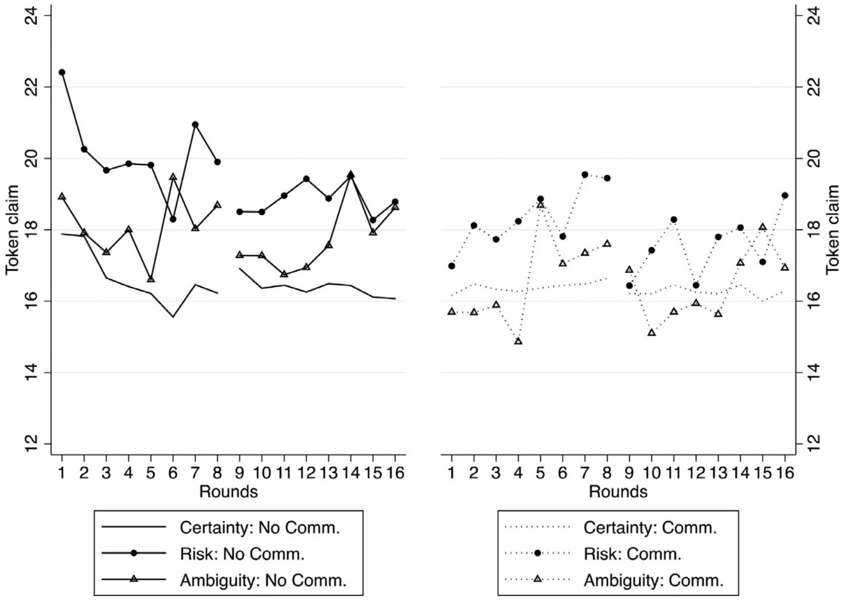

Fig. 6. Round-wise mean token claims.

token claims across rounds compared to that in the certainty treatment. This suggests that there is learning in the threshold ambiguity treatment across rounds as participants observe realizations of the threshold.

Our findings contradict those from public goods provision in the presence of both risk and ambiguous thresholds (Dannenberg et al., 2015). In particular, Dannenberg et al. (2015) find that participants in the case of public good provision contribute more in a risk treatment compared to an ambiguity treatment.[15] The analogous finding of Dannenberg et al. (2015) in the CPR case would be to claim fewer tokens in the risk compared to the ambiguity treatment. However, our results align with the theoretical predictions outlined in Section 2 and the related literature on CPR use (Aflaki, 2013; Maas et al., 2017). Lower average token claims in the presence of an ambiguous threshold may imply that subjects in the ambiguity treatment have beliefs about the threshold distribution that associates more weight on the lower bound of the threshold than the upper one(s).

5.3. Communication

Each participant made choices in 16 decision rounds with two groups – the first group assigned before the first round, and the second group randomly reassigned before the beginning of the 9th round. Opportunities for communication were varied across sessions so that participants in some sessions made all 16-round choices without communication, some sessions allowed communication only in the first 8 rounds, and the remaining sessions had communication only in the last 8 rounds. We find that communication lowered average token claims in the treatments with uncertainty (Fig. 4), resulting in a reduced incidence of exceeding the realized threshold or the threshold of 100 (Fig. 5). In particular, communication among group members resulted in a 16 percent reduction in token claims in the risk and ambiguity treatments (Table 3) (p-values associated with the test of equality of token claims with and without communication for certainty, risk, and ambiguity treatments are 0.58, <0.01, and <0.01, respectively). In addition, the incidence of resource collapse also shrinks by approximately 18 percentage points in each treatment due to communication among participants which represent 78, 29, and 35 percent reductions relative to pre-communication resource collapse rates for certainty, risk, and ambiguity treatments, respectively (p-values of differences in means are <0.001 in all cases).[16]

Fig. 6 shows the mean group token claims by round, and we observe that communication reduces mean token claims in both types of threshold uncertainty. By examining the distribution of token claims by treatment in Fig. 7, we also observe that communication narrows the range of token claims in each treatment. Such behavior, in turn, leads to a lower frequency of group token claims exceeding the threshold in all treatments. Communication has the greatest effect on narrowing the

[15] The same pattern holds when the incidence of resource collapse is measured using a common threshold of 100 across communication for all treatments.

[16] Similar results are found using median requests (Fig. B2 in appendix). We observe that using the median user, communication performs much better in obtaining desirable outcomes in all treatments. In particular, communication in the ambiguity treatment led participants to claim fewer tokens than that with the certain threshold. It is important to note, however, that median claims exhibit more variation in token claims even with communication in the ambiguity treatment compared to almost non-existent variation in median claims in the risk treatment.

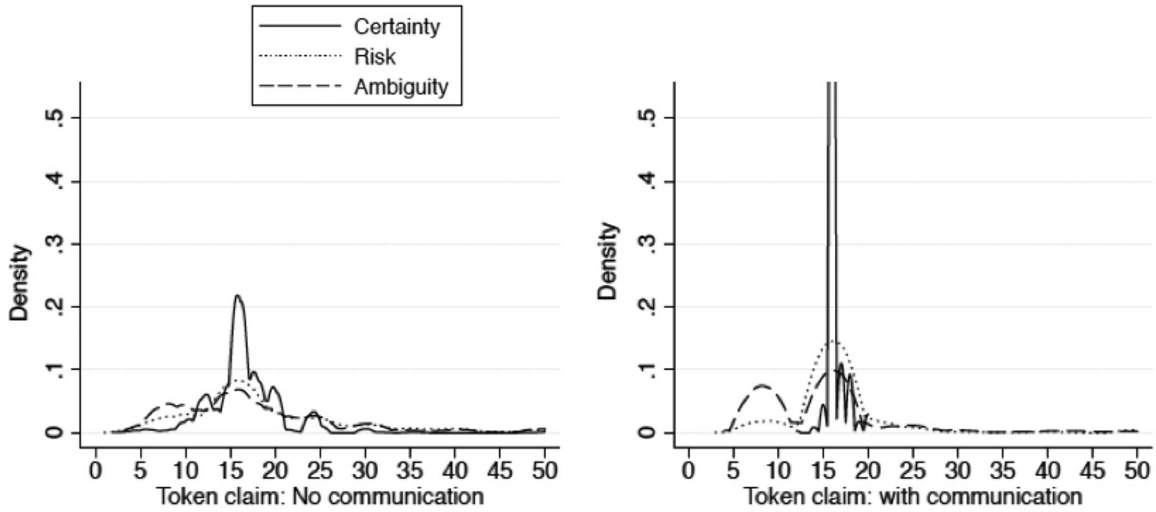

Fig. 7. Token claims without communication (left panel) and with communication (right panel) across treatments.

range of token claims in the certainty treatment (2–50 tokens without communication vs. 12–20 tokens with communication and is heavily concentrated around 16 tokens). Token claims with communication in the risk treatment are characterized by a thin tailed distribution (right panel in Fig. 7) compared to that without communication (left panel in Fig. 7). In the ambiguity treatment, communication resulted in a bimodal distribution with peaks at 8 (the lower bound) and 16. As a result, communication results in a reduction in token claims in the certainty treatment and the incidence of token claims exceeding the threshold.

Communication reduced both mean individual token claims and the dispersion of claims as measured by the standard deviation across all claims in each treatment (see Table 3 and Fig. 7). Communication generated the largest drop in dispersion of token claims in the certainty treatment (by 81% versus 52% and 28% in risk and ambiguity treatments, respectively. Bartlett's F test statistics for certainty, risk, ambiguity treatments are 27.76, 4.39, and 1.94; $p < 0.01$ in all three cases.). The standard deviation of token claims in the ambiguity treatment is not statistically different from that in the risk treatment without communication (F-test statistic = 1.10; p-value = 0.59), and therefore communication has less impact in reducing variation in the ambiguity treatment compared to the risk treatment. In particular, the decline in the standard deviation of claims in the ambiguity treatment after communication is small (by 28%) compared to the risk treatment (by 52%), leading to a higher standard deviation in the ambiguity treatment compared to the risk treatment after communication (F test statistic = 0.49; p-value < 0.01). This implies that while communication might reduce strategic uncertainty leading to a reduction in token claims on average, this type of communication is less effective in narrowing the range of token claims in the ambiguity treatment compared to the risk treatment.

The regression results reported in Table 4 suggest that communication plays an important role in reducing token claims in each treatment. In particular, reductions in token claims due to communication are 0.18, 1.9 and 2.99 tokens for the certainty, risk and ambiguity treatments, respectively. Our results further suggest that introducing communication in the initial rounds, leads to significantly larger reductions in token claims than in the later stage (by 1.92 tokens) for the risk treatment.

Communication has been shown in the literature to alter behavior by making participants less risk and ambiguity averse in some cases while increasing aversion to risk and ambiguity in other cases (Bougheas et al., 2013; Brunette et al., 2015; Harrison et al., 2013; Keck et al., 2014; Levati et al., 2017; Masclet et al., 2009). To investigate whether the source of reductions in token claims with communication is correlated with attitudes toward uncertainty, we also estimated a model similar to Eq. (5) that adds interactions of the attitudes toward uncertainty with the communication dummy. None of the coefficients associated with the interaction of risk and ambiguity attitude variables with communication across treatments are significant in this model (see Table A1 in the appendix). Our results do not help to resolve how communication impacts risk and ambiguity preferences but do suggest that the impact of communication on CPR use does not vary as a function of baseline risk and ambiguity preferences. This suggests that the source of reductions in token claims after communication is primarily through changes in strategic uncertainty.

5.4. Earnings and efficiency

The coefficient results from the earnings model are provided in Table 5. These results are indicative of how treatment conditions impact social efficiency, assuming risk neutral preferences. Although earnings are lower in the risk and ambiguity treatments compared to the certainty treatment, regression results suggest that neither coefficient is significantly different from zero (test statistic from testing both coefficients are jointly equal to zero is: $\chi^2_2 = 1.31$, p-value $= 1.00$). After controlling for other covariates, we find that the presence of threshold uncertainty alone does not significantly affect the efficiency in token claims (Table 5). Communication, however, plays an important role in coordination and hence increases the earnings in the certainty treatment, particularly when communication occurs in the first 8 rounds. Communication in the first 8 rounds also leads to a significant increase in earnings in the risk treatment. Although communication also increases earnings in the ambiguity treatment, the change is not statistically significant. Interestingly, earnings increase across rounds in the certainty and ambiguity treatments but decrease across rounds in the risk treatment, suggesting that the efficiency of resource use can diminish over time in the presence of uncertain thresholds with known probabilities.

In summary, our four hypothesis tests generate the following key results. First, uncertainty about the threshold increases token claims and reduces earnings, on average, compared to the case when the threshold is known with certainty (Hypothesis 1). In addition, while average token claims in the ambiguity treatment are not statistically different from that of the certainty treatment, the proportion of groups exceeding thresholds in the ambiguity treatment are higher compared to the certainty treatment (Hypothesis 1). Risk averse participants claim more tokens in the risk treatment relative to the certainty treatment; however, risk preferences do not affect decisions in the ambiguity treatment (Hypothesis 2). Further, we find no relationship between ambiguity attitudes and token claims in the ambiguity treatment (Hypothesis 3). Finally, communication is very effective in reducing token claims in the risk and ambiguity treatments, and often depends on the timing of communication and the type of threshold uncertainty (Hypothesis 4). In particular, early communication is more effective at reducing token claims in the risk treatment, and communication diminishes the likelihood of resource collapse in all treatments. Therefore, introducing early communication can be an effective strategy to minimize the negative effect of threshold uncertainty and strategic uncertainty on CPR use.

6. Conclusion

Tipping points exist in many complex environmental systems, and exceeding thresholds associated with these tipping points can generate damaging and irreversible changes. Uncertainty about the level and distribution of environmental thresholds creates challenges for managing shared natural resources. Understanding how uncertainty influences behavior has important implications for agricultural, environmental, and resource management and policymaking, and economic experiments are powerful tools for analyzing this behavior, particularly when decisions deviate from what we would predict based on economic theory (Cárdenas, 2016). We use a CPR framework to investigate the impact of two types of threshold uncertainty on individual resource use and group-level coordination. Theoretically-derived hypotheses are tested using an economic laboratory experiment in which participants made CPR use decisions under three threshold treatments – a known threshold (certainty), an uncertain threshold with a known probability distribution of thresholds (risk), and an uncertain threshold with an unknown probability distribution (ambiguity). We also tested the effect of communication on coordination in each treatment. We find that threshold uncertainty increases CPR use relative to when the threshold is known; however, communication reduces CPR use under uncertainty. Communication reduces individual CPR use the most in the ambiguity setting, with varying effects depending on the stage of the game and the timing of communication. More importantly, communication is found to reduce the probability of coordination failure among group members. Our results suggest that improvements in CPR management can be gained from technological advancements that can identify critical thresholds with greater certainty and by encouraging communication among CPR users to improve coordination.

While the introduction of uncertainty and communication moves our framework one step closer to reality for many CPR settings, our study does not attempt to capture the dynamic nature of uncertainty. In particular, an underlying assumption in our study is that threshold uncertainty is constant over time. Future research that evaluates the impacts of uncertainty in a dynamic setting would provide further insight into CPR use behavior. We also assume that thresholds apply uniformly to all CPR users and impose identical costs on users if exceeded. This may not be the case in many natural resource contexts in which CPR users are heterogeneous and face different threshold environments. A fruitful avenue for future research would be to investigate such behavior when threshold uncertainties and consequences vary across time and space.

Declaration of Competing Interest

There is no conflict of interest of authors associated with this study. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The data that support the findings of this study are available from the corresponding author upon request.

Appendix A

In order to study the effects of the participants' subjective beliefs about the probabilities of the thresholds, we assume that the participants behave according to the smooth ambiguity model of (Klibanoff et al., 2005). One interesting feature of the smooth ambiguity model is that it distinguishes between the individuals' subjective beliefs about the threshold probabilities and their ambiguity preference (between taste and attitudes) (Gollier, 2011) that govern individuals' resource claims. The uncertainty (ambiguity) about the threshold in our model is represented by the parameter θ whose distribution is unknown to the participants. Consequently, the deterioration function in Eq. (1) is replaced by $h_\theta(R,\ \tilde{R}_\theta)$. $\tilde{R}_\theta$ is a random variable that is distributed as F_θ describing the ambiguity of the threshold as a set $\Pi = (F_\theta)$ for $\theta = 1,\ 2,\ \ldots,\ n$ where $F_1,\ F_2, \ldots,\ F_n$ are plausible cumulative distributions for $\tilde{R}_\theta$. Furthermore, we assume that individuals' subjective beliefs associate a second-order probability distribution $p_1, p_2, \ldots,\ p_n$ over the set of priors Π such that $\Sigma_{\theta=1}^{n} p_\theta = 1$. Here $p_\theta \geq 0$ implies the probability that F_θ is the true probability distribution for the thresholds which, from now on, we denote θ the random variable $(1,\ p_1; 2,\ p_2; \ldots; n, p_n)$. In order to maximize utility, individuals compute the expected utility for each plausible probability distribution F_θ. Hence, individual's problem is to maximize utility from token claims r_θ.

$$r_\theta^* \in argmax\ [Eu(r_i h_\theta)] \tag{8}$$

It is assumed that $u' > 0$, and $u'' \leq 0$. That is, u is increasing and concave. This implies that, for all θ, $u(R,\ \theta)$ is concave in the level of resource claims r_θ. In addition, the shape of ϕ which is the individual's ambiguity function describes her attitudes toward ambiguity: linear ϕ indicates ambiguity neutrality in which case the compound probability reduces to a single one $\Sigma_\theta p_\theta F_\theta$. ϕ, on the other hand, is concave for ambiguity averse individuals in which case individuals have detest for any mean-preserving spread of the conditional expected utility $Eu(r_i h_\theta)$ (Taboga, 2005). In addition, the objective function is strictly concave in r_i if both u and ϕ are strictly concave ensuring a unique solution to Eq. (8), when it exists.

In order to establish that increased aversion to ambiguity leads one to reduced token claims, we make a comparison between two users' behavior with the same beliefs and the same utility function u. However, two individuals differ in their attitudes toward ambiguity represented by the concave functions ϕ_1 and ϕ_2. Token claim by individual $\phi_1$that is expressed by r_1^* is derived satisfying the following first order condition:

$$\Sigma_{\theta=1}^{n} p_\theta\ \ \phi_1'[Eu(r_1^*, h_\theta)]Eu'(r_1^*, h_\theta)h_\theta = 0 \tag{9}$$

We assume that the individual with the ambiguity function $\phi_2$is more ambiguity averse than one with ϕ_1. This assumption holds under the condition that there is an increasing and concave transformation function k such that $\phi_2(u) = k(\phi_1(u))$ for all u in the relevant domain. Our objective is to establish the condition under which increased ambiguity aversion leads to reduced token claims implying $r_2^* \leq r_1^*$. $r_2^* \leq r_1^*$ if and only if the following condition holds:

$$\Sigma_{\theta=1}^{n}\ \ \phi_2'[u(r_1^*, h_\theta)]E\ \ u'(r_1^*, h_\theta)h_\theta \leq 0 \tag{10}$$

Establishing $r_2^* \leq r_1^*$ for individual with ambiguity function ϕ_2, which is more ambiguity averse than individual ϕ_1 essentially requires identifying the condition under which Eq. (9), when it is true, implies Eq. (10).

Let the individual's beliefs about the random variable h_θ be expressed by compound random variable $\tilde{z}_i$ with probability $\hat{p}_\theta^i,\ \ \theta = 1, \ldots,\ \ n$ such that

$$\hat{p}_\theta^i = \frac{p_\theta \phi_i'\left(u\left(r_1^*, \theta\right)\right)}{\Sigma_{t=1}^{n} p_t \phi_i{}'\left(u\left(r_1^*,\ \ t\right)\right)} \tag{11}$$

then

$$E\tilde{z}_1 u'(r_1^*, \tilde{z}_1) = 0 \Rightarrow\ \ E\tilde{z}_2 u'(r_2^*, \tilde{z}_2) \leq 0 \tag{12}$$

where the equality on the left of Eq. (13) comes from the first order condition of the individual $1'$s expected utility maximizing problem whose beliefs are represented by $\tilde{z}_1 \sim (h_{\theta 1}^1,\ \ \hat{p}_1^1; \ldots, h_{\theta n}^1, \hat{p}_n^1)$. Holding the conditions in Eqs. (11) and (12) implies that an ambiguity averse individual ϕ_1 behaves in the same way as an expected utility maximizing agent with distorted second-order beliefs from $(p_1, \ldots,\ \ p_n)$ to $\hat{p}^1 = (\hat{p}_1^n, \ldots,\ \ \hat{p}_n^1)$ where the latter is the "observationally equivalent probability distribution" of the former with the distortion factor $\frac{\phi_1'(u(r_1^*,\theta))}{\Sigma_{t=1}^{n} p_t \phi_i{}'(u(r_1^*,\ t)}$ being a Radon-Nikodym derivative (Taboga, 2005; Gollier, 2011). Careful inspection of Eq. (11) suggests that one's distortion factor depends on one's token claim making the distortion of the probability/beliefs endogenous. In particular, Eq. (12) suggests that someone shifting beliefs from $\tilde{z}_1$ to $\tilde{z}_2$ reduces the ambiguity averse individual's token claims. Such claim is summarized in the following lemma.

Lemma 1. $\hat{\mathrm{p}}_\theta^{\mathrm{i}}$ being defined by Eq. (11), if the expected utility maximizing individual with the utility function u reduces her token claim from a resource stock with uncertain threshold when her beliefs about the threshold shifts from $\tilde{\mathrm{z}}_1 \sim (\tilde{\mathrm{h}}_\theta^1;\ \ \hat{\mathrm{p}}_1^1; \ldots, \tilde{\mathrm{h}}_{\theta\mathrm{n}}^1; \hat{\mathrm{p}}_\mathrm{n}^1)$ to $\tilde{\mathrm{z}}_1 \sim (\tilde{\mathrm{h}}_\theta^1;\ \ \hat{\mathrm{p}}_1^1; \ldots, \tilde{\mathrm{h}}_{\theta\mathrm{n}}^1; \hat{\mathrm{p}}_\mathrm{n}^1)$, then changing her preference from (u, ϕ_1) to (u, ϕ_2) reduces her token claims.

The claim in Lemma 1 solely depends on the existence of an observationally equivalent probability distribution that is due to Taboga (2005). Hence, proving Lemma 1 is essentially equivalent to proving that the following two conditions in Lemma 2 are equivalent.

Lemma 2. *The following two conditions are equivalent:*

(a) Individual ϕ_2 is more ambiguity averse than individual ϕ_1, and
(b) In the sense of monotone likelihood ratio (MLR), beliefs $\hat{p}^2$ are dominated by beliefs $\hat{p}^1$.

Property (b) means that $u(r_1^*, \theta_i) \le u(r_1^*,\ \theta_j)\ \forall\ i \le j$ implying the ratio $\frac{\hat{p}_\theta^2}{\hat{p}_\theta^1}$ is decreasing in θ. That is, an increase in ambiguity aversion affects individual's token claims that are observationally equivalent to an MLR-dominated shift in the prior beliefs. The implication of property (b) is that ambiguity aversion distorts beliefs in a way that it favors the worst priors. For example, if individual ϕ_1 prefers prior h_θ over prior h'_θ, then the more ambiguity averse individual $\phi_2$distorts probability $\hat{p}_{\theta'}^2$, relative to individual 1, more than the probability $\hat{p}_\theta^2$. In sum, Lemma 2 justifies the claim, in case of resource use, that increased ambiguity aversion is observationally equivalent to increased pessimism.

Proof. The ambiguity functions ϕ_1 and ϕ_2 are increasing in u and . Hence, there exists k, an increasing function such that $\phi_2(u) = k(\phi_1(u))$ with the first derivative $\phi_2'(u) = k'(\phi_1(u))\phi_1'(u)$ for all u. In can be shown, using definition in Eq. (11), that

$$\frac{\hat{p}_\theta^2}{\hat{p}_\theta^1} = k'(\phi_1(u(r_1^*, \theta))) = \frac{\Sigma_{t=1}^n p_t \phi_1'\big(u\big(r_1^*, t\big)\big)}{\Sigma_{t=1}^n p_t \phi_2'\big(u\big(r_1^*, t\big)\big)}\ \forall\ \theta = 1, \ldots, n. \tag{13}$$

Eq. (12) implies Lemma 2 as $\frac{\hat{p}_\theta^2}{\hat{p}_\theta^1}$ is decreasing in θ if k' is decreasing in ϕ_1.

Appendix B

Table A1, Table A2
Fig. B1, Fig. B2

Table A1
Alternative specification of token claim request with interaction of attitudes toward uncertainty with communication across treatment.

Individual request	Coef.	Std. Err.
Treatment:		
Risk	2.65**	1.28
Ambiguity	0.50	0.65
First 8 round dummy[a] x treatment:		
Certainty	0.17**	0.09
Risk	0.50	0.74
Ambiguity	0.05	0.44
Treatment x communication dummy[b]:		
Certainty	−0.27***	0.07
Risk	−2.10**	1.03
Ambiguity	−2.81***	0.41
Treatment x communication time dummy[c]:		
Certainty	−0.15	0.17
Risk	−1.95***	0.77
Ambiguity	−1.11	1.14
Attitudes toward uncertainty:		
Risk attitude (ρ)	−0.02	0.03
Ambiguity attitude (θ)	−0.95	1.27
$\rho \times$ Risk	−0.15*	0.08
$\rho\times$ Ambiguity	0.16	0.17
$\theta\times$ Risk	1.07	1.96
$\theta\times$ Ambiguity	0.31	2.35
Round effect	−0.06	0.08
Round X Risk	0.16	0.16
Round X Ambiguity	0.30***	0.10
$\rho \times$ *communication*	0.02	0.03
$\rho \times$ *communication* $\times$ Risk	0.06	0.07
$\rho \times$ *communication* $\times$ Ambiguity	−0.15	0.16
$\theta \times$ *communication*	0.39	1.36
$\theta \times$ *communication* $\times$ Risk	1.67	1.94
$\theta \times$ *communication* $\times$ Ambiguity	1.03	2.52
Constant	16.83***	0.43
N	4928	

[a]: 1 if the first 8 round, 0 otherwise;
[a]: 1 if the communication took place prior to making choices in that round, 0 otherwise;
[a]: 1 if the communication was in the first 8 round, 0 otherwise.

Choice	Option A: Play the lottery		Your Decision	Option B: Sure amount
	The likelihood/chance of a white ball being drawn is: **50%** Payoff if white (U.S. Dollar)	The likelihood/chance of an orange ball being drawn is: **50%** Payoff if orange (U.S. Dollar)		Payoff of the sure amount (U.S. Dollar)
1	0	100	o A o B	5
2	0	100	o A o B	10
3	0	100	o A o B	15
4	0	100	o A o B	20
5	0	100	o A o B	25
6	0	100	o A o B	30
7	0	100	o A o B	35
8	0	100	o A o B	40
9	0	100	o A o B	45
10	0	100	o A o B	50
11	0	100	o A o B	55
12	0	100	o A o B	60
13	0	100	o A o B	65
14	0	100	o A o B	70
15	0	100	o A o B	75
16	0	100	o A o B	80
17	0	100	o A o B	85
18	0	100	o A o B	90
19	0	100	o A o B	95
20	0	100	o A o B	100

Fig. B1. Screenshot of risk elicitation task.

Table A2
Regression results of the effects of threshold uncertainty on efficiency in token claim (utility as the dependent variable).

Individual request	Coef.	Std. Err.
Treatment:		
Risk	−6.31	25.24
Ambiguity	34.60	42.30
First 8 round dummy x treatment[a]:		
Certainty	5.13.73	23.52
Risk	14.92	15.02
Ambiguity	−0.10	4.28
Treatment x communication dummy[b]:		
Certainty	5.06	14.40
Risk	24.12	18.82
Ambiguity	9.90	8.01
Treatment x communication time dummy[c]:		
Certainty	−55.70	57.57
Risk	39.14	48.21
Ambiguity	−43.07	28.47
Attitudes toward uncertainty:		
Risk attitude (ρ)	2.46	3.40
Ambiguity attitude (θ)	−76.30	1.27
$\rho \times$ Risk	4.41	8.74
$\rho\times$ Ambiguity	−1.59	3.70
$\theta\times$ Risk	146.25	104.30
$\theta\times$ Ambiguity	73.63	95.09
Round effect	11.54	10.93
Round X Risk	−18.53	12.73
Round X Ambiguity	−15. 09	1.56
Constant	34.29*	20.35
N	4928	

[a]: 1 if the first 8 round, 0 otherwise;
[b]: 1 if the communication took place prior to making choices in that round, 0 otherwise;
[c]: 1 if the communication was in the first 8 round, 0 otherwise

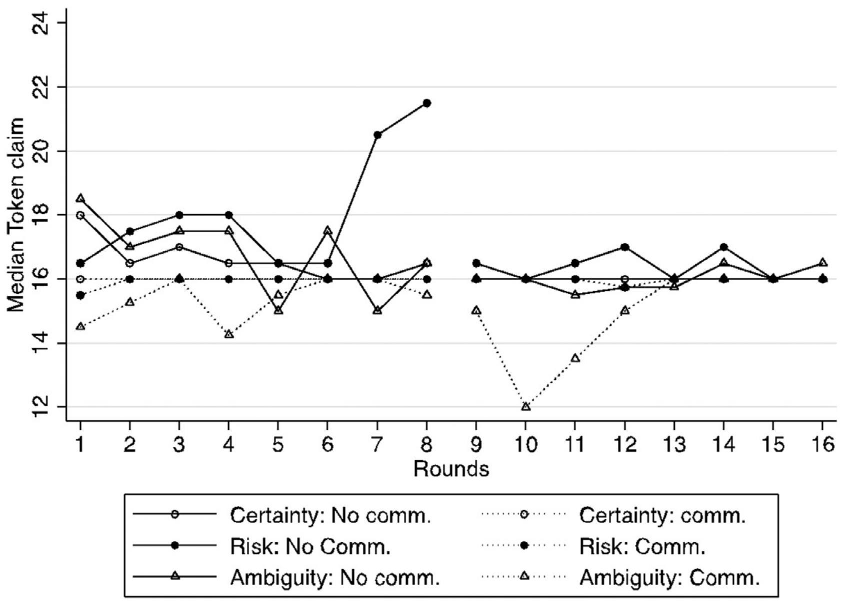

Fig. B2. Round-wise median token claim.

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