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Time and uncertainty in resource dilemmas: equilibrium solutions and experimental results

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Abstract Most common pool resource (CPR) dilemmas share two features: they evolve over time and they are managed under environmental uncertainties. We propose a stylized dynamic model that integrates these two dimensions. A distinguishing feature of our model is that the duration of the game is determined *endogenously* by the users' collective decisions. In the proposed model, if the resource stock level below which the irreversible event occurs is known in advance, then the optimal resource use coincides with a unique symmetric equilibrium that guarantees survival of the resource. As the uncertainty about the threshold level increases, resource use increases if users adopt decision strategies that quickly deplete the resource stock, but decreases if they adopt path strategies guaranteeing that the unknown threshold level is never exceeded. We show that under relatively high uncertainty about resource size, CPR users frequently implement decision strategies that terminate the game imme-

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diately. When this uncertainty is reduced, they maintain a positive resource level for longer durations.

Keywords Common pool resources · Social dilemmas · Uncertainty · Sustainability

1 Introduction

The most natural common pool resource (CPR) dilemmas share two main features: they evolve over time and they are managed under environmental uncertainties. Examples include groundwater, fishery resources, and climate change, all of which are dynamic in nature, with uncertainty about the size of the resource changing over time, in part, as a function of previous appropriations (Koundouri 2004; Bailey et al. 2010; Barrett and Dannenberg 2012). While each of these two features has been analyzed separately in the experimental literature, no attempt has been made to integrate them into a single experimental setup. In particular, the analysis of strategic behavior in the face of environmental uncertainty about the size of the CPR has traditionally been conducted under the assumption of single-period interaction, whereas the analysis of strategic behavior in time-dependent settings has ignored environmental uncertainties. The latter literature uses dynamic game theory to compare cooperative and non-cooperative time paths for resource appropriation in a deterministic framework, and experimental results tend to show aggregate behavior consistent with the predicted non-cooperative equilibria. The former literature uses static game theory to address the question of whether increased uncertainty about the size of the CPR leads to more or to less appropriation at the predicted Nash equilibrium of the CPR dilemma, and experimental results show a strong positive relationship between pool-size uncertainty and resource appropriation.

Our goal in this paper is to integrate these two strands of the experimental literature. This involves the development of a stochastic dynamic game-theoretic model of the CPR dilemma. Although the solutions to stochastic dynamic games can be particularly difficult to characterize analytically, there are two reasons for doing this. The first is to examine whether the conclusions derived from models of dynamic games with no environmental uncertainty are still valid when uncertainty is introduced, and whether the conclusions from static models of environmental uncertainty in the basic CPR game transfer to time-dependent settings. The second reason for integrating these two strands of the experimental literature is to address questions that cannot be answered without this integration. We are particularly concerned with two major questions: (1) what are the strategies that appropriators adopt when both environmental uncertainties and temporal considerations are present, and (2) are the strategies that they adopt sensitive to different levels of environmental uncertainty?

These two questions are addressed in our paper by proposing and experimentally testing a stochastic dynamic game integrating the effects of environmental uncertainty in time-dependent CPR dilemmas. The paper is organized as follows. Section 2 provides a brief review of the related literature that considers time-dependency and environmental uncertainty separately. Section 3 presents the model and solves it for alternative theoretical benchmarks. Section 4 outlines the experimental design and presents the theoretical predictions that are later used as benchmarks for the analysis of the experimental data. Section 5 reports the results of the experiment, and Sect. 6 concludes.

2 Related literature

The bulk of the experimental literature (e.g., Ostrom et al. 1994) has analyzed unrestricted resource-use decisions by placing subjects in the context of repeated *time-independent* CPR dilemmas characterized only by *strategic* uncertainty about the behavior of other group members. A major finding is that aggregate behavior is consistent with the theoretically predicted resource misallocations (Gordon 1954; Hardin 1968). Brown (2001) has noted that while the time-independent framework may be an adequate representation of CPRs characterized by flows, in which the availability of the resource in the future is independent of current requests, it fails to capture the important temporal feature of stock resources, like groundwater systems, fisheries, and forests, where decisions concerning resource-use are typically made in the "shadow of the future".

When temporal factors are incorporated into the model, it is a priori not clear if the appropriation decisions that they elicit should differ from the ones observed in time-independent settings. Because current appropriations not only affect the future profits of other group members, but also their individual profits, CPR users may adopt precautionary strategies that lead them closer to Pareto optimal outcomes (e.g. Reinganum and Stokey 1985). On the other hand, the consideration that current appropriation decisions affect future request possibilities creates a dynamic optimization problem that complicates the attainment of Pareto optimal outcomes even in single-agent contexts (Messick and McClelland 1983; Hey et al. 2009). Moreover, as shown by Dutta (1995), the standard intuition from infinitely repeated time-independent games, whereby Pareto optimal outcomes can be sustained in equilibrium through threat of credible punishment by patient players, does not necessarily carry over to time-dependent games with stock variables. Rather, players' payoffs in these games depend not only on current and previous periods' decisions, but also on state variables that change over time. Theoretically, this renders tacit agreements on Pareto optimal paths more difficult to attain than in purely repeated frameworks.

Seminal experimental investigations placing subjects in time-dependent CPR contexts have been conducted by Herr et al. (1997) and Mason and Phillips (1997). Herr et al. (1997) have concluded that their subjects did not internalize the future increased costs, and that behavior in the time-dependent setting intensified the race for resources appropriation relative to time-independent settings. Mason and Phillips (1997) have considered an infinite-time horizon supergame in which subjects were given an initial stock, and request strategies endogenously determined the stock size (and exploitation costs) thereafter. They have concluded that lack of cooperative behavior is exacerbated when time-dependency is included in CPR dilemmas. In yet another study, Osés-Eraso et al. (2008) have modified this game by implementing a more realistic finite-horizon supergame and allowing for early extinction of the stock as a function of cumulative group requests. Exogenously manipulating the initial stock size, they reported that early extinction of the resource occurs irrespective of the initial scarcity condition and costs.

Osés-Eraso et al. (2008), and one of the experimental conditions in Mason and Phillips (1997), have excluded the possibility of more complex resource dynamics involving threshold effects and sudden changes in the resource state.[1] The only study that partially addressed this possibility experimentally is Gardner and Walker (1992), who implemented a 20-period supergame in which resource extinction (end of the game) could occur within a given period with an endogenously determined probability modeled as an increasing function of total group requests. In their model, the critical threshold stock level triggering the catastrophic event was known in advance, but subjects were unable to avoid the damage, and the resource was quickly destroyed with a median duration of six periods. In contrast to our study, their model does not capture the effects of incomplete information regarding the size and growth of natural resources, which characterizes most real-world commons.

Experimental assessments of the impact of environmental uncertainty on appropriation requests from a CPR have been reported by Rapoport and Suleiman (1992) and Budescu et al. (1995) in the context of repeated single-trial CPR experiments. In their experiments, subjects could request resources from pools whose parameters were randomly selected from a set of commonly known uniform probability distributions. Using mean-preserving spreads to capture increasing levels of uncertainty regarding the resource size, these experiments have demonstrated that increased uncertainty causes subjects to significantly increase their appropriation from the shared resource. Alternative explanations for this finding have been proposed by Rapoport and Suleiman (1992), Budescu et al. (1995) and Gustafsson et al. (1999). Despite the merit of these explanations, the literature seems to have overlooked that the observed relationship between environmental uncertainty and individual requests pertains to single-trial experiments. Under these circumstances, a significant restraint in individual requests by the group members that can be considered cooperative behavior may not yield the highest collective payoffs as it may constitute resource under-use from an economically efficient perspective. Indeed, increased exploitation of the CPR as a response to an increase in environmental uncertainty levels in time-independent settings conforms to Pareto-efficient solutions, and not just Nash behavior. However, this observation is unlikely to be true in time-dependent settings. A number of theoretical articles on various resource management problems (e.g., Tsur and Zemel 1995; Yin and Newman 1996; and Clarke and Reed 1994) have generally established that efficient solutions to the dynamic management of resources under uncertain critical threshold levels require more prudence and conservative behavior than those under conditions of certainty. Thus, whether the positive relationship between environmental uncertainty and request decisions from a shared resource is likely to be observed in a time-dependent laboratory setting remains an open empirical question.

[1] See, for example, Muradian (2001) for a survey of real world examples of ecosystems characterized by ecological discontinuities and uncertain threshold levels.

3 Stochastic dynamic CPR game

We develop a stochastic dynamic game-theoretic model of the appropriation of a CPR by non-cooperative players under conditions of environmental uncertainty. The game involves a fixed set of n agents who play a stage game $\mathbf{\Gamma}_{\mathrm{t}}$ in each period t, where an upper bound T to the length of the game is common knowledge, and earnings accumulate through the course of play. However, in contrast to purely dynamic time-dependent games with no uncertainty in the evolution of the game environment (Dutta 1995), the particular game to be faced by the players at time t in the present setup is randomly selected from a commonly known finite set of games, thereby falling in the category of stochastic games (Shapley 1953; Sobel 1971). In addition, in order to capture the effects of environmental uncertainty on the CPR dilemma, players do not know which game has been selected when the game at time t is to be played.

In each of the stage games $\mathbf{\Gamma}_{\mathrm{t}}$ that make up the dynamic game a group of n players decide simultaneously and anonymously on how much to request from a shared resource (CPR) whose precise size is unknown. However, it is commonly known that the resource size, denoted by S_t, is uniformly distributed on the $[\alpha, \beta]$ closed interval.[2] Each of the n individuals may request anything between 0 and β from the shared resource,[3] and *after* the requests are made, the precise size of the resource is publicly announced, corresponding to the random realization s_t of S_t. Thus, the precise value of s_t corresponds to the particular stage game $\mathbf{\Gamma}_{\mathrm{t}}$ randomly selected by "nature" at time t. Furthermore, if the sum of group requests is smaller than or equal to s_t, then each individual keeps his or her own request. On the other hand, if the sum of group requests exceeds the size s_t of the resource, then each individual's payoff is zero.

Assuming linear utility functions for all agents, and letting r_{jt} stand for the request made by agent j on trial t, the expected payoff to each agent in stage game $\mathbf{\Gamma}_{\mathrm{t}}$ is given by

$$\pi_{jt} = \begin{cases} r_{jt} & \text{if } \sum_{j=1}^{n} r_{jt} \leq \alpha \\ r_{jt} \times \text{Prob}(\sum_{j=1}^{n} r_{jt} \leq s_t) & \text{if } \alpha < \sum_{j=1}^{n} r_{jt} \leq \beta \\ 0 & \text{if } \sum_{j=1}^{n} r_{jt} > \beta \end{cases} \tag{1}$$

where $\sum_{j=1}^{n} r_{jt}$ is the sum of group requests in stage game $\mathbf{\Gamma}_{\mathrm{t}}$, and $\text{Prob}(\sum_{j=1}^{n} r_{jt} \leq s_t) = (\beta - \sum_{j=1}^{n} r_{jt})/(\beta - \alpha)$.

[2] The use of the uniform distribution to model players' imperfect knowledge about the resource is made primarily to simplify the experimental task, as the uniform distribution is most easily explained to the participants.

[3] As noted by one of the referees, this feature of the game yields a large appropriation capacity to each player in the group. A design option modifying the Suleiman and Rapoport (1988) stage game (from which this feature is drawn) would be to limit each player's appropriation to some fraction of β, which may be at odds with the possibility of unrestricted resource-use at the individual level. For example, if we think of this CPR as a groundwater system from which a group of n farmers pump water to irrigate their crops, and if each knows that the size of the groundwater system may go up to a number β, limiting a priori their water extraction to a fraction of β presupposes in itself that there is some technology limit common to them all or that there is some external regulator that has the ability to dictate and impose upon each of them such a limit. Therefore, we maintained this feature of the stage game in Suleiman and Rapoport (1988).

We introduce structural time dependence in this model through the definition of transition probabilities governing how the game proceeds from period t to period $t+1$, which we condition on the actual game $\boldsymbol{\Gamma}_t$ played in period t as randomly selected by "nature," and on the actions chosen by the players in period t. Specifically, if the aggregate requests are smaller than or equal to the resource size at time t, then the game continues to period $t+1$. If the aggregate requests are infeasible, in the sense that they exceed the resource size at time t, then the game terminates.[4] Formally, the continuation probability from period t to period $t+1$ is given by

$$p_t = \begin{cases} 1 & \text{if } \sum_{j=1}^{n} r_{jt} \leq \alpha \\ \frac{\beta - \sum_{j=1}^{n} r_{jt}}{\beta - \alpha} & \text{if } \alpha < \sum_{j=1}^{n} r_{jt} \leq s_t \\ 0 & \text{if } \sum_{j=1}^{n} r_{jt} > s_t \end{cases} \tag{2}$$

In words, if the group request is below a minimum pre-determined quantity α, the game continues to a subsequent period with certainty, implying an economically unchanged resource size between the periods. If the group request exceeds the randomly determined resource size, then the resource is degraded and the game is terminated. If the group request belongs to this interval of quantities, then the game continues to a subsequent period with a positive probability corresponding to the *ex-ante* probability that the group request does not exceed the resource size. Thus, while players may request resources over a predetermined and commonly known time horizon, a distinguishing feature of this model is that the precise duration of the game is determined *endogenously* by the players whose collective decisions determine the probability of an irreversible environmental event.[5]

Because the CPR game is composed of interdependent stochastic dynamic programming problems, it may be solved by dynamic programming/Bellman's equation method, and because it is symmetric, we focus on symmetric outcomes as benchmarks for data analysis. In particular, we solve the game for three types of outcomes: the social optimum (joint payoff maximization) outcome, the subgame perfect equilibrium outcome, and a "conservative" outcome guaranteeing survival of the resource over the entire time horizon.

[4] Although admittedly extreme, this rule accounts for a basic characteristic of a variety of ecological systems which can be exploited up to some *critical* (threshold) level while maintaining their integrity and retaining much of their use value. Once the exploitation level exceeds the (often largely uncertain) threshold, the resource value drops catastrophically, and may not be reversed even after stopping the perturbation that caused the shift during many years (Muradian 2001, pp. 18–19).

[5] As noted, for example, by Hine and Gifford (1996), many real-world commons are characterized not only by pool-size uncertainty but also by regeneration-rate uncertainty. Although the present model focuses on pool-size uncertainty, it may also be seen as capturing those circumstances that are characterized by regeneration-rate uncertainty. When group requests exceed α but the resource is not depleted, the intertemporal effect of group requests may be interpreted as captured by a stochastic regeneration rate g_t applied to end of period remaining stock, $s_t - \sum_{j=1}^{n} r_{jt}$. The parameter g_t determines the stock available in the subsequent period, $s_{t+1} = (s_t - \sum_{j=1}^{n} r_{jt})g_t$, where g_t is uniformly distributed with limits endogenously determined by group requests and the stochastic resource size; its lower limit is given by $\alpha/(s_t - \sum_{j=1}^{n} r_{jt})$, which happens if the resource size in the subsequent period takes its lowest possible value, and its upper limit is given by $\beta/(s_t - \sum_{j=1}^{n} r_{jt})$, which happens if the resource size in the subsequent period takes its highest possible value.

We first construct the symmetric subgame perfect Nash equilibrium outcome, in which players are assumed to adopt "decision rule strategies" (Reinganum and Stokey 1985) since they cannot credibly commit to future requests. In this context, each player j independently seeks to maximize the value of the resource at any time t by choice of appropriation strategy, taking the decision rule strategies of all the other players exploiting the resource as given. Assuming no discounting of future payoffs, the value of the resource for player j at time t, $V_{jt}(r_{jt})$, satisfies the Bellman equation:

$$V_{jt}(r_{jt}) = \pi_{jt} + p_t \times V_{jt+1}(r_{jt+1}), \quad t = 1, 2, \ldots, T-1. \tag{3}$$

The transversality condition for this maximization problem is that the value of the resource after the final period T is zero (meaning that players leave behind no resources, or if they do, then those extra resources do not contribute anything to the maximized value):

$$V_{jT+1}(r_{jT+1}) = 0. \tag{4}$$

The recursive equation defining player's j value function at final time T is therefore:

$$V_{jT}(r_{jT}) = \pi_{jT}. \tag{5}$$

Maximizing $V_{jT}(r_{jT})$ in the quadratic region of (1) with respect to r_{jT}, yields:

$$\frac{\partial V_{jT}(r_{jT})}{\partial r_{jT}} = \frac{\partial \pi_{jT}}{\partial r_{jT}} = \frac{\partial (r_{jT} \frac{\beta - \sum_{j=1}^{n} r_{jt}}{\beta-\alpha})}{\partial r_{jT}} = \frac{\partial (r_{jT} \frac{\beta - r_{jT} - r_{n\setminus jT}}{\beta-\alpha})}{\partial r_{jT}} = 0, \tag{5'}$$

so that $\partial V_{jT}(r_{jT})/\partial r_{jT} = (\beta - 2r_{jT} - r_{n\setminus jT})/(\beta - \alpha) = 0$.

Invoking symmetry to write the sum of requests by all the n players excluding player j as $r_{n\setminus jT} = (n-1)r_{jT}$, yields the subgame perfect request at time T:

$$r^*_{jT} = \frac{\beta}{n+1}. \tag{6}$$

The value function at time T is then given by (using (6) in (5)):

$$V_{jT}\left(r^*_{jT}\right) = \frac{[\frac{\beta}{n+1}]^2}{\beta - \alpha}. \tag{7}$$

Similarly, the value function at time $T-1$ is given by

$$V_{jT-1}(r_{jT-1}) = \pi_{jT-1} + p_{T-1} \times V_{jT}\left(r^*_{jT}\right). \tag{8}$$

Maximizing $V_{jT-1}(r_{jT-1})$ with respect to r_{jT-1}, and assuming that $r_{n\setminus jT-1} = (n-1)r_{jT-1}$, yields the subgame perfect request at time $T-1$:

$$r^*_{jT-1} = \left[\frac{\beta}{n+1}\right]\left[1 - \frac{\beta}{(n+1)^2(\beta-\alpha)}\right]. \tag{9}$$

The value function at time $T-1$ is then given by (using (9) and (7) in (8)):

$$V_{jT-1}\left(r^*_{jT-1}\right) = \left[\frac{(\frac{\beta}{n+1})^2}{\beta-\alpha}\right]\left[1+\frac{n\beta}{(n+1)^2(\beta-\alpha)}\right]^2. \tag{10}$$

Letting $a = n\beta/(n+1)^2(\beta-\alpha)$, the value function at time $T-1$ can be re-written as:

$$V_{jT-1}\left(r^*_{jT-1}\right) = V_{jT}\left(r^*_{jT}\right)[1+a]^2, \tag{11}$$

and the subgame perfect request at time $T-1$ can be written as

$$r^*_{jT-1} = r^*_{jT}\left[1-\frac{a}{n}\right]. \tag{12}$$

Using mathematical induction, one can show that the equilibrium value function at any time t is given by

$$V_{jt}\left(r^*_{jt}\right) = V_{jT}\left(r^*_{jT}\right)[1+a\gamma_t]^2 = \left[\frac{(\frac{\beta}{n+1})^2}{\beta-\alpha}\right][1+a\gamma_t]^2, \tag{13}$$

and the subgame perfect request at time t is given by

$$r^*_{jt} = r^*_{jT}\left[1-\left(\frac{a}{n}\right)\gamma_t\right] = \left[\frac{\beta}{n+1}\right]\left[1-\left(\frac{a}{n}\right)\gamma_t\right], \tag{14}$$

where the recursive factor γ_t is given by

$$\gamma_t = (1+a\gamma_{t+1})^2. \tag{15}$$

One starts solving the recursion by noting that (7) can also be written as:

$$\frac{[\frac{\beta}{n+1}]^2}{(\beta-\alpha)} = r^*_{jT}\left[\frac{\beta}{(n+1)(\beta-\alpha)}\right], \tag{16}$$

and using (14) and (15), the equation above can also be written as:

$$\frac{[\frac{\beta}{n+1}]^2}{(\beta-\alpha)} = \left[\frac{\beta}{n+1}\right]\left[1-\left(\frac{a}{n}\right)(1+a\gamma_{t+1})^2\right]\left[\frac{\beta}{(n+1)(\beta-\alpha)}\right]. \tag{17}$$

Solving (17) with respect to γ_{T+1} yields:

$$\gamma_{T+1} = -\frac{1}{a}. \tag{18}$$

The value of γ_{T+1} in (18) can then be substituted into (15) to get γ_T, and working backward from there to the first period at time $t=1$.

Note, however, that the solution in (14) does not constitute the subgame perfect equilibrium request in all cases. At any time t, if $r_{jt} + r_{n\backslash jt} \le \alpha$, then any vector of requests $\boldsymbol{r}^*_t = (r_{1t}, r_{2t}, \ldots, r_{nt})$, whose elements satisfy the condition $\sum_{j=1}^{n} r^*_{jt} = \alpha$,

$r_{jt} \geq 0$, is also an equilibrium solution whereby the group ensures a continuation probability equal to one. Assuming a symmetrical solution, the result following this condition can be written as:

$$r^*_{jt} = \frac{\alpha}{n}. \tag{19}$$

To summarize, the subgame perfect equilibrium request at any time t is then given by:

$$r^*_{jt} = \max\left(\frac{\alpha}{n}, \left[\frac{\beta}{n+1}\right]\left[1 - \left(\frac{a}{n}\right)\gamma_t\right]\right). \tag{20}$$

Moving next from the equilibrium solution to joint payoff maximization, the social optimum path can be constructed by applying dynamic programming to (3) under the assumption that only a single agent is in charge of the resource. Eliminating the algebra, it can be shown that the social optimum request by player j at any time t in all cases is then given by:

$$r^{**}_{jt} = \max\left(\frac{\alpha}{n}, \left[\frac{\beta}{2n}\right]\left[1 - (b)\lambda_t\right]\right), \tag{21}$$

where $b = \beta/4(\beta - \alpha)$, $\lambda_t = (1 + b\lambda_{t+1})^2$, and $\lambda_{T+1} = -1/b$.

Comparison of Eqs. (20) and (21) reveals that the subgame perfect path involves higher requests than the social optimum path as long as $(\beta - \alpha) > \alpha/n$, rendering the decision rule strategies Pareto deficient for levels of uncertainty beyond a relatively small threshold level which depends on the two parameters of the distribution of the resource size. In turn, the social optimum path only guarantees the survival of the resource over the entire time horizon for moderate levels of uncertainty, that is, as long as $\beta < 2\alpha$. Beyond this level of uncertainty, survival of the resource over the entire time horizon could only be attained by the adoption of "path" strategies requiring each player to commit to a "conservative" request equal to α/n at each stage of the game. This is the third benchmark that we propose for our data analysis.

4 Experimental design and theoretical predictions

4.1 Procedures, parameters and treatments

We designed a simple experiment operationalizing the game described by Eqs. (1) and (2) with groups composed of six ($n = 6$) subjects and maximum time horizon of ten periods ($T = 10$). Each subject participated in thirty repetitions of the same dynamic game. Prior to the first game, each subject was randomly and anonymously assigned to a fixed group for the duration of a session. We implemented two mean-preserving uncertainty conditions in a between-subject design. In one of the uncertainty conditions (hereinafter, "high" uncertainty condition), the commonly known resource size was uniformly distributed on the [150, 850] closed interval, for an uncertainty range of 700 and an expected value of 500. Subjects were provided with written instructions informing them that they could, individually, request from 0 up to 850 tokens, and that the precise value of the resource (called "random draw") in any period was to be randomly extracted (and announced) after all group members made their requests. They were also informed that if the sum of group requests exceeded the randomly determined resource size in any period, then their individual payoffs in that period would be zero, and the game would be terminated; otherwise, their individual payoffs in that period would equal their individual requests, and the game would continue to a subsequent period unless it had reached the final period T.[6] Specifically, subjects were informed that the game would be terminated either if the sum of the group requests exceeded the value of the resource on any given period or after 10 periods, whichever came first. In addition to $5 participation fee, at the end of the session subjects were paid for the tokens accumulated in four (randomly determined for each subject) out of the thirty repetitions, in which each token was worth 2 cents. This procedure was implemented to prevent wealth effects. Exactly the same procedures were used to implement a second uncertainty condition (hereinafter, "low" uncertainty condition) in which the commonly known resource size was uniformly distributed on the [270, 730] closed interval, for a smaller uncertainty range of 460 and the same expected value of 500. In each of the two conditions, the sessions lasted for about 2 hours.

The experiment was implemented using the *z-Tree* (Fischbacher 2007) software. No communication between the subjects was allowed. All experimental sessions were conducted at the Behavioral Research Lab of the University of California, Riverside, which is a standard computerized laboratory with subjects' stations placed in separate "cubicles" ensuring privacy. Subjects were recruited from the pool of students registered to participate in research studies through the web-based subject recruitment system, ensuring that no subject had participated in a similar experiment before. A total of 114 subjects participated in this experiment, 60 of them in the high uncertainty condition (10 different groups) and 54 of them in the low uncertainty condition (9 different groups).

4.2 Theoretical predictions

We present the theoretical predictions that are later used as benchmarks for the analysis of the data from the two treatments.[7] The top panel in Table 1 shows the dynamic

[6] At the end of each period, each subject was presented with a screen displaying her/his request in the period, the requests by each of the other group members, the total group request, the value of the random draw, and her/his payoff (in tokens) for the period. The instructions to participants are presented in Electronic supplementary material (ESM).

[7] These numerical predictions result from the direct application of the solutions developed for the model in Sect. 3, which assumes that in determining the size of his or her request, the subject is motivated to maximize expected payoff. The generalization of the model to account for the maximization of expected utility is given in ESM, showing that, compared with the risk-neutral case, equilibrium requests are lower (higher) under the assumption of (common) risk-aversion (risk-preference) by subjects in *both* of the considered uncertainty conditions, leaving practically unaffected the predicted *differences* in equilibrium requests across the conditions. The main conclusion in the text with respect to the effect of different degrees of environmental uncertainty on subjects' behavior does not depend on the assumed shape of the subjects' (common) utility functions.

programming paths for the high uncertainty condition. If players follow a conservative path (not shown in Table 1), then the symmetric individual request (r) is 25 tokens in each period of the game, for a total group request (R) of 150 tokens. The overall payoff across the 10 periods of the game (Π) for each player is, therefore, $25 \times 10 = 250$ tokens. Next, consider the social optimum (SO) path displayed in Table 1 (top panel). In the last period of the game, when only a single period remains to the end of the game, the optimal solution is an individual request of 71. The probability of receiving this request (p) is about 0.61, yielding an expected payoff of $\Pi = 43$ tokens. If only two periods remain, the optimal solution is an individual request of 49. The probability of receiving this request is about 0.79. The individual's expected payoff across these two periods is, therefore, $49 \times 0.79 + 0.79 \times 43 = 73$ tokens. Working backwards in this fashion, the individual's expected payoff across the 10 periods of the game from following the social optimum path is equal to 274 tokens, the value of Π shown in Table 1 when ten periods are remaining (i.e., at the beginning of the game). This corresponds to the maximum symmetric expected payoffs that subjects may achieve in this game. Comparing the expected payoffs from following a conservative path to the social optimum path yields an efficiency index of $(250/274) \times 100 = 91\ \%$ for the conservative path. This means that subjects are expected to achieve 91 percent of the maximum expected payoffs in this game if they follow the very simple conservative path. The subgame perfect equilibrium (SPNE) path shown in Table 1 is constructed in the same manner, considering the predicted (symmetric) Nash equilibrium requests by each player. In this case, the individual's expected payoff across the ten periods of the game from following this path is only 31 tokens, yielding a meager efficiency index of about 11 percent.

The bottom panel in Table 1 shows the dynamic programming paths for the low-uncertainty condition. If players follow the conservative path in this condition, then the symmetric individual request is 45 tokens in each period of the game, for a total group request of 270 each period of the game. The overall payoff across the ten periods of the game for each player is $45 \times 10 = 450$ tokens. The individual's expected payoff across the 10 periods of the game from following the social optimum path is 453 tokens, and it is only 44 tokens from following the subgame perfect equilibrium path. In this case, the subgame perfect path yields an efficiency index of about 10 percent.

Comparison of the upper and lower parts of Table 1 shows that, as might be expected, payoffs increase under all three benchmarks as the uncertainty about the size of the resource decreases. Table 1 shows that each of these two uncertainty conditions yields different predictions concerning players' requests from the shared resource, with the social optimum path entailing substantially lower requests than the respective subgame perfect path. Therefore, the subgame perfect paths are Pareto deficient in the two uncertainty conditions implemented in the laboratory. Importantly, the efficiency index of the subgame perfect path is maintained approximately equal in both uncertainty conditions (11 % and 10 %), so that the incentives for any cooperative behavior do not differ much between them. Moreover, any increase in the requests that might be observed in response to an increase in the uncertainty levels cannot simultaneously constitute part of a competitive (subgame perfect) and a cooperative (conservative or social optimum) path. Indeed, as shown in Table 1, while the increased uncertainty in the high uncertainty condition elicits higher requests than in

Table 1 Dynamic programming paths for high- and low-uncertainty conditions

Time remaining	Social optimum (SO) path				Subgame perfect (SPNE) path			
	R	r	p	Π	R	r	p	Π
A. High-uncertainty condition: $n = 6$, $\alpha = 150$, $\beta = 850$, *Expected Value* = 500, *Range* = 700								
1	425	71	0.61	43	729	121	0.17	21
2	296	49	0.79	73	711	118	0.20	28
3	206	34	0.92	99	705	117	0.21	30
4	150	25	1.00	124	703	117	0.21	31
5	150	25	1.00	149	702	117	0.21	31
6	150	25	1.00	174	702	117	0.21	31
7	150	25	1.00	199	702	117	0.21	31
8	150	25	1.00	224	702	117	0.21	31
9	150	25	1.00	249	702	117	0.21	31
10	150	25	1.00	274	702	117	0.21	31
Efficiency index (%)				100				11
B. Low-uncertainty condition: $n = 6$, $\alpha = 270$, $\beta = 730$, *Expected Value* = 500, *Range* = 460								
1	365	61	0.79	48	626	104	0.23	24
2	270	45	1.00	93	605	101	0.27	34
3	270	45	1.00	138	597	99	0.29	39
4	270	45	1.00	183	593	99	0.30	41
5	270	45	1.00	228	591	98	0.30	42
6	270	45	1.00	273	589	98	0.31	43
7	270	45	1.00	318	589	98	0.31	43
8	270	45	1.00	363	589	98	0.31	43
9	270	45	1.00	408	588	98	0.31	44
10	270	45	1.00	453	588	98	0.31	44
Efficiency index (%)				100				10

Note: R is total group request; r is individual (symmetric) request; p is the probability of receiving the request and continuing the game; Π is individual expected payoff from conforming to the paths described. Adoption of a conservative strategy yields an efficiency index of 91 % ($25 \times 10 = 250/274$) in the high uncertainty condition, and an efficiency index of 99 % ($45 \times 10 = 450/453$) in the low-uncertainty condition. All numbers are rounded up to their nearest value

the low condition, if subjects follow the subgame perfect equilibrium path, it overall elicits significantly lower requests than in the low-uncertainty condition, if subjects follow the conservative path or the social optimum path.

5 Experimental results

Our analysis of the experimental data focuses on the effects of environmental uncertainty on resource-use decisions at the group level. We organize the analysis of group behavior by examining in order: (A) behavior in the high-uncertainty condition, (B) behavior in the low-uncertainty condition, and (C) comparison of the behavior across the two uncertainty conditions.[8] In each case, the main results are presented in the form of summary observations.

5.1 High-uncertainty condition

Panel A in Tables 2 and 3 summarize the main results of the high-uncertainty condition. Table 2 presents the duration of the games played by each group. Pooling across all 10 groups, the median length of the games is one period, with three of the ten groups registering a median length of two periods. Clearly, none of the groups adopted a conservative path, and depletion of the resource stock occurred rather quickly.

Figure 1 depicts the probability of resource destruction in the high-uncertainty condition as implied by the social optimum and equilibrium paths (broken lines) along with the observed proportions. Using the predictions in the top panel of Table 1, the probability of resource destruction prior to period 8 is 0 percent at the social optimum path, increasing to 8 percent ($(1 - 0.92) \times 100$) prior to period 9 and to 27 percent ($(1 - 0.92 \times 0.79) \times 100$) prior to period 10. In the context of dynamic games, theory informs us that we should observe an immediate depletion of the resource stock if groups are unable or unwilling to make commitments about future extraction rates (Reinganum and Stokey 1985), corresponding to the assumption that behavior is guided by decision rule strategies underlying the predicted SPNE path. In fact, as implied by the numbers in Table 1, the probability of resource destruction prior to period two is 79 percent ($(1 - 0.21) \times 100$) at the equilibrium path, increasing to 96 percent ($(1 - 0.21 \times 0.21) \times 100$) prior to period three, and reaching about 100 percent in subsequent periods. With such high destruction probabilities, the probability of observing games lasting for more than a single period is quite small if subjects do not deviate from the predicted equilibrium path. As Fig. 1 reveals, despite the variability of group behavior, the rates of resource destruction are quite above those predicted by the social optimum path, and considerably closer to the equilibrium path.

Table 3 shows that group requests terminating the game immediately, which accounted for about 55 percent of the data, average 688 tokens. This mean compares

[8] Because subjects participated in 30 repetitions/series of the same dynamic game, we first investigated whether play of the games changed as subjects gained more experience. A common finding in purely repeated CPR games is that behavior is consistent with efficient outcomes in the first rounds of play, and approaches the equilibrium prediction in the last rounds. Under this pattern of behavior, we would expect to observe longer games in the first series of play, and shorter games as the series approach the end. The figure in the ESM plots the maximum number of periods played by each group in each of the games, where the title in each of the panels identifies the uncertainty condition. In each case, the figure suggests that there is no systematic association between the length of the games and order of play. This impression was confirmed by several statistical analyses (available from the authors) at the group level. The same result occurs by regressing the natural logarithm of individual requests on dummy variables identifying each of the dynamic games, while controlling for group membership, the period within the game, and intra-subject correlation. Therefore, we pool the data across the games for the statistical analysis of the data in both uncertainty conditions.

Table 2 Number of games played by group (Gi) and length of game by uncertainty condition

Length	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	Total	%
A. High-uncertainty condition												
1	11	20	19	19	12	10	20	20	16	17	164	54.7
2	6	6	5	6	6	7	9	6	5	5	61	20.3
3	5	3	4	2	7	6	1	3	5	4	40	13.3
4	3	1	2	2	2	5	0	1	2	1	19	6.3
5	1	0	0	0	0	0	0	0	0	0	1	0.3
6	2	0	0	0	1	0	0	0	0	2	5	1.7
7	0	0	0	0	1	0	0	0	2	1	4	1.3
8	2	0	0	1	1	1	0	0	0	0	5	1.7
9	0	0	0	0	0	0	0	0	0	0	0	0.0
10	0	0	0	0	0	1	0	0	0	0	1	0.3
Median	*2*	*1*	*1*	*1*	*2*	*2*	*1*	*1*	*1*	*1*	*1*	
Mean	*3*	*2*	*2*	*2*	*2*	*3*	*1*	*2*	*2*	*2*	*2*	
SD	*2*	*1*	*1*	*1*	*2*	*2*	*1*	*1*	*2*	*2*	*2*	
B. Low-uncertainty condition												
1	17	13	10	15	8	17	13	19	11		123	45.6
2	4	7	8	6	8	8	8	6	5		60	22.2
3	4	3	4	0	1	1	5	1	4		23	8.5
4	3	1	1	0	2	0	3	1	2		13	4.8
5	0	1	1	4	5	3	0	1	0		15	5.6
6	1	2	1	1	1	1	1	0	2		10	3.7
7	0	1	3	0	0	0	0	0	4		8	3.0
8	0	0	0	0	1	0	0	0	0		1	0.4
9	0	0	0	4	4	0	0	1	1		10	3.7
10	1	2	2	0	0	0	0	1	1		7	2.6
Median	*1*	*2*	*2*	*2*	*2*	*1*	*2*	*1*	*2*		*2*	
Mean	*2*	*3*	*3*	*3*	*4*	*2*	*2*	*2*	*3*		*3*	
SD	*2*	*3*	*3*	*3*	*3*	*1*	*1*	*2*	*3*		*2*	

Note: Column % indicates the percentage of games of length $l = 1, \ldots, 10$ out of the total 300 (270) games played by the groups in the high-uncertainty (low-uncertainty) condition

closely to the equilibrium prediction of 702 tokens. As expected, first-period requests are negatively associated with the length of the game. The mean first-period group request for games longer than one period, which account for 45 percent of the data, is 487 tokens. These requests are in between the efficient and the equilibrium values.

Using Wald tests while adjusting standard errors for clustering at the group level, the signed mean differences between the observed first-period group requests (R^{Obs}) and the equilibrium (R^{SPNE}) and efficient (R^{SO}) values were tested for statistical significance. The results are summarized in Panel A of Table 4; they show that group requests in games terminated in the first period (Length = 1) are not significantly different from the predicted equilibrium value. The mean estimated difference between

Table 3 Mean group requests by period and length of game by uncertainty condition

Length of game	Period within the game									
	1	2	3	4	5	6	7	8	9	10
A. High-uncertainty condition										
1	688									
	(219)									
2	549	589								
	(139)	(174)								
3	435	442	495							
	(103)	(75)	(160)							
4	459	468	421	432						
	(102)	(76)	(89)	(77)						
5	375	375	400	325	325					
	(0)	(0)	(0)	(0)	(0)					
6	427	398	366	387	357	564				
	(53)	(73)	(46)	(76)	(52)	(362)				
7	454	417	349	378	384	366	395			
	(58)	(83)	(66)	(33)	(54)	(29)	(23)			
8	393	369	353	369	403	398	410	458		
	(81)	(107)	(74)	(46)	(82)	(84)	(68)	(132)		
10	395	385	320	337	335	309	343	282	335	277
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)
B. Low-uncertainty condition										
1	569									
	(186)									
2	430	506								
	(101)	(166)								
3	464	425	455							
	(112)	(73)	(89)							
4	394	398	404	447						
	(93)	(105)	(89)	(83)						
5	375	381	384	397	463					
	(114)	(82)	(86)	(69)	(102)					
6	372	386	390	398	387	397				
	(102)	(64)	(49)	(82)	(73)	(62)				
7	358	338	401	405	334	351	461			
	(65)	(60)	(74)	(94)	(56)	(59)	(85)			
8	270	420	320	500	420	370	470	620		
	(0)	(0)	(0)	(0)	(0)	(0)	(0)	(0)		
9	351	373	371	371	342	359	343	329	497	
	(64)	(74)	(56)	(83)	(57)	(73)	(54)	(38)	(105)	
10	416	369	350	433	353	405	341	389	376	449
	(67)	(37)	(54)	(59)	(34)	(70)	(55)	(52)	(51)	(141)

Note: Standard deviation is in parentheses. In the high-uncertainty condition, games of length 5 and 10 were only observed once; the average first-period (last-period) group requests for games longer than one period is 487 (524) tokens with a standard deviation of 130 (179) tokens. In the low-uncertainty condition, games of length 8 were only observed once; the average first-period (last-period) group requests for games longer than one period is 412 (476) tokens with a standard deviation of 105 (133) tokens

Fig. 1 Probability of destruction: Predicted (SO, SPNE) and observed values under the high-uncertainty condition

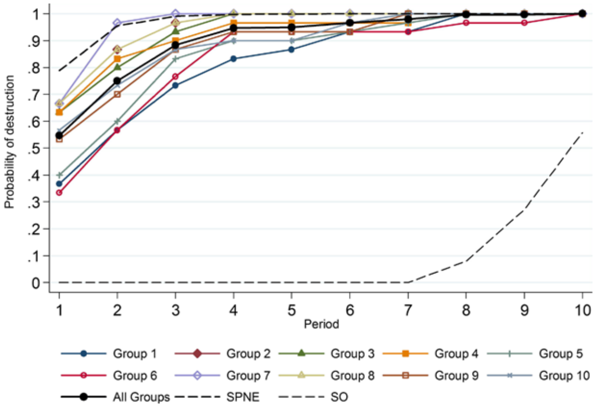


Table 4 Statistical analysis of differences between observed and predicted values

Length games	Variable	Coefficient	Wald *z* statistics	*p*-value	Lower 95 % CI	Upper 95 % CI
A. High-uncertainty condition						
Length = 1	$R^{\text{Obs}} - R^{\text{SPNE}}$	−13.757	−0.39	0.699	−83.461	55.947
	$R^{\text{Obs}} - R^{\text{SO}}$	537.854	15.12	0.000	468.150	607.558
	$\Delta = \lvert\frac{R^{\text{Obs}} - R^{\text{SPNE}}}{R^{\text{Obs}} - R^{\text{SO}}}\rvert$	0.026	0.38	0.706	−0.107	0.158
Length > 1	$R^{\text{Obs}} - R^{\text{SPNE}}$	−214.397	−8.37	0.000	−264.601	−164.194
	$R^{\text{Obs}} - R^{\text{SO}}$	337.213	13.16	0.000	287.010	387.417
	$\Delta = \lvert\frac{R^{\text{Obs}} - R^{\text{SPNE}}}{R^{\text{Obs}} - R^{\text{SO}}}\rvert$	0.636	5.12	0.000	0.392	0.879
B. Low-uncertainty condition						
Length = 1	$R^{\text{Obs}} - R^{\text{SPNE}}$	−18.977	−0.60	0.545	−80.464	42.510
	$R^{\text{Obs}} - R^{\text{SO}}$	299.415	9.54	0.000	237.923	360.902
	$\Delta = \lvert\frac{R^{\text{Obs}} - R^{\text{SPNE}}}{R^{\text{Obs}} - R^{\text{SO}}}\rvert$	0.063	0.57	0.569	−0.155	0.282
Length > 1	$R^{\text{Obs}} - R^{\text{SPNE}}$	−176.841	−9.50	0.000	−213.315	−140.367
	$R^{\text{Obs}} - R^{\text{SO}}$	141.551	7.61	0.000	105.077	178.025
	$\Delta = \lvert\frac{R^{\text{Obs}} - R^{\text{SPNE}}}{R^{\text{Obs}} - R^{\text{SO}}}\rvert$	1.249	4.22	0.000	0.670	1.829

Note: Test results for the high-uncertainty (low-uncertainty) condition are based on 164 (123) observations corresponding to games terminated in the first period (Length = 1), and on 136 (147) observations corresponding to games lasting for more than a single period (Length > 1). Due to the "panel" nature of our data, we use a "clustering" specification that allows for intragroup correlation in the computation of the standard-errors (10 groups in the high-uncertainty condition, and 9 groups in the low-uncertainty condition)

R^{Obs} and R^{SPNE} is about −14 tokens; it is not significantly different from zero at conventional significance levels using the Wald statistics. The mean differences between first-period group requests and predicted equilibrium and efficient values are both significantly different from zero for games lasting for more than a single period

(Length > 1). Mean group requests are 214 tokens below the equilibrium value, and 337 tokens above the efficient value. In order to evaluate whether the observed deviations from equilibrium requests are either larger or smaller than the observed deviations from efficient requests, the delta method (Oehlert 1992) was used to calculate the standard error and 95 percent confidence interval of the absolute value of the ratio of the estimated difference between observed requests and the respective equilibrium and efficient requests (Δ). The confidence interval for the ratio is [0.4; 0.9]. It indicates that the observed deviations from equilibrium requests are smaller than the observed deviations from efficient requests.

To complement the analysis of group behavior in the high-uncertainty condition, we computed the per-period mean square deviation (MSD) of requests from predicted requests (either SPNE or SO) for each group in each of the 30 played games. For each group separately, Panel A in Table 5 presents the number of games in which the MSD from the SPNE path is smaller than the MSD from the SO path. Also reported in the table are the binomial probabilities associated with the observed number of games under the null hypothesis that it is equally likely for either of the two predicted paths to result in the smaller MSD in any given game. The results show that the SPNE path is the best predictor of behavior for eight of the ten groups, and that for two of the groups we cannot reject the hypothesis that both paths are equally likely at a significance level of 5 percent. Defining success as an observation in which the SPNE path is the best predictor of group behavior, the probability of observing 8 or more groups following the SPNE path is 0.003 under the null hypothesis that the three events (SPNE, SO, or both) are equally likely. For any one-tailed significance level lower than 5 percent, we reject the null hypothesis in favor of the alternative hypothesis that the SPNE path is the overall best predictor of behavior for the groups in this uncertainty condition.

Considered jointly, these findings are summarized in the following observation.

Observation 1 *Groups in the high-uncertainty condition adopt decision strategies that quickly deplete the resource stock. Group requests are uniformly closer to the SPNE path than to the SO path.*

5.2 Low-uncertainty condition

Panel B in Tables 2 and 3 summarize the main results in the low-uncertainty condition. The median length of the games in the low-uncertainty treatment across all groups is two periods, with four of the nine groups (44 percent) registering a median length of one period. It is twice as large as the same median in the high-uncertainty condition. Again, none of the groups adopted a conservative path, with depletion of the resource stock occurring rather quickly.

Figure 2 depicts the probability of resource destruction as implied by the SO and SPNE paths, along with the observed proportions. Although the destruction probability curves are more dispersed than in Fig. 1, they are closer to the SPNE than the SO path.

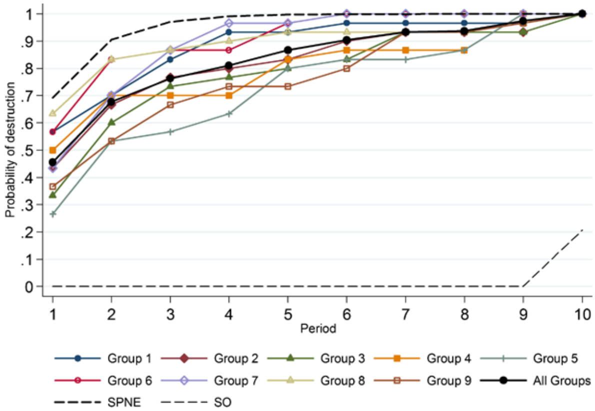
Panel B in Table 3 shows that group requests terminating the game immediately, which accounted for about 46 percent of the data, average 569. This mean request

Table 5 Number of games with smallest MSD from the SPNE path

Group	No. games	Proportion	Hypotheses	p-value	Decision
A. High-uncertainty condition					
1	17	0.567	H0: $p = 0.5$ H1: $p > 0.5$	0.292	Do not Rej. H0
2	29	0.967	H0: $p = 0.5$ H1: $p > 0.5$	< 0.001	Rej. H0
3	27	0.900	H0: $p = 0.5$ H1: $p > 0.5$	< 0.001	Rej. H0
4	28	0.933	H0: $p = 0.5$ H1: $p > 0.5$	< 0.001	Rej. H0
5	27	0.900	H0: $p = 0.5$ H1: $p > 0.5$	< 0.001	Rej. H0
6	17	0.567	H0: $p = 0.5$ H1: $p > 0.5$	0.292	Do not Rej. H0
7	30	1.000	H0: $p = 0.5$ H1: $p > 0.5$	< 0.001	Rej. H0
8	29	0.967	H0: $p = 0.5$ H1: $p > 0.5$	< 0.001	Rej. H0
9	20	0.667	H0: $p = 0.5$ H1: $p > 0.5$	0.05	Rej. H0
10	21	0.700	H0: $p = 0.5$ H1: $p > 0.5$	0.02	Rej. H0
B. Low-uncertainty condition					
1	21	0.700	H0: $p = 0.5$ H1: $p > 0.5$	0.02	Rej. H0
2	17	0.567	H0: $p = 0.5$ H1: $p > 0.5$	0.292	Do not Rej. H0
3	11	0.367	H0: $p = 0.5$ H1: $p < 0.5$	0.100	Do not Rej. H0
4	8	0.267	H0: $p = 0.5$ H1: $p < 0.5$	0.008	Rej. H0
5	4	0.133	H0: $p = 0.5$ H1: $p < 0.5$	< 0.001	Rej. H0
6	23	0.767	H0: $p = 0.5$ H1: $p > 0.5$	0.003	Rej. H0
7	30	1.000	H0: $p = 0.5$ H1: $p > 0.5$	< 0.001	Rej. H0
8	27	0.900	H0: $p = 0.5$ H1: $p > 0.5$	< 0.001	Rej. H0
9	15	0.500	H0: $p = 0.5$ H1: $p > 0.5$	0.572	Do not Rej. H0

Note: The per period mean square deviation (MSD) of requests from predicted requests for each group in each game $k = 1, \ldots, 30$, is computed as $\sum_{tk=1}^{l_k} (R_{tk} - R^*_{tk})^2 / l_k$, where R_{tk} is the observed group request in period t of game k, R^*_{tk} is the respective prediction (either at the SPNE or SO path), and l_k is the length of game k. For each group, we define a "success" as a game in which the MSD from the SPNE path is smaller than the MSD from the SO path. Let s_g represent the number of successes for each group. Under the null hypothesis that it is equally likely for either of the two predicted paths to result in the smaller MSD in any given game (H0: $p = 0.5$), the probability of observing at least s_g successes (H1: $p > 0.5$) in 30 games is given by $(\frac{1}{2})^{30} \times \sum_{i=sg}^{30} (\frac{30}{i})$, and the probability of observing at most s_g successes (H1: $p < 0.5$) in 30 games is given by $(\frac{1}{2})^{30} \times \sum_{i=0}^{s_g} (\frac{30}{i})$. In each case, construction of 95 % confidence intervals (available from the authors) around the proportions allowing for intragroup correlation does not change the hypotheses testing' decisions

Fig. 2 Probability of destruction: Predicted (SO, SPNE) and observed values under the low-uncertainty condition



compares closely to the equilibrium prediction of 588 tokens. The mean first-period group requests for games longer than one period is 412 tokens. These requests are in between the efficient and the equilibrium values.

Panel B in Table 4 addresses the issue of whether first-period requests are significantly different from the SPNE and SO paths. In games terminating in the first period, the mean difference between R^{Obs} and R^{SPNE} is -19 tokens; the null hypothesis of zero difference could not be rejected by the Wald test at conventional significance levels. The mean differences between first-period group requests and predicted equilibrium and efficient values are both significantly different from zero for games lasting for more than a single period (Length > 1). Mean group requests are 177 tokens below the equilibrium value, and 142 tokens above the efficient value. Although the absolute value of the ratio of these two differences is greater than 1, suggesting that the distance between observed requests and the SPNE prediction is larger than the distance between observed requests and the SO prediction, the computed confidence interval for the ratio is [0.7; 1.8]. Thus, at the 5 percent significance level, we cannot reject the hypothesis that the observed deviations from the SPNE path are equal to the observed deviations from the SO path.

Panel B in Table 5 addresses the issue of whether groups' behavior is better described by the SPNE or the SO path. The results show that the SPNE path is the best predictor of behavior for four of the nine groups. The SO path is the best predictor of behavior for two other groups, and the results are inconclusive for the remaining three groups. Defining success as an observation in which the SPNE path is the best predictor of group behavior, the probability of observing four or more groups following the SPNE path is 0.35 under the null hypothesis that the three events (SPNE, SO, or both) are equally likely. Therefore, we do not reject the null hypothesis at conventional significance levels.[9]

We summarize these findings in the following observation.

[9] As pointed out by one of the referees, because the observed effects at the group level could result from the mere aggregation of weak effects at the individual level, we also computed the per-period MSD of individual requests from predicted individual requests (either SPNE or SO) for each subject in each of the 30 played games. The results show that the SPNE path is the best predictor of individual behavior for 24 out of the 54 subjects (44.4 %) in the low-uncertainty condition, and for 36 out of the 60 subjects (60 %) in

Observation 2 *Groups in the low-uncertainty condition tend to adopt decision strategies that quickly deplete the resource stock. However, the SPNE path is not uniformly the best predictor of group requests, with some groups adopting behavior closer to the SO path and other groups adopting behavior falling in between these two polar cases.*

5.3 Comparing uncertainty conditions

We would expect higher uncertainty about the size of the resource to elicit *higher* group requests, if groups adopt decision strategies, but to elicit *lower* group requests, if groups adopt path strategies leading to perfectly efficient outcomes. As seen above (Table 3), and consistent with the adoption of decision strategies, group requests are *higher* in the high-uncertainty condition than in the low-uncertainty condition.[10,11] Given that the same differences in requests generate different probabilities of resource destruction across different manipulations of uncertainty ranges, a general assessment of the effects of increased uncertainty is better accomplished by analyzing the implied differences in destruction probabilities rather than by analyzing the differences in requests observed across the different manipulations of uncertainty ranges.

Panels A and B in Table 6 report the estimated effects of the higher-uncertainty level on the implied probabilities of resource destruction by first-period requests. For completeness, also reported in Table 6 (panel C) is the estimated effect implied by all non-first-period requests. Given that the dependent variable is naturally bounded

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the high-uncertainty condition. In each case, these proportions do not differ from the observed proportion of groups with behavior closer to the SPNE path (4/9 and 8/10 in the low and high uncertainty conditions, respectively; the p-value of a proportions test is 0.23 in the high-uncertainty condition, not rejecting the null hypothesis that a proportion 8/10 is equal to a proportion of 36/60). Thus, the results at the individual level concur with those at the group level.

[10]This result was confirmed by regressing the natural logarithm of group requests on a dummy variable identifying the experimental conditions, while controlling for each of the dynamic games, the period within the game, and intra-group correlation. The statistical significance of the difference in the length of the games between the experimental conditions was also confirmed by a random effects Poisson regression controlling for each of the dynamic games and intra-group correlation (random-effects).

[11]A referee cautioned that although the efficiency index of the subgame perfect paths is approximately equal in the two uncertainty conditions, it is possible that the differences in α between them may have an important impact on behavior since the individuals' choice of α/n is presumably less attractive as it moves to a smaller value. Accordingly, we would expect to observe subjects' choice of the $\alpha/n = 25$ token value in the high-uncertainty condition to be less frequent than the subjects' choice of the $\alpha/n = 45$ token in the low-uncertainty condition. While this behavioral hypothesis points to the development of different experimental treatments, we do not find this behavior in the current experimental data. In fact, the choice of the 25 token is observed in 8.24 % of all the individual decisions in the high-uncertainty condition, whereas the choice of the 45 token is observed in 4.89 % of all the individual decisions in the low-uncertainty condition. On the other hand, the choice of the $\beta = 850$ tokens is more frequent in the high-uncertainty condition (representing 0.2 % all the individual decisions) than the choice of the $\beta = 730$ tokens in the low-uncertainty condition (representing 0.09 % all the individual decisions). Because the choice of these extreme values is very rare in both conditions, we also computed the proportion of individual decisions falling above a 25 % bandwidth around the mean request of the respective group members; these decisions account for about 1/4 of all individual decisions in both conditions (26.97 % and 24.87 % in the high and low-uncertainty conditions, respectively), suggesting that the difference in aggregate outcomes between the conditions is not affected by different propensities to choose extreme values by the subjects in each condition.

Table 6 Maximum likelihood estimates of treatment effects on destruction probabilities

Variable	Coefficient	Wald z statistics	p-value	Lower 95 % CI	Upper 95 % CI
A. Length of Games = 1					
HIGH	0.1232	4.39	0.000	0.0681	0.1782
B. Length of Games > 1—*First Period Requests*					
HIGH	0.1713	6.88	0.000	0.1225	0.2201
C. Length of Games > 1—*Non-First Period Requests*					
HIGH	0.1338	8.73	0.000	0.1038	0.1638

Note: Estimates in panel A (B) are based on 287 (283) observations corresponding to all first-period decisions made by groups in both conditions in single period games (in games lasting for more than a single period). Estimates in panel C are based on 748 observations corresponding to all non-first-period decisions made by groups in both conditions in games lasting for more than a single period. Given that the dependent variable in each case is naturally bounded between 0 and 1, the estimation of the models' coefficients uses the specification developed by Papke and Wooldridge (1996) for fractional dependent variables: the log-likelihood of observation i is specified as $l_i(\beta) = y_i \log[G(x_i\beta)] + (1 - y_i)\log[1 - G(x_i\beta)]$ for destruction probability y_i, explanatory variables x_i, parameter vector β, and some known function $G(.)$ satisfying $0 < G(.) < 1$, such as the logistic function. The reported marginal effect of the treatment variable HIGH is obtained as the difference between the estimated values of the nonlinear conditional mean function when HIGH takes the unit value (high-uncertainty condition) and when HIGH takes the zero value (low-uncertainty condition)

between 0 and 1, the estimation of treatment effects uses the specification developed by Papke and Wooldridge (1996) for fractional-dependent variables. In addition, because the conditional expectation function in the specification used is nonlinear (so as to generate predictions naturally bounded between 0 and 1), the estimated parameter value associated with the treatment variable does not directly measure the treatment effect on the mean value of the dependent variable. Thus, to aid in interpretation, the coefficient estimates reported in Table 6 are the marginal effects of a discrete change in explanatory variable HIGH taking the unit value for the high-uncertainty condition and the zero value for the low-uncertainty condition.

Table 6 shows that the implied probabilities of destruction induced by the higher request in the high-uncertainty condition are significantly higher than the probabilities of destruction observed in the low-uncertainty condition. Considering only the subset of games terminated in period 1, the probabilities of destruction are, on average, 12 percentage points higher in the high than the low-uncertainty condition. Moreover, the width of the 95 percent confidence interval indicates that we cannot reject the hypothesis that the difference in destruction probabilities between the two treatments is 10 percentage points, corresponding to the predicted difference generated by the SPNE paths. This result is not particularly surprising, given that group requests in both treatments are consistent with the respective SPNE paths for this subset of the data.

Considering only the first-period requests in the subset of games lasting for more than one period, the difference in destruction probabilities between the treatments is 17 percentage points, significantly higher than the predicted difference by the SPNE paths.[12] Because first-period requests in games terminated after the first period are lower than the predicted SPNE values in *both* treatments, it could still be the case that the difference in the implied destruction probabilities remained at about the 10 percentage points, generated by the respective SPNE paths. Clearly, this is not the case, suggesting that reducing uncertainty levels positively impacts resource conservation beyond what would be predicted by common inability of the groups to commit to future extraction rates (i.e., by behavior consistent with the SPNE path).

This observation is further corroborated by the results in Panel C, considering only the subset of all non-first requests in both treatments. Had groups approximated their requests to the SPNE paths after the first period of the game, then the mean differences in destruction probabilities between the treatments would have been 8.5 percentage points, since the difference declines systematically as the game evolves. Consistent with this pattern of behavior, we observe lower differences in destruction probabilities between the treatments in subsequent periods. However, as indicated by the 95 percent confidence interval, the difference is again significantly higher than would be predicted by groups approximating their respective SPNE paths.

Coupled with those summarized in Observations 1 and 2 above, these findings indicate not only that treatment effects cannot solely be attributed to Nash behavior, but also that it is groups' behavior in the low-uncertainty condition that explains the differential treatment effect with respect to equilibrium predictions.

These findings are summarized in the following observation.

Observation 3 *Compared with the high-uncertainty condition, the low-uncertainty condition elicits lower requests from the shared resource. Moreover, it also induces a qualitative change in groups' behavior in the sense that it positively impacts resource conservation beyond what would be predicted by groups adopting decision rule strategies under both conditions.*

6 Conclusions

The stochastic dynamic game-theoretic model proposed in this paper focuses on the effects of environmental uncertainty in time-dependent CPR dilemmas. While CPR users may extract resources over a predetermined and commonly known time horizon, a distinguishing feature of our model is that the duration of the game is determined endogenously by the players whose collective decisions determine the probability of an irreversible environmental outcome. The abrupt intrusion of salt water in coastal aquifers once the groundwater table declines below an unknown threshold level is an example of such an event. In the present model, if the resource stock level below which the irreversible outcome occurs is known in advance, then the optimal

[12] These results stand in contrast with the findings from previous experimental implementations of Suleiman and Rapoport (1988)'s single-stage game. Using uncertainty ranges of 500 and 750 tokens (similar to the 460 and 700 uncertainty ranges used in the present conditions), Rapoport and Suleiman (1992) report mean requests supporting the respective Nash equilibrium solutions, implying differences in destruction probabilities consistent with the equilibrium solutions.

resource use coincides with a unique symmetric equilibrium use guaranteeing survival of the resource over the finite horizon. As the uncertainty about an otherwise equally expected threshold level increases, resource use increases if users adopt decision strategies that quickly deplete the resource stock. Resource use decreases if users adopt path strategies guaranteeing that the unknown threshold level is never exceeded over the entire horizon.

In an experiment that manipulates the common uncertainty about the threshold resource level, we find that CPR users implement decision strategies that quickly terminate the game. Notwithstanding, reducing the uncertainty about the resource level induces a *qualitative* change in behavior with users more frequently maintaining a positive resource level for a longer duration (Observation 3). If replicated and extended, these results have potentially important theoretical and policy implications. At the theoretical level, they suggest decision strategies that CPR users may use when they may not make credible commitments. At the policy level, these results provide evidence that the reduction of environmental uncertainty by creating and disseminating more accurate scientific information may play a major role in long-range planning to elicit synergy between the economic and ecological systems that jointly govern the dynamic management of shared natural resources. Estimated as the difference between the high- and the low-uncertainty outcomes, the value of this information is an indicator to the policy maker about how much to invest in acquiring and disseminating information to the user that reduces uncertainty about the size of the CPR.

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