Theory and Decision

Individual and strategic behaviors in a dynamic extraction problem: results from a within-subject experiment in continuous time

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Individual and strategic behaviors in a dynamic extraction problem: results from a within-subject experiment in continuous time*

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Abstract

We conduct a laboratory experiment to test a continuous-time model that represents a dynamic groundwater extraction problem in an infinite horizon. We compare the observations to the equilibrium path of the usual behaviors, for the case where the player is alone in extracting the resource (optimal control) and when two players extract the same resource simultaneously (differential game). We use a within-subjects design. This allows us to identify individual profiles of players playing alone and then characterize groups based on their composition with respect to these individual behaviors. We find that approximately a quarter of the players and groups succeed in playing (significantly) optimally, and none behave myopically. We also identify other categories of players and groups that account for nearly 50% of the observations and that require attention.

Keywords : Differential Games; Dynamic Optimization; Experimental Economics; Renewable Resources; Applied Econometrics

JEL Codes : C01; C73; C91; C92; Q20

1 Introduction

Although Ostrom (1990) shows that in numerous cases, institutional arrangements emerge without government intervention, the "tragedy of the commons", first mentioned by Hardin in 1968, is still relevant today for many common resources, like forests or groundwater, that continue to be overexploited (Boyd et al., 2018; Frischmann et al., 2019). Consequently, this market failure has attracted the attention of many natural resource economists over the past several decades. Until the 1970s, common-pool resources (CPRs) were conceptualized using static models. However, to keep up with the reality, it is necessary to account for the evolution of these resources over time and to study the behavior of agents in a dynamic context. Dynamic models are generally distinguished according to whether they are based on discrete or continuous time. Models based on the latter, called differential games, are widely used to model economic problems (Dockner et al., 2000), but very few are tested in the laboratory, especially on the issue of CPR. One of the reasons for this is that these games are quite complicated to implement with experimental economics methods. To our knowledge, only Tasneem et al. (2017) test a differential game in the lab. They focus on the feedback pattern to determine whether subjects adopt a linear or nonlinear strategy. We contribute to the literature by proposing a differential CPR game model and testing various types of behaviors in a continuous-time experiment.

Our CPR model is based on that of Rubio & Casino (2003). We consider a problem of groundwater extraction in continuous time with an infinite horizon and determine the equilibrium paths for three well-identified types of behavior: myopic, feedback, and optimal. In addition, we develop the experimental protocol that creates laboratory conditions close to those of the model. This allows us to collect data and compare them to the theoretical predictions. Our main contributions to the existing literature are the following. First, we propose a rare study that brings CPR differential games into the laboratory and is the first to consider socially optimal and myopic behaviors in addition to feedback behavior. Second, we go beyond these theoretical patterns of behavior by proposing new categories based on observations. Finally, we are, to our knowledge, the first to analyze the extraction decisions of individuals both with and without strategic interactions in a within-subject design. This allows us to (i) identify individual player profiles and (ii) study how players behave in strategic interaction situations. That is, we identity the profiles of the players pairs that succeed in adopting optimal behavior and study how individual profiles observed when subjects play alone evolve when those subjects are placed in a strategic interaction context. We also make two secondary contributions. First, we present the experimental protocol allowing the implementation in the laboratory of a continuous-time model with an infinite horizon. Second, to compare the behavior of subjects in the laboratory to theoretical projections, we propose combining mean squared deviation statistics and linear regressions.

In the optimal control scenario, we find that slightly more than one-quarter of the players behave as predicted by the optimal theoretical pattern. A further 50% percent fall into two distinct categories based on similarities in the observed trajectories of their behavior – we named these player profiles of players respectively the *Convergent* and the *Under-Exploiter*. In the two-players game, we find 20% of groups that exhibit a trajectory significantly close to the socially optimal one (the cooperative solution). Most of these groups include at least one player who had already behaved optimally when extracting the resource alone. We also identify groups of *Convergent* and *Under-Exploiter* groups in the game and a new category that brings together groups that overexploited the resource (the *Over-Exploiter*). Overall, we show that the behaviors predicted by the theoretical models represent only one-fourth of the experimental observations in the optimal control scenario and in the game. This indicates further investigation is needed, as well as models that better fit actual behaviors. We hope that this article offers a basis for future research on this fruitful topic.

The remainder of the article is organized as follows. In Section 2, we review the literature on dynamic CPR, focusing on studies that test their model in the laboratory. In Section 3, we describe our theoretical setup. In Section 4, we explain the experimental design and how we implement the continuous-time and infinite-horizon models. In Section 5, we present the results. We conclude this article in Section 6.

2 Related Literature

The management of common resources has been an important area of research for many decades. Studies were initially conducted using static models without taking into account the evolution of the resources over time. The adoption of a dynamic framework allows this evolution to be captured through one or more state variables. Closer to reality, dynamic models can determine the evolution of the resource according to its own natural growth and the extractions by individuals or groups of individuals (Basar & Olsder, 1999; Dockner et al., 2000; Haurie & Zaccour, 2005; Engwerda, 2005; Van Long, 2010). However, even if they are very useful from a theoretical point of view, dynamic models are complex to test in the laboratory. As a result, very few scholars focusing on dynamic models perform laboratory experiments, and most experiments are in discrete time.[1]

In this article we test a CPR game in continuous time with an infinite horizon. The aim of this section is to present a selection of studies that constitute important steps in the implementation in the laboratory of dynamic games in continuous time with an infinite horizon. We start by presenting two papers studying dynamic CPR models in discrete time with a finite horizon (Herr et al., 1997; Hey et al., 2009). Then we present two papers studying dynamic CPR models in discrete time with an infinite horizon (Suter et al., 2012; Vespa, 2020). Finally, we present pioneering papers on the implementation of continuous time in the laboratory (Oprea et al., 2014; Bigoni et al., 2015), before describing the paper closest to ours (Tasneem et al., 2017). For a more detailed review of this literature see Tasneem & Benchekroun (2020) and Djiguemde (2020).

One of the first studies to experiment with a dynamic CPR model in the laboratory is Herr et al. (1997). In their groundwater model with n players, the authors compare static and discrete-time dynamic frameworks with a finite horizon. In the former, extraction by a player in a given period produces a negative externality (through the cost of extraction) for the other players in that period only. In the latter, the externality is present in both the current and following periods. More precisely, the marginal cost

[1] It should be kept in mind that dynamic common-pool games constitute a small part of dynamic games, which are a very rich environment (Vespa, 2020).

from one period to the next is equal to the cost of the last extraction unit ordered, plus a constant. As a result, costs increase monotonically with each repetition. Observations from the experiment show that as compared to the case for the static framework, the tragedy of the commons is exacerbated in the dynamic framework due to the higher number of myopic behaviors.[2]

Considering a discrete-time dynamic model with a finite horizon, Hey et al. (2009) study the management of a fishery by a single agent who makes harvesting decisions. The authors focus on the role in decisions of information such as the number of fish units and the species growth function. They observe that without information, subjects have a biased perception of the evolution of the resource and, as a result, perhaps out of caution, they under-harvest compared to the optimal trajectory. With a noisy information environment, they exhibit a pulse behavior, consisting of alternating periods of extractions and non-extraction. Finally, when subjects have accurate information, they keep constant the resource stock and their extraction in an attempt to control the dynamic of the system.

In a discrete-time dynamic model, but this time over an infinite horizon, Suter et al. (2012) investigate how the introduction of the spatial characteristics of an aquifer influence the pumping decisions of individuals. In their experiment, the authors ran four treatments in a between-subject design. In the first three treatments, players played in groups of six, while in the last treatment, they played without interaction. In one of the treatments, the cost function was the same for all players, while in the other two treatments, the cost function was asymmetric, depending on the location on the 2x3 lattice. The main result of the study is that in the 6-player game with symmetric costs, the proportion of observed behavior that is myopic is higher than in the other cases (optimal control and games with asymmetric costs).

Another paper that uses a discrete-time framework with an infinite horizon is that of Vespa (2020). The author conduct an experimental study of the trade-off between opportunistic behavior and efficiency within a dynamic common-pool game. Using a simplified version of Levhari & Mirman (1980), they study the extent to which sub-

[2] Gardner et al. (1997) and Mason & Phillips (1997) also experiment with a discrete-time dynamic model in the laboratory, Gardner et al. (1997) to address the issue of property rights, and Mason & Phillips (1997) to address the issue of the impact of group size on cooperation.

jects in the laboratory can reach efficient outcomes in a dynamic common-pool game. In their experiment, two agents share access to a savings account and must simultaneously and independently decide how much to withdraw in each period. The total amount available in the next period is determined in-between periods by the unused funds, which grow at an exogenous rate of interest. The infinite horizon was implemented as an uncertain horizon. The main finding was that, unlike an infinitely repeated prisoner's dilemma, a dynamic common-pool game involves greater strategic uncertainty. Thus, as the stock of funds increases, achieving cooperation in a dynamic common-pool game becomes more difficult even when the incentives to cooperate are relatively large.

Some authors have shown interest in the implementation of continuous-time models in the laboratory. Oprea et al. (2014) are among the first to perform continuous experiments in the laboratory.[3] They compare continuous and discrete-time decisions in a public goods game. In the continuous-time treatment, players could change their decision at any time during the game's 10 minutes duration, with an immediate information available about the updated payoffs and the choices made by the others in the group. In the discrete-time treatment, players played ten one-minute periods during which they could change their decision without information about the choices of the other members of their group. At the end of the one-minute period, the last decision made applied for the period. The authors find that in continuous-time, players contribute slightly more to the public good than they do in discrete-time and that this observation is stronger when communication between players is allowed. For the authors this is because the players' decision adjustments are faster and thus make it possible for cooperation to emerge in the group.

Bigoni et al. (2015) investigate the impact on the extent of cooperation of the time horizon in a prisoner's dilemma game played in continuous time. The authors' experiment is composed of four treatments that differ along two dimensions, the period

[3] Ryan Oprea and Daniel Friedman conducted continuous time experiments slightly before Oprea et al. (2014), but we choose to present their 2014 paper because it is the closest to our own. Indeed, as CPR games, public goods games present relatively complex social dilemmas compared to Hawk-Dove games (Oprea et al., 2011) or prisoner's dilemma games (Friedman & Oprea, 2012).

duration – short (20 seconds) vs. long (60 seconds) – and whether this duration is deterministic or stochastic (with an average realized duration close to that of the deterministic duration). In treatments where the duration is deterministic, players knew they had 20 seconds (or 60) to make decisions. They could change their decision and observe the consequence of that (individual payoff) as often as they wanted during the time of play. The highest level of cooperation is observed when the period duration is long and deterministic. The main explanation is that this combination of conditions favors the prevalence of the cut-off strategy, which involves cooperating until a certain point in time and then, toward the end of the period, defecting forever. Conversely, the short stochastic duration favors the use of the "tit-for-tat" strategy, which, on average, leads to weaker cooperation than the "cut-off" strategy.

Although Oprea et al. (2014) and Bigoni et al. (2015) conduct continuous laboratory-based experiments, these experiments are not dynamic, as they do not account for the evolution of a state variable.[4] Instead, they use models belonging to the family of extensive games, as defined by Simon & Stinchcombe (1989).[5]

To our knowledge, only two papers have laboratory-tested dynamic models in continuous time over an infinite horizon; these are Tasneem et al. (2017) for differential games and Tasneem et al. (2019) for optimal control. These papers are the closest to what we propose in this study. However, while they focus on Markovian strategies, we are also interested in other types of behaviors such as feedback, myopic, and socially optimal behaviors. Furthermore, we study the manifestation of these behaviors both with and without strategic interactions. Tasneem et al. (2017) consider simultaneous exploitation of a common renewable fishery by two identical players, in a

[4] See also Leng et al. (2018) for a laboratory experiment that compares, in a minimum effort game, decisions in continuous time to decisions in discrete time.

[5] Simon & Stinchcombe (1989) defined, in a [0, 1] time interval, a finite set of agents and imposed some limitations on the decisions players could change. This allowed agents to play games in continuous time in the limit as the interval approaches zero. In this paragraph dedicated to quasi-continuous time, all expressions that refer to «continuous time» in fact refer to «quasi-continuous time». See Calford & Oprea (2017) for a laboratory implementation of the timing game developed in Simon & Stinchcombe (1989). Janssen et al. (2010) and Cerutti (2017) also run experiments in continuous time in the laboratory, but without an underlying theoretical model. Their objective is to implement renewable resources along both spatial and temporal dimensions. Their experiments are conducted in real time to simulate the real-life conditions of ecological systems.

linear-quadratic game, to determine whether subjects in the laboratory will choose between linear or nonlinear strategies. To that end, they build an experiment designed to ensure subjects have a good understanding of the idea of feedback strategies. The results suggest that most players employ nonlinear reasoning. Based on a similar experimental design, Tasneem et al. (2019) explore whether a single player can manage a renewable fishery in a sustainable and efficient manner. Their results suggest suboptimal behavior due to the initial over-extraction of the resource because of the trade-off between instantaneous payoff and the future sum of payoffs.

In this article, we start from the theoretical model of Rubio & Casino (2003), which we modify for implementation in the laboratory. Specifically, we modify the cost function so that it remains consistent outside the equilibrium paths. Next, we define the theoretical trajectories of three standard behaviors, the optimal behavior, the feedback behavior, and the myopic behavior. For the implementation in the laboratory of continuous time and an infinite horizon, we draw inspiration from Tasneem et al. (2017, 2019). However, our research question is different from theirs; we want to test the adequacy of the fit between theoretical and observed behaviors. Moreover, like Suter et al. (2012), we test our model under two conditions: when the individual is alone in extracting the resource (optimal control) and when two players simultaneously extract the same resource (two-player game in a strategic interaction). However, unlike Suter et al. (2012), we test these two conditions using a within-subject design. We proceed in this way so we can identify the profiles of players when they play alone and then study how they behave when placed in strategic interaction situations, including determining which profiles make up the pairs that succeed in adopting optimal behavior.

3 The model

We consider a continuous-time linear-quadratic model in which farmers harvest a renewable resource that can be assimilated to groundwater. Water is the only input in the production process, and for purposes of simplification, the aquifer is assumed to have parallel sides and a flat bottom.[6] At a given time t, extraction done by farmers gives them a revenue $B(w)$ depending only on the extraction rate w. They also incur a cost $C(H, w)$, which is positively dependent on the extraction rate w and negatively dependent on the level of the groundwater H. a, b, c_0 and c_1 are positive parameters. The farmers' instantaneous payoff is given by the difference between revenue and cost, as shown by Equation (1):[7]

$$\overbrace{aw - \frac{b}{2}w^2}^{B(w)} - \underbrace{\overbrace{\max(0,\ c_0 - c_1 H)}^{marginal\ cost\ (c(H))}\, w}_{C(H,w)} \tag{1}$$

One must keep in mind that H refers to the elevation of the water table above the bottom of the aquifer so that c_0 is the maximum average cost. Our model is based on that of Rubio & Casino (2003) adapted to a special case of a laboratory experiment in which we account for the positivity of the marginal or unitary cost $c(H)$. More precisely, most theoretical models make assumptions on the positivity of the marginal cost, considering for their solutions only situations where this constraint is verified. However, even in the case where our parameters verify that all theoretical solutions are in the admissible set (that is that extractions, resources, and costs are positive), subjects will generally not follow exactly the recommended theoretical behavior. This produces a piecewise marginal cost function, allowing us to study the different regime types, including the steady-state regime.

In the model, each farmer's problem is to choose, at time t, an extraction rate w, for all $t \in [0, \infty]$. We consider two specific situations. The first involves an optimal control problem, where a single farmer exploits the groundwater and can adopt either a myopic or an optimal behavior. The second situation refers to a game in which two identical and symmetrical farmers exploit the groundwater. Here we derive the feedback behavior, in addition to the behaviors mentioned above.

In an optimal control problem, the social optimum can be defined as a behavior in which a farmer's extraction decision allows them to maximize their discounted net payoffs to maintain the resource at an efficient level. The difference in the game, as

[6] We use a simple "bathtub" model to describe the groundwater extraction.
[7] We omit the subindex t when it is unnecessary.

compared to the optimal control problem, is that in the game, the resource is maintained at an efficient level by maximizing the joint discounted net payoff to all farmers. In this case, the social optimum is also called the cooperative solution. In both the optimal control problem and the game, the myopic solution is given by a situation in which the farmer is only interested in the maximization of their current payoff. Finally, the feedback equilibrium can be seen as a scenario in which farmers adopt non-cooperative behavior, maximizing their own discounted net payoffs and taking into account the evolution of the groundwater. Additional details for the different behaviors are provided in Appendices A and B.

4 Experimental Design

The experiment took place at the Experimental Economics Laboratory of Montpellier (LEEM), during the second half of 2018. A total of 70 students from the University of Montpellier participated.[8] Before describing the different steps of the experiment and the parameters used in the experimental game, we present the way we implemented the continuous time and infinite time horizon in the laboratory.

4.1 Continuous time and infinite horizon

The implementation of continuous time in the laboratory is challenging because, by definition, continuous time means that time does not stop. This is incompatible with the time that necessarily elapses between an individual's decision and its visible consequences on the resource and payoff. This time includes the sending of the information to the server, the calculations made by the server, the return of the information after these calculations, and their display on the screen of the player. In practice, the time that elapses between two instants must be short enough that the subject in the experiment feels like it is continuous. We chose to set one second as the time interval between two instants. To our mind, the second, even if not the shortest possible interval we could have implemented in the laboratory (Oprea et al., 2014; Tasneem et al., 2017, 2019), is nevertheless pertinent for our experiment; it is understood by everyone,

[8] The subject pool is managed by the ORSEE platform (Greiner, 2015), and has about 3 000 volunteers.

and enough time elapses between two seconds for computers to perform calculations and exchange information across the network. Moreover, the fact that one instant in the model corresponds to one second in the real time of the experiment facilitates the explanations in the instructions, and without doubt the understanding by the subjects.

From a practical point of view, the subject's computer sent the decision to the server every second, triggering its calculations and returning updated information (on the resource level and payoffs). Upon receiving this updated information, the subject's computer updated the graphs and information displayed on the screen.[9] Between two instants, we considered the player's decision unchanged, whereas the resource evolved continuously. In other words, the calculations were performed in continuous time, whereas the decisions made by the individuals and the information displayed were updated every second. To our knowledge, only Tasneem et al. (2017, 2019) use a procedure close to this one.[10] Concretely, the subjects had a horizontal cursor on their screen, that they could move during play whenever desired. The computer they were each at sent the value of the cursor to the server every second, and the server then used this value to perform calculations and return the updated information. Hence, if a subject did not move the cursor, the existing value was sent to the server and the same extraction level was applied.

The standard way to implement the infinite horizon in experimental economics is to set a probability that the current period is the final one (e.g., Suter et al., 2012; Vespa, 2020). On this approach, the subject does not know exactly when the repetitions will

[9] Technically, in the optimal control, a timer on the player's computer sent the extraction value on the cursor to the server every second, triggering its computations (new resource stock and payoffs). The server then returned the updated data to the player's computer. Upon receiving this data, the player's computer updated the graphs and displayed the numeric values. In the two-player game Player 1's computer had a timer that sent the current extraction on the cursor to the server every second. Player's 2 computer sent the value as soon as the player changed it, which set the current extraction for this player on the server side. When the server received the extraction from the computer of Player 1 (every second), it took the current extraction of Player 2 and performed the computations (total extraction of the group, new resource stock, and payoffs), and returned the updated data to both players. Upon receiving this data, the players' computers displayed the updated graphs and numerical values. In this way the time was perfectly synchronized for the two interacting players. A screenshot of the decision screen is provided in the Appendix.

[10] The experimental protocol is not sufficiently detailed in the stydy to confirm that this procedure was applied, in particular for computations between two instants.

end. However, this method has two drawbacks. First, if the probability is defined individually or even per experimental session, it implies different endings to the game, which means a different number of decisions and a different history. This complicates analysis and comparison. Second, it may be interpreted by the subject as an unknown end rather than an infinite horizon.

Another method is to use a continuation payoff. This involves adding the payoff if the game were to continue indefinitely to the current payoff with the player's current extraction unchanged. More precisely, for a given instant t, the computer calculates the payoff from instant t to infinity, on the assumption that the player keeps the same extraction level while the resource continues to evolve, and this continuation payoff is added to the current payoff. This procedure has two advantages. First, the player is informed at all times of their payoff at the infinite horizon with their current extraction decision, regardless of the actual end of the game. They can, therefore, observe the consequences of their choice over the long term. Second, it implies that all the players in the experiment play for the same effective duration, set by the experimenter, making data more easily comparable and facilitating analysis.

This "scrap value" mechanism is also the one adopted by Tasneem et al. (2017, 2019). However, in their protocol, the game stops if the player holds their decision unchanged for thirty seconds or if the resource is exhausted. We proceeded differently. First, even if the subject left their decision unchanged, the game continued until the end. In this way, all subjects played for the same amount of time and could modify their decision even after 30 seconds without any change. In addition, rather than stopping the play, we defined a rule for when the available resource became scarce: if the extraction was greater than the available resource, the server automatically set the extraction to zero. This rule also applied in the game; if the total extraction exceeded the resource stock, the extraction of both players was set to zero. The rule was explained in the instructions and was commonly understood. If implemented, the players could see when their extraction was set to zero by the computer. This information was obvious, on the graph that displayed their extraction and on the slider since the cursor moved automatically to the corresponding zero mark. The player had to move the cursor if they wanted to then extract a positive quantity. Other rules would have been possible, such as providing the remaining available resource or, in the two-players game, dividing the remainder equally or proportionally to the quantity requested. We thought it easier for subjects' comprehension to keep the same rule whether they played alone or shared the resource. Moreover, setting an allocation rule for the extraction in proportion to the available resource would have led to a multiplicity of equilibria. This would have greatly complicated the empirical strategy needed to compare laboratory results to equilibrium paths without revealing any (particularly) interesting information on the behavior of agents.

4.2 Experiment

The experiment was divided into two parts : in the first part, subjects played alone, and in the second part, they played in groups of two. On arriving in the laboratory, subjects read the instructions for Part 1. These instructions specified that there were two independent paid parts and that subjects would receive the instructions for Part 2 after completing Part 1. The instructions explained the evolution of the resource, the decision to be made (expressed as a rate of extraction), the cost of extraction, and the payoff calculation. After the time allowed for silent individual reading, an experimenter read the instructions aloud. Subjects then answered a computerized comprehension questionnaire to ensure they understood the resource dynamics and the payoff calculations. Subjects were allowed to ask clarifying questions. To ensure that subjects had a good understanding of the dynamic environment and became familiar with the graphical interface, they played two five-minute training phases for each part before an effective five-minute phase, which counted in calculating the payoff of the experiment. A session lasted around 90 minutes.

As a first step, subjects had to choose an initial level of extraction (corresponding to instant $t = 0$) between 0 and 2.8, by moving a cursor on a graduated slider, which allowed values with two decimals. We chose these values to ensure a positive benefit, given the quadratic nature of our benefit function. Figure D.2 in the Appendix shows the concave revenue curve, where the maximum benefit is reached for an extraction rate of 1.4. Figure D.3 shows the unitary cost function, which decreases as the level of groundwater increases and becomes equal to zero as soon as the level of the groundwater reaches the steady-state level of 20. Once the initial extraction rate was selected, a new screen appeared, and the countdown began. Subjects could change their extraction rate at any moment by simply moving the cursor. Every second the graphic and textual information on the screen was updated. More precisely, the screen was composed of three graphs and a textual area: the graph at the top left showed the subject's extraction rate; the graph at the bottom left displayed the evolution of the resource and the graph at the top right showed the subject's payoff for the part, which corresponded to the sum of the cumulative and continuation payoff. At the bottom right of the screen, the same information was displayed in text form. All the subjects in the room started and finished at the same time. A screenshot of the user interface is given in Figure D.4 in the Appendix.

Once Part 1 was completed, the subjects were given new instructions, specifying that the environment remained the same except that instead of extracting the resource individually, players would now be doing so in pairs. Part 2 also included two identical and successive training phases, followed by the third phase for pay. It was also understood that the pairs were randomly re-formed after each phase. The screen, given by Figure D.5 in the Appendix was identical to that in Part 1, except that in the top-left graph, two additional curves showed the extraction of the other player and the total extraction of the pair.

4.3 Parameters

Table 1 reports the parameters used in both the theoretical model and the experiment, which were determined by taking into account theoretical and experimental constraints. First, the speed of convergence to the steady state had to be reasonable, neither too short – a few seconds – nor too long – several minutes. In fact, the steady state can be interpreted as a static framework, which simplifies the experiment and allows subjects to stabilize their extraction rate and pay attention to the sustainability of the resource. Given the infinite horizon, this required setting a small discount rate r.

Second, as the steady-state extraction rate is the same for all types of behavior, we wanted a clear difference in the paths leading to the steady-state groundwater level

Variable	Description	Value
a	Linear parameter in the revenue function	2.5
b	Quadratic parameter in the revenue function	1.8
c_0	Maximum average cost	2
c_1	Variable cost	0.1
$c_0 - c_1 H$	Marginal or unitary cost	$2 - 0.1H$
r	Discount rate	0.005
R	Natural recharge (rain)	0.56
α	Return flow coefficient	1
H_0	Initial resource level	15

Table 1: Parameters for the experiment

for the socially optimal, feedback, and constrained myopic behaviors. More precisely, we chose these parameters to obtain a steady state for the social optimum, leading to a high level of groundwater while lowering the level of groundwater for the Nash feedback and constrained myopic paths. Third, for simplification, we set α, the return flow coefficient, equal to 1, and the natural recharge R somewhat smaller to avoid floods and highlight the renewable nature of the resource.[11] Figures 1 and 2 report the theoretical trajectories for the different types of behavior, for both the optimal control problem and for the game, according to the chosen parameters.

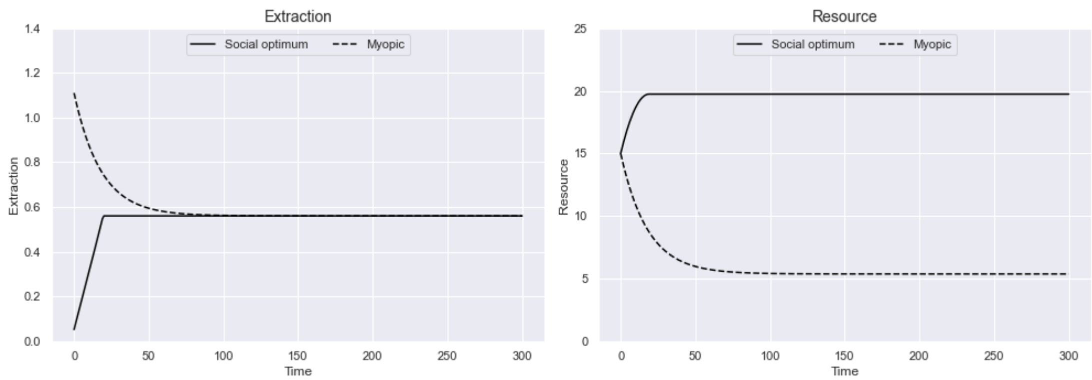

Figure 1: Extraction rates and groundwater levels for the optimal and myopic behaviors in the optimal control problem

[11] The return flow coefficient is the quantity of water returning to the groundwater after each extraction.

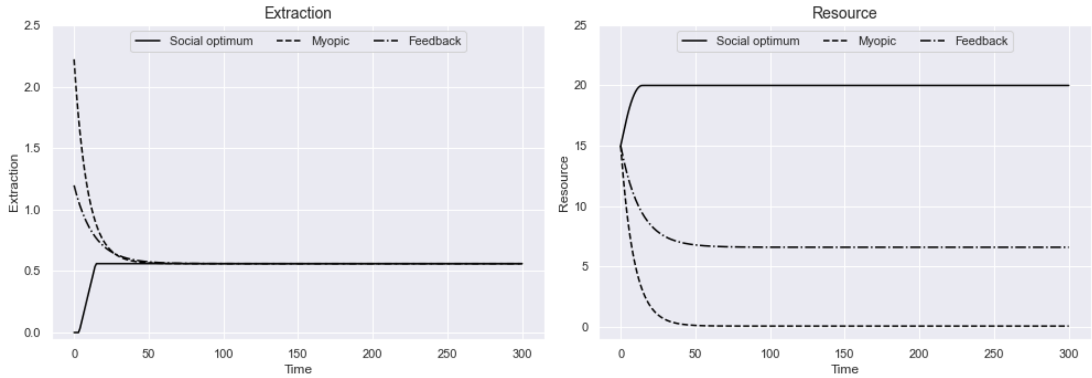

Figure 2: Extraction rates and groundwater levels for the optimal, feedback and myopic behaviors in the game

5 Results

5.1 Descriptive statistics

Figure 3 reports the evolution over time of the average extraction and the average resource in the optimal control problem and in the game. Visual inspection of the graphs led us to notice three main points. First, whatever the context (with or without interaction), on average, players started with a high extraction level, as myopic or feedback players would do. However, after a few instants (10 seconds in the optimal control and 15 in the game), the players adjusted their extraction level to a rate lower than 0.56 (the natural recharge) and therefore let the resource increase. Consequently, the curves that depict the evolution of the resource seem to be more consistent with the optimal than the myopic path (and feedback in the game). Second, there is more dispersion in the game than in the optimal control problem (the colored areas represent the 95% confidence interval around the mean). As will be shown with a more detailed analysis in the next subsections, this dispersion explains why, on average, the resource is close to 20 in the second half of play. Third, in the optimal control, the average stock exceeds 20 after 1'40" (100 seconds) and stays above that level until the end, meaning that some players under-exploit the resource, as also observed by Hey et al. (2009) and Tasneem et al. (2019).

Table 2 reports the averages and standard deviations based on individual and group observations depending on the interaction context.[12] The difference in initial extraction (0.655 vs. 0.741) is not statistically significant, and neither is the difference at the last instant (0.579 vs. 0.551). However, the difference in extraction levels between the control and the game is significantly different from zero when considering the total duration of play. Conversely, the average stock of the resource is not significantly different between the two contexts on average (18.320 vs. 21.000), but it is if we focus on the last instant (24.183 vs. 20.242).

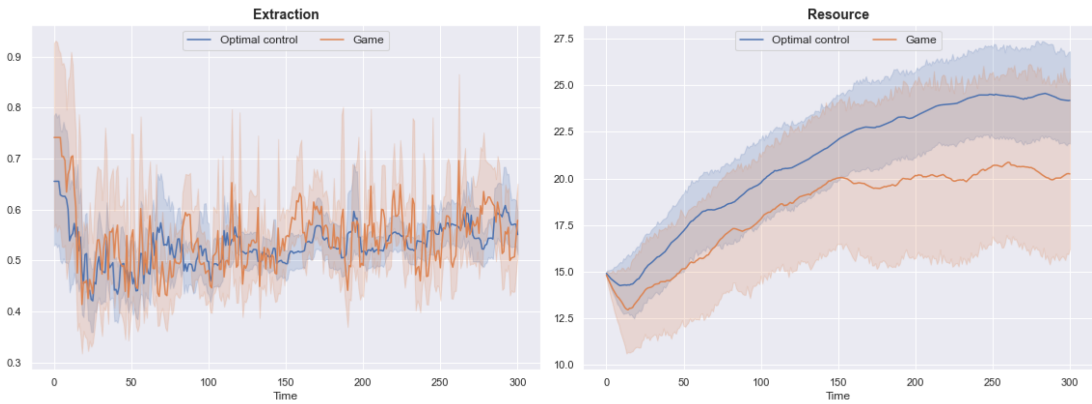

Figure 3: Evolution of extraction and resource in the optimal control problem and the game. For the game the extraction curve represents the average group extraction. The area around the curves represents the 95% confidence interval.

	Observations	Extraction t=0	Extraction Average	Extraction t=300	Resource Average	Resource t=300
Optimal Control	70	0.655	0.529	0.551	21.000	24.183
		(0.560)	*(0.190)*	*(0.183)*	*(4.363)*	*(10.657)*
Game (Group level)	35	0.741	0.543	0.579	18.320	20.242
		(0.543)	*(0.236)*	*(0.225)*	*(3.840)*	*(14.173)*
Mann-Whitney two-sided p-value		0.217	0.012	0.220	0.112	0.012

Table 2: Summary statistics of the optimal control problem and the game.

Since the model and the experiment consider an infinite horizon, the last instant of play is of particular importance since it determines whether the resource will vanish

[12] We are aware that the Mann-Whitney test usually involves independent samples and that a Wilcoxon test would be more appropriate. However the former imposes the same number of observations, which is not the case here since we have, by construction, half as many observations in the game as the optimal control.

in the long run. Specifically, if the extraction at $t = 300$ exceeds the natural recharge (0.56), the resource will be depleted in the future. Figure 4 shows the distribution of extraction rates and resource stocks at the end of the 5 minutes of play in the optimal control problem and in the game. In the game 14 groups out of 35 (40%) set the last extraction to a level strictly greater than 0.56, and 17 players out of 70 (24.29%) in the optimal control did the same; this difference is, however, not statistically significant based on a Fisher Exact Test (p-value=0.115). More than 50% of the players in the optimal control problem ended with a resource stock between 20 and 30, compared to less than 40% in the game. A similar proportion of groups ended with a resource stock between 10 and 20, which explains why, in Figure 3, the curve representing the game is close to 20 at the end of play. As a result, the two distributions are significantly different according to a Kolmogorov-Smirnov test (p-value=0.005).

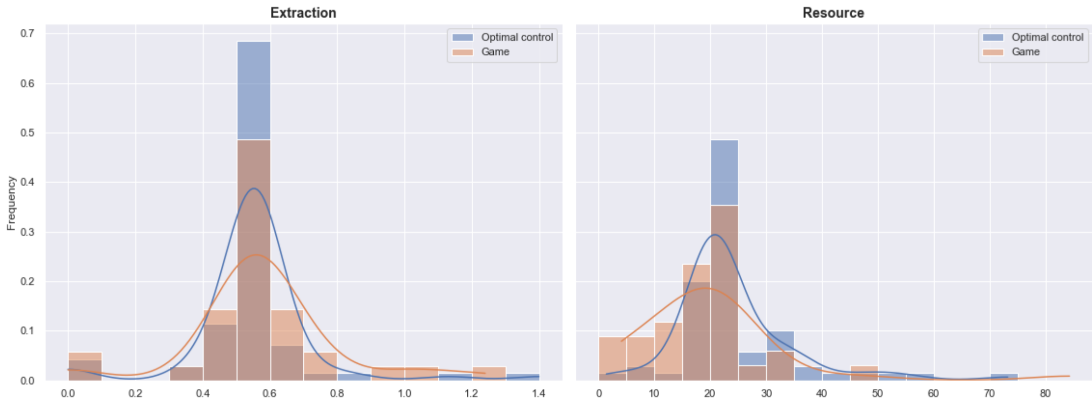

Figure 4: Distribution of the extraction rate and the resource stock in the last instant of play (t=300)

In sum, we observe an average extraction rate in the optimal control problem that is lower than the extraction rate of groups in the game and, as a result, an average resource stock that is higher, particularly toward the end of the play. This is in line with the competition for the exploitation of the resource induced by its nature as a CPR. Nevertheless, it is worth noting that groups in the game, on average, understood that it is socially optimal to let the resource increase to the steady state level of 20. A candidate explanation is that we used a within-subject design that allowed players to learn when playing alone.

5.2 Profiles

5.2.1 Empirical strategy

Each of the 70 subjects who participated in the experiment made 301 (from $t = 0$ to $t = 300$) extraction decisions in the optimal control problem and in the game. With this dataset we intend to determine whether players exhibited myopic or optimal behavior (or feedback behavior in the game). We start by examining the behavior of players in the optimal control problem. The common practice in the related literature is to compute the mean squared deviation (MSD) to identify the theoretical pattern of extraction to which a player's extraction comme closest; for example, Herr et al. (1997). The minimum MSD gives the player's type. The MSDs are calculated for each player such as:

$$
\begin{aligned}
MSD^{th}_{my} &= \frac{\sum_{t=1}^{T}\left(w(t) - w(t)^{th}_{my}\right)^2}{T} \\
MSD^{th}_{op} &= \frac{\sum_{t=1}^{T}\left(w(t) - w(t)^{th}_{op}\right)^2}{T}
\end{aligned}
\tag{2}
$$

where $w(t)$ is the extraction rate of the player at time t, $w(t)^{th}_{my}$ is the constrained myopic theoretical extraction at time t, and $w(t)^{th}_{op}$ is the optimal theoretical extraction at time t. A player is classified as myopic or optimal depending on which of their MSD, MSD^{th}_{my} or MSD^{th}_{op} is the smallest.

However, comparing the extractions of the player to the theoretical constrained myopic and optimal extraction in this way is imperfect since a player can make mistakes and begin to play perfectly optimally after, say, for example, 30 seconds. This would not be captured correctly by this method. For instance, if a player under-extracts for the first 30 seconds, the optimal extraction at time $t = 31$, given the observed groundwater level H (called conditional, $w(31)^{c}_{op}$) is greater than the optimal extraction if the player would behave perfectly optimally on the same 30 seconds ($w(31)^{th}_{op}$). Thus, in order to correctly identify a player's behavior type - myopic or optimal -, for the rest of the article, we compare observed extraction to conditional extractions. Conditional extractions are computed with respect to the $t - 1$ groundwater level. The conditional groundwater level H^c is also computed, using an approximation involving the observed $t-1$ groundwater level, the natural recharge, and the conditional extraction. Thus, the MSDs we will consider are given by the following formula:

$$\begin{aligned} MSD^c_{my} &= \frac{\sum_{t=1}^{T}\left(w(t)-w(t)^c_{my}\right)^2}{T} \\ MSD^c_{op} &= \frac{\sum_{t=1}^{T}\left(w(t)-w(t)^c_{op}\right)^2}{T}, \end{aligned} \tag{3}$$

where $w(t)^c_{my}$ is the conditional constrained myopic extraction of the player at each second, and $w(t)^c_{op}$ is the conditional optimal extraction of the player at each second. Players are classified as myopic or optimal depending on which MSD, MSD^c_{my}, or MSD^c_{op} is the smallest.

The discommoding feature of the classification of players based on the MSD alone, is that a player is always classified, even if they do not follow the theoretical pattern studied in any way.[13] To overcome this flaw, we add a second criterion, based on a regression analysis. More precisely, if we suppose that for a given player, we have:

$$\begin{aligned} &w(t)^c_{my} < w(t)^c_{op}, \quad \mathit{or} \\ &w(t)^c_{my} > w(t)^c_{op}, \end{aligned} \tag{4}$$

then we will perform the following regression:

$$\begin{aligned} &w(t) = \beta_0 + \beta_1 w(t)^c_{my} + \varepsilon_t, \quad \mathit{or} \\ &w(t) = \beta_0 + \beta_1 w(t)^c_{op} + \varepsilon_t. \end{aligned} \tag{5}$$

Therefore, we will consider a player to be significantly myopic (or optimal) if β_1 is positive and significantly different from 0. Consequently, players will be classified either as *Myopic*, *Optimal*, or *Undetermined*.[14] Regarding the econometric time series

[13] To take a concrete example, instead of comparing the player's extraction $w(t)$ to the conditional constrained myopic and conditional optimal extraction, $w(t)^c_{my}$ and $w(t)^c_{op}$, we could compare it to the temperature in Moscow and Istanbul, and we would find that our player's extraction is closer to the temperature in Moscow or in Istanbul, because one MSD will always be smaller than the other, even if completely irrelevant.

[14] An alternative is proposed by Suter et al. (2012), who run a similar regression (without the constant

treatments, we implement an augmented Dickey-Fuller test to detect the presence of unit roots in the series. In the case of the non-stationarity of the variables, we run our regressions on differentiated series. Serial correlation of the error terms is dealt with using Newey-West standard errors and sensitivity tests using 1, 5, and 10 lags are implemented.[15] A player is classified as *Undetermined* if the trajectory of their decisions is neither significantly *Optimal* nor *Myopic*. We follow the same method to analyze the game data, but these are analyzed at the group level and for the three rather than the two theoretical behaviors, namely myopic, optimal, and feedback. An example of the application of the methodology is given in Appendix C.

5.2.2 Optimal control

With the MSD classification method, we find 65 optimal players (92.86%) and 5 myopic players (7.14%), as shown in Figure 5. This figure presents the location of players with respect to the conditional optimal MSD (MSD^c_{op}) on the y-axis and the conditional constrained myopic MSD (MSD^c_{my}) on the x-axis. Players located above the bisector are considered as myopic ($MSD^c_{op} > MSD^c_{my}$) and those located below the bisector as optimal ($MSD^c_{my} > MSD^c_{op}$).

However, as explained in the previous subsection, the sole criterion of the MSD is not fully satisfactory and may lead to misinterpretations. Therefore, we applied our proposed regression filter, which drastically changed the picture. Specifically, we now find only 19 players (27.14%) that can be classified as significantly *Optimal* (olive markers in Figure 5), instead of 65, while the remainder (51, 72.86%, brown markers in Figure 5) is classified as *Undetermined*, since they cannot be classified either as significantly *Optimal* or *Myopic*.

term) and consider that a player follows a given behavior if the coefficient is not significantly different from 1. A natural way to do this is to implement a Wald test with:

$$\begin{cases} H_0 : \beta_1 = 1 \\ H_A : \beta_1 \neq 1, \end{cases} \quad and \;\; W = \frac{(\hat{\beta_1} - 1)^2}{var(\hat{\beta_1})} \rightarrow F_{(1,300)}$$

In this case, a very imprecisely estimated coefficient β_1 (very large $var(\hat{\beta_1})$) will lead us to reject H_A and classify the player as myopic or optimal, while they follow neither an optimal nor myopic path. This is the reason we propose the alternative classification rule.

[15] We present regression results using 5 lags. Results using 1 and 10 lags are available upon request.

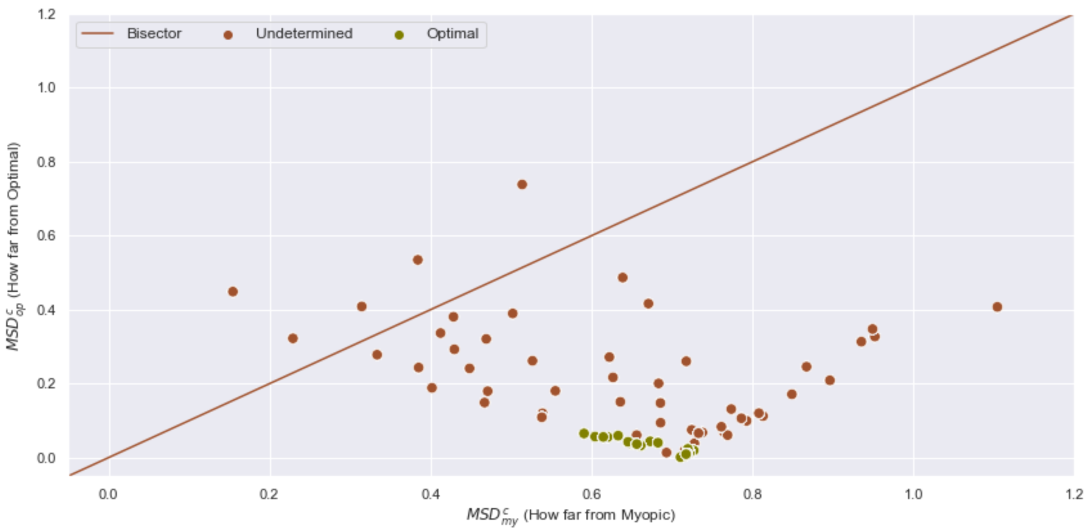

Figure 5: MSD position of players in the optimal control. Colors represent the identified profiles after the regression filter.

Since actual observations do not always match theoretical behaviors, it is usual to visually inspect individual curves to complete the analysis and gain more insight into behaviors (see Hey et al., 2009, for example). We followed this method and looked at the evolution of the extraction and resource stock for the 51 players that we classified as *Undetermined*.[16] This led us to identify two distinct patterns. In the first, players who started by decreasing the stock of the resource, with a pattern close to the myopic behavior, and after a short time let it increase slowly and regularly toward the optimal steady state. Since the evolution of the resource stock for these players converges toward the optimal solution, we name this category *Convergent*. We identified 15 players who could be placed in this category. Second, we found 17 players who mostly extracted less than the rate of natural recharge, and thus let the resource increase beyond the threshold where extraction is cost-free and called them *Under-exploiters*. Hey et al. (2009) and Tasneem et al. (2019) identify similar behaviors, which they interpret as a manifestation of prudence.

Figure 6 reports the evolution of the average resource stock of the different cate-

[16] The individual curves of each of the 51 players are available at `https://tinyurl.com/h45z7hrz`

gories identified. The solid blue line represents the players classified as significantly *Optimal* and the dotted black line nearby represents the theoretical trajectory of the socially optimal solution. As can be seen, even though these players behaved optimally, they did not let the resource increase fast enough. More specifically, on average, they reached the threshold of 20 after 101 seconds when, in theory, it should be reached after 20 seconds. Also, their steady-state level was slightly higher than the theoretical level.

Players classified as *Convergent* are represented by the dotted green line. In the beginning, the curve is very close to the theoretical curve for myopic behavior (dash-dotted black line), but it starts to move away after 25 seconds and goes slowly in the direction of the social optimum. On average, they reached the threshold of 20 after 259 seconds, which is significantly later than the players classified as *Optimal* (Mann-Whitney p-value=0.002). We suspect those players to be "nearsighted" during the first periods; that is they did not maximize their decision over the long term (infinite horizon) but over a finite horizon. Another possibility is that they were not sufficiently patient to let the resource increase rapidly to 20. Finally, *Under-exploiters* are represented by the dashed orange curve. On average, they reached the threshold of 20 after 42 seconds, which is less than the group classified as *Optimal*. However, the difference was not statistically significant (Mann-Whitney p-value=0.117) due to a large variance; some did not establish a strong positive slope before two minutes had elapsed.

We were not able to identify a specific pattern for the other 19 players who therefore remain in the *Undetermined* category. Note, however, that some of the behavior in this category resembles what is referred to as "Pulse" in the literature, that is, alternating low and high extraction rates, depending on the level of the resource (Schnier & Anderson, 2006; Muller & Whillans, 2008; Hey et al., 2009; Tasneem et al., 2017).[17] Other trajectories resemble the one we identified, but with noise and changes over time.

After this second round of classification, subjects split into four behavior categories in a fairly balanced way: 19 were *Optimal*, 15 *Convergent*, 17 *Under-Exploiter* and 19 *Undetermined*.

[17] See for example players 50 or 51 in the file mentioned in the footnote 16.

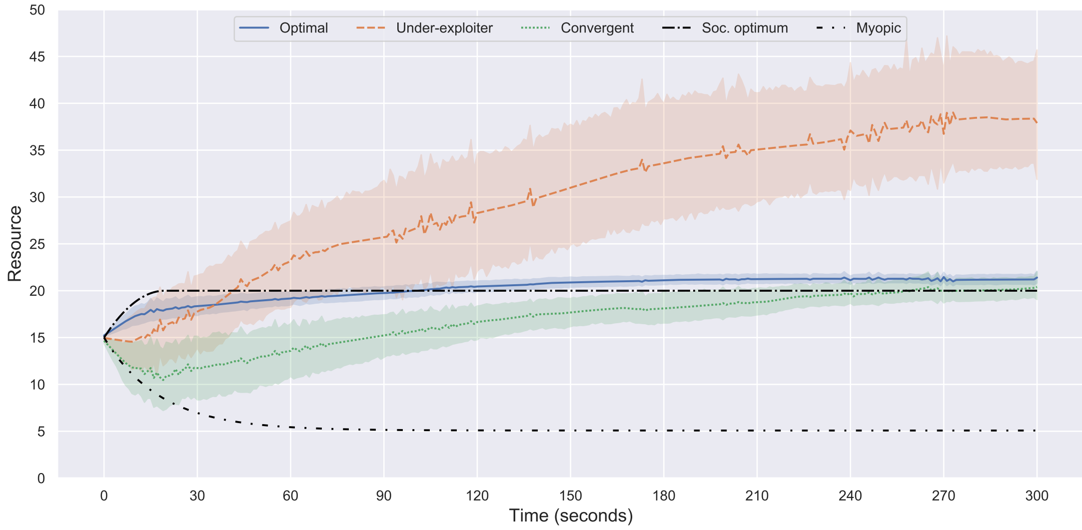

Figure 6: Average resource stock of players classified as *Optimal*, *Convergent* and *Under-Exploiter*. Area represent the 95% confidence interval around the mean.

To complete the analysis we look at the efficiency of players' decisions by calculating the ratio of their payoff to the maximum possible payoff, as is common practice in the literature. With our set of parameters, a perfectly optimal player would have achieved a payoff of 215 ECUs.[18] The average ratio, with all categories included, is 0.78 (Std Dev. 0.23, Median 0.86), which is lower than in Tasneem et al. (2019) (0.85) and Suter et al. (2012) (0.95). A possible explanation is that in Tasneem et al. (2019) the game lasted only 2 minutes and stopped after 30 seconds without any movement from the player, whereas Suter et al. (2012) implemented a discrete-time experiment. On average, the efficiency rate in the *Optimal* player category is 0.97 (Std Dev. 0.02), which is significantly higher than the other categories (Mann-Whitney p-value< 0.001 for each test performed), of 0.79 (Std Dev. 0.17) for *Convergent*, 0.79 (Std Dev. 0.19) for *Under-Exploiter* and 0.58 (Std Dev. 0.27) for *Undetermined*).

Figure 7 reports the ratios of each player in the experiment, taking care to separate the categories we just defined. The Figure shows that the Optimal category is very close to the ratio of 1, with low variance, which suggests the empirical strategy we

[18] Remember that the total payoff is the sum of the discounted payoff at each instant plus the continuation payoff.

proposed is very relevant for this exercise. We can also observe that some players who belong to the other categories also succeeded in achieving a high ratio of efficiency, even if these categories clearly exhibit much more heterogeneity than the *Optimal* one.

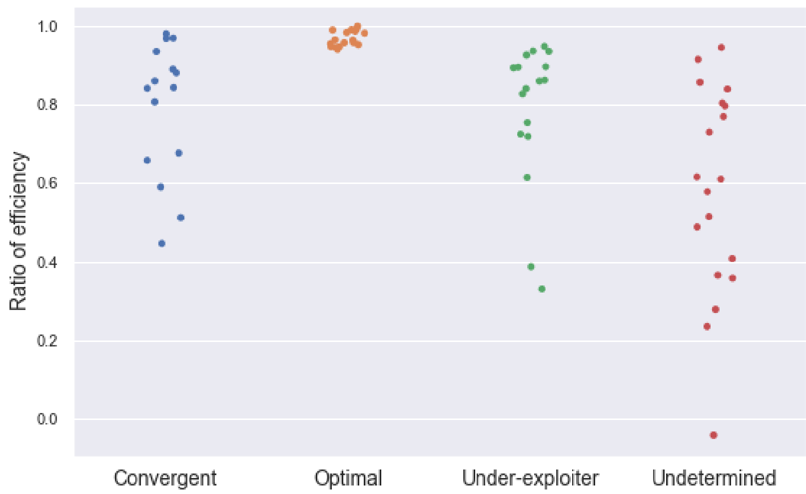

Figure 7: Ratio of efficiency by category

To summarize, we had a theoretical benchmark with two profiles of behavior, *Optimal* and *Myopic*, but only one (*Optimal*) was observed in our data and it represents only 27.14% of the sample. However, we have clearly identified two other behavioral patterns namely *Convergent* and *Under-exploiter*. Together, these behaviors account for three-quarters (72.46%) of the sample.

5.2.3 Game

As the game protocol is based on a within-subject design, the players were the same as in the optimal control problem but were grouped in pairs in which both extracted the same resource. Figure 8 reports the location of groups with respect to the conditional MSD_{op} and MSD_{my}. Based on this criterion, 32 groups are closer to the optimal than the myopic pattern, and 3 groups are, by contrast, closer to the myopic than the optimal pattern. However, after the application of the regression filter, we find that 7 groups out of 35 are significantly *Optimal* (olive markers in Figure 8) and the remaining (28) are *Undetermined*, that is, neither significantly *Feedback* nor *Myopic* (brown markers in Figure 8). In other words, 20% of groups were able to adopt the cooperative socially optimal solution.

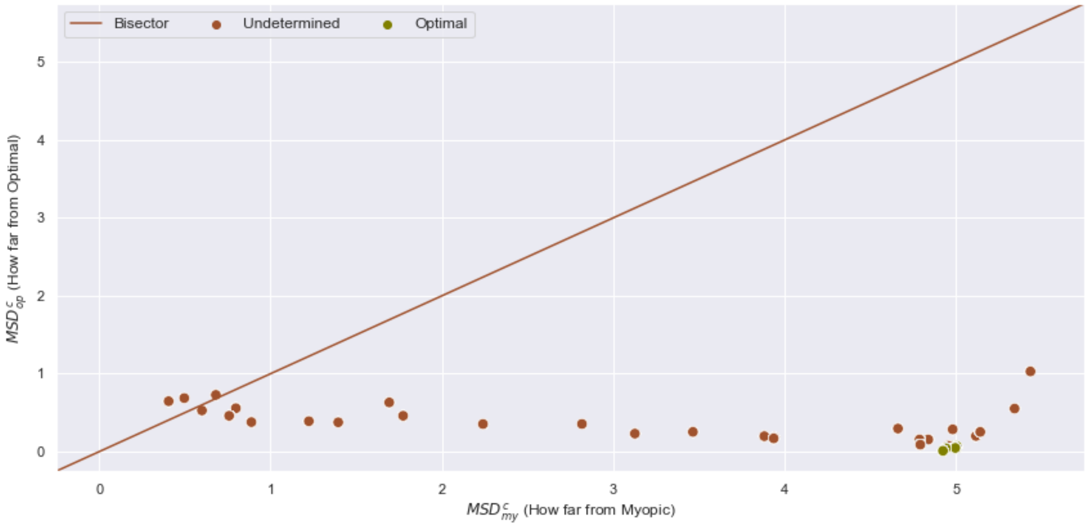

Figure 8: MSD position of groups in the game. Colors represent the identified profiles after the regression filter.

A visual inspection of the extraction and resource curves of the 28 *Undetermined* groups [19], lead us to identify 9 groups that converged toward the optimum (*Convergent*), 5 groups that let the resource increase to a very high level (*Under-Exploiter*) and 6 groups that, by contrast, overexploited the resource (*Over-Exploiter*). There are still 9 groups we could not classify, and these therefore remained in the *Undetermined* category. Figure 9 reports the evolution of the average resource stock for each category, as well as the three theoretical trajectories. Groups that behaved as significantly *optimal* are represented by the dotted blue line. On average, they started with a trajectory very close to the theoretical path, but after a few seconds, they maintained the resource stock at a slightly higher than optimal level.

As in the optimal control problem, the *Convergent* category (solid red line) differs from the *Optimal* category in that at the beginning of the game, the extraction level is too high, and thereafter the trajectory toward the equilibrium value of 20 is

[19] Curves for each group separately are available at `https://tinyurl.com/2ztchw6x`

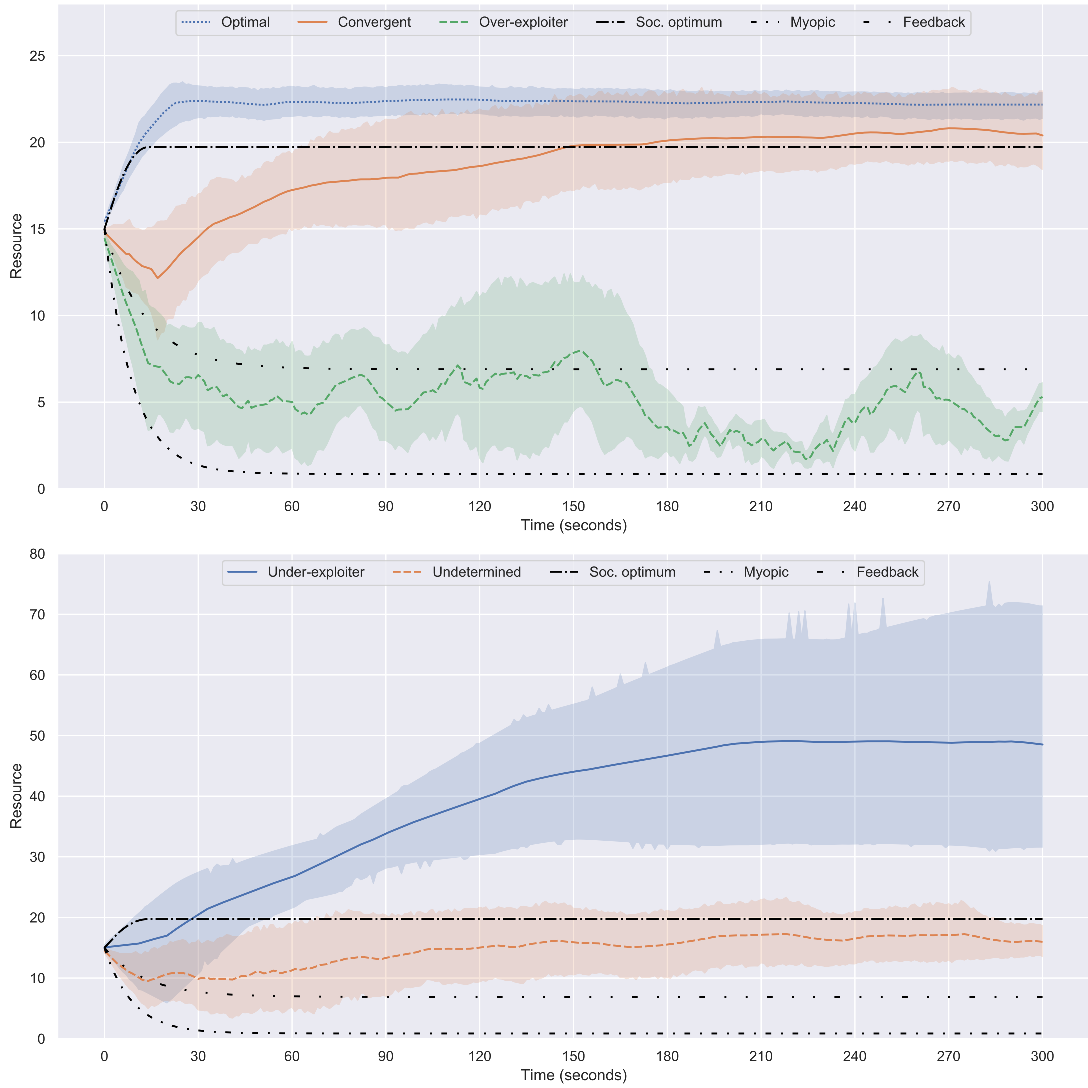

Figure 9: Average resource stock of groups classified as *Optimal*, *Convergent* and *Over-Exploiter* (graph at the top of the figure), and *Under-Exploiter* and *Undetermined* (graph at the bottom of the figure). Area represent the 95% confidence interval around the mean.

slow; it is reached after 177 seconds compared to fewer than 12 seconds by the *Optimal* groups (a significant difference, Mann-Whitney p-value=0.001). Like the *Optimal* groups, the *Under-Exploiter* groups (solid blue line) let the resource stock grow quickly, on average after 29 seconds (not significantly different from *Optimal*, Mann-Whitney p-value=0.503). However, those in this category maintain the growth path almost to the end, which is not optimal. We do not know why they do not stop under-extracting the resource once the steady-state level is reached. We did not include control tasks in the experiment, for example, to capture the attitude toward risk or impatience. As a result, we are unable to provide any explanatory insights. What is new in this multiple-agent setting is the *Over-Exploiter* category. On average, with some variation, groups in this category started with a trajectory close to the feedback solution. However, in the second part of the play, they fall between feedback and myopic behavior, which is why the regression filter failed to conclude significant feedback behavior. If we look at these groups individually (file referenced in footnote 19), they seem to be characterized by a high frequency of alternation between high and low levels of extraction, revealing a difficulty within the group in agreeing on a path or strategy.

Overall, if we combine the *Optimal* and *Convergent* categories as group that understood the cooperative solution, this represents 45.71% of the observations, which is not significantly different from the proportion observed in the optimal control problem (48.47%, Fisher-Exact test p-value > 0.05). A candidate explanation is the use of a within-subjects design and the learning process enabled by the first part of the experiment where subjects played alone. As in the control problem, the categories identified represent almost 75% of the observations, with only 25% that do not seem to exhibit a particular pattern of play.

The maximum combined payoff the group could achieve is 240 ECUs. We first calculated the efficiency ratio at the group level by summing the payoff at the last instant of the two members of the pair. The average ratio of efficiency, for all categories combined, is 0.68 (Std Dev. 0.28, Median 0.77). Those in the *Optimal* category reach an average efficiency ratio of 0.98, followed by the *Convergent* (0.80), the *Under-Exploiter* (0.79), and the *Undetermined* (0.58) categories, and, in a distant last place the *Over-Exploiter* (0.22) category. Figure 10 reports on the left side the ratio of efficiency at the group level and on the right side at the individual level. For the calculation of the individual efficiency ratio, we compared the final individual payoff to 120 ECUs, half of the maximum the group could achieve. It was nevertheless possible for a player to obtain more than 120 ECUs, when the other member of their pair extracted a smaller quantity. As a result, it was possible to achieve an efficiency ratio greater than 1. This happened to one player in the *Undetermined* groups and to three in *Convergent*, four in *Under-Exploiter* and five in the *Optimal* groups. The latter number means that in groups that behaved according to the theoretical social optimum, individual behaviors were not symmetric. That is, one player has benefited from the low extraction of the other.

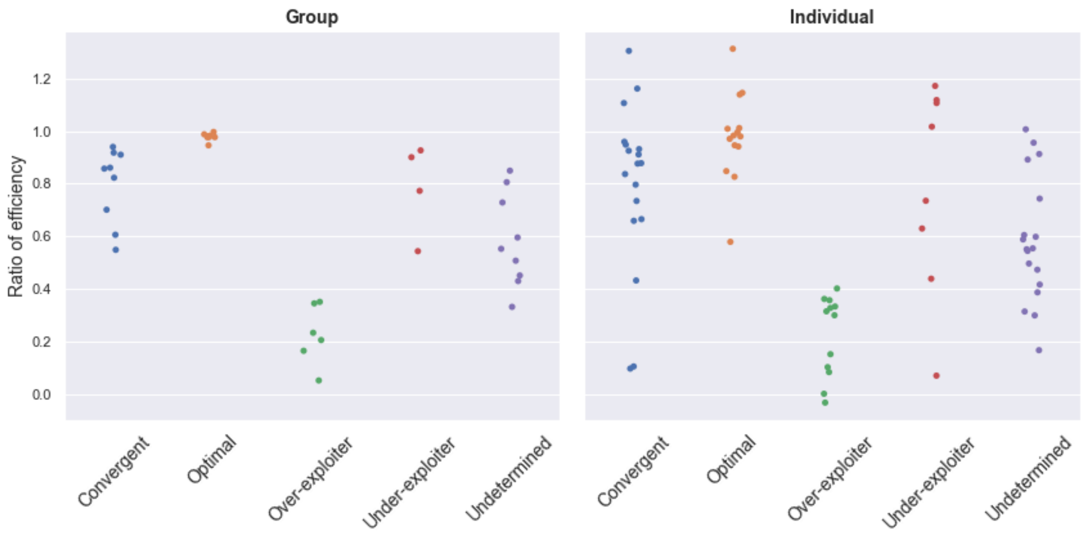

Figure 10: Ratio of efficiency by category

5.2.4 Group behavior according to the profiles in the control

The within-subjects design allows us to analyze how groups are composed in terms of profiles identified in the control problem. Table 3 reports the contingency table of individual profiles in the control (rows) and group profiles in the game (columns). If we read the table by rows, we see that most players classified as *Optimal* in the control problem ended up in groups that we classified as either *Optimal* or *Convergent* (15 out of 19 or 78.95%); that is, groups that were somewhat successful in understanding and reaching the cooperative solution. In addition, one-third of those in the *Convergent* category, when playing alone, were in groups categorized as *Undetermined*, suggesting that the trajectory followed by this category is fragile under strategic interaction. Finally, 8 players out of 19 (42.11%), classified as *Undetermined* in the control problem, were in groups *Over-Exploiter* groups in the game. These observations show that even for experienced players, strategic interaction complicates the management of the resource. If we read the table by columns, we see that groups classified as *Optimal* were predominantly (50%) composed of players identified as *Optimal* in the control problem. The *Convergent* groups were also overwhelmingly composed of those earlier classified as either *Convergent* or *Optimal*. It seems that in the case of the latter, they were not able to impose on the resource the rate of growth that they held when they were playing alone.

		Game					
		Convergent	Optimal	Over-exploiter	Under-exploiter	Undetermined	All
Control	Convergent	7	1	1	1	5	15
	Optimal	8	7	0	1	3	19
	Under-exploiter	1	4	3	6	3	17
	Undetermined	2	2	8	0	7	19
	All	18	14	12	8	18	70

Table 3: Contingency table of players' profile in the control and groups in the game

In Table 4, we detail, for each identified category of groups, the group composition in terms of profiles identified in the control problem. Remember that we did not control for the group composition; this was done randomly by the server at the beginning of the game. If we read the table by rows we see that 13 of the 17 groups (76.47%) with at least one *Optimal* player had a trajectory identified either as significantly *Optimal* or *Convergent*; having an *Optimal* player in the pair increases the likelihood that the group cooperates. This is confirmed by reading the table by columns: of the *Optimal* groups, 6 out of 7 include at least one player that behaved as *Optimal* in the control problem.

		Game					
		Convergent	Optimal	Over-exploiter	Under-exploiter	Undetermined	All
Control	Optimal - Optimal	1	1	-	-	-	2
	Optimal - Convergent	5	1	-	-	-	6
	Optimal - Undetermined	1	2	-	-	2	5
	Optimal - Under-exploiter	-	2	-	1	1	4
	Convergent - Convergent	-	-	-	-	1	1
	Convergent - Under-exploiter	1	-	-	1	-	2
	Convergent - Undetermined	1	-	1	-	3	5
	Under-exploiter - Under-exploiter	-	1	-	2	-	3
	Under-exploiter - Undetermined	-	-	3	-	2	5
	Undetermined - Undetermined	-	-	2	-	-	2
	All	9	7	6	4	9	35

Table 4: Contingency table of groups' profiles and groups' composition in terms of profiles in the control

6 Conclusion

Using a simple groundwater extraction game, we provided theoretical solutions and compared them to observations from a laboratory experiment. Implementing a single-player (optimal control) and multi-player (game) setup in a within-subjects design allowed us to study subjects' behaviors in both contexts. To our knowledge, we offer the first study taking on the challenge of implementing continuous time and an infinite horizon in the laboratory, and comparing individual and collective decisions to the full set of standard theoretical solutions (Optimal, Feedback, and Myopic).

We were able to classify 75% of the observations in the optimal control problem, into three distinct categories, namely *Optimal*, *Convergent*, and *Under-Exploiter*, using a two-step methodology. First, we used a regression filter on the conditional MSD measure, which allowed us to identify players whose behavior was significantly optimal, that is, consistent with the theoretical solution of the social optimum. Next, we visually inspected the individual resource trajectories of the remaining players and grouped them into two patterns: those who started out myopically and then slowly converged to the optimal steady state (*Convergent*), and those who started out optimally but allowed the resource to grow well beyond the steady-state threshold (*Under-Exploiter*). Further research is needed to better understand these behaviors, perhaps including additional observations and control tasks in the experimental design to capture individual characteristics that might explain behaviors in this dynamic context, such as attitude toward risk or impatience.

In the second part of the experiment, the "experienced" players were randomly paired to participate in the same extraction problem, but with strategic interaction. Following the same two-step process as that in the optimal control problem, we were able to identify different group profiles, accounting for 75% of the observations. Of the groups, 20% were found to be significantly *Optimal*. We believe that this rate would be much lower in the absence of the first part where subjects learned by playing alone. We also identified *Convergent* and *Under-Exploiter* groups. A new category, which we named *Over-Exploiter*, was identified for those who exhibited a high level of extraction that led to the depletion of the resource. These players started with a behavior close to Nash (feedback) behavior, that is, optimal but ignoring the other player in the pair and, in the end, they alternated between a myopic and a feedback pattern. Most players who made up the groups classified in this category had a behavior that we defined as *Undetermined* in the control phase, meaning that they were already not following a clearly identified pattern when they extracted the resource alone.

Most players who seemed to understand that their long-term payoff maximizing trajectory, when playing alone, required letting the resource increase until the level at which the extraction was cost-free pursued their reasoning in the game; this was the case even if not always successful, depending on the behavior of their counterpart. Therefore, if our goal were to foster cooperation in the multiple-agent setting, we would recommend starting with an intervention that helps players understand how to maximize their long-term payoff in the context of a single-agent scenario.

We hope our theoretical model, the solutions to experimental challenges and the empirical strategy implemented can serve as a benchmark for more complex frameworks to study dynamic CPR. We can think of several interesting additional investigations that would complement our study. First, from a theoretical perspective, it would be helpful to model the behavior of the players and groups we identified as *Convergent*. These seem to have understood the path to the cooperative solution but were unable to reach it quickly. Our intuition is that they are "nearsighted", that is, they are not able to optimize their extraction over the long term but only on a finite horizon. Another possible explanation is that these players and groups are not sufficiently patient. A control task like Andreoni & Sprenger (2012)'s Convex Time Budget procedure might be useful in determining the extent to which impatience matters in this dynamic context. Second, as stated earlier, the fairly high frequency at which socially optimal behavior was observed in the game could, in part, be a consequence of the experimental design. Our original intention was for participants in the game to have experience, but it would be interesting to see if, without the first solo learning phase, the frequency of socially optimal behavior would be similar. Finally, many extensions of the game setting are possible, such as: increasing the group size (Herr et al., 1997), changing the hydrogeologic properties of the groundwater model (Suter et al., 2012), allowing for various types of communication (Oprea et al., 2014), or introducing exogenous and/or endogenous shocks to the resource stock to simulate, for example, the possibility of catastrophic events (De Frutos Cachorro et al., 2014).

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Appendices

A The Optimal Control Problem

A.1 Social Optimum Solution

The social optimum problem, where r is the discount factor is:

$$\max_{w(t)} \int_0^\infty e^{-rt} \left[aw(t) - \frac{b}{2}w(t)^2 - \max(0,\ c_0 - c_1 H(t))w(t) \right] dt \tag{6}$$

s.t

$$\begin{cases} \dot{H}(t) = R - \alpha w(t) \\ H(0) = H_0 \; and \; H_0 \geq 0,\ H_0 \;\; given \\ H(t) \geq 0 \\ w(t) \geq 0 \end{cases}$$

Condition 1 *: We suppose that:*

$$\frac{R}{\alpha} < \frac{a}{b}, \quad \frac{R\alpha c_1 + Rbr - a\alpha r + \alpha c_0 r}{\alpha c_1 r} > \frac{c_0}{c_1}$$

This condition is given to ensure that the steady-state of the optimal solution is: $H^\infty = \frac{c_0}{c_1}$, allowing us to better differentiate the two types of behavior. In fact, when the resource is less than $\frac{c_0}{c_1}$ and not so small, the optimal level of the water table increases to $\frac{c_0}{c_1}$, while the myopic solution decreases the water table to its steady-state, which is smaller than $\frac{c_0}{c_1}$.

Theorem 1 *: Under condition 1, the steady-state of the optimal solution is:*

$$H^\infty_{op} = \frac{c_0}{c_1}, \quad w^\infty_{op} = \frac{R}{\alpha}$$

The optimal groundwater path has two regimes: it increases to this steady-state when $H_0 < \frac{c_0}{c_1}$ (decreases when $H_0 > \frac{c_0}{c_1}$) till a certain time T where $H(t) = \frac{c_0}{c_1}$ for all $t \geq T$.

The optimal extraction rate follows the same trajectory towards its steady-state. It can be preceded by a null extraction regime.

To prove theorem 1, we first prove that under condition 1 it is not possible to have a steady-state other than $\frac{c_0}{c_1}$. To do this, we separately consider the case where the optimal solution lies in the regime with the level of the groundwater, H, smaller than $\frac{c_0}{c_1}$ and the case with H greater than $\frac{c_0}{c_1}$. The two regimes are differentiated by the cost function.

Proposition 1 *: When $H(t) < \frac{c_0}{c_1}$ for all t, the steady-state of the following problem*

$$\max_w \int_0^\infty e^{-rt} \left[aw - \frac{b}{2}w^2 - (c_0 - c_1 H)w \right] dt, \tag{7}$$

s.t

$$\begin{cases} \dot{H} = R - \alpha w, \\ H(0) = H_0 \end{cases}$$

is

$$H^\infty = \frac{R\alpha c_1 + Rbr - a\alpha r + \alpha c_0 r}{\alpha c_1 r}, \quad w^\infty = \frac{R}{\alpha}$$

Proof 1 *: The associated Hamiltonian is:*

$$Hamiltonian = aw - \frac{b}{2}w^2 - (c_0 - c_1 H)w + \lambda(R - \alpha w),$$

where λ is the adjoint variable and the result is given by first order conditions at the steady-state.

Furthermore, this steady-state cannot be a steady-state of our problem because by condition 1 it is greater than $\frac{c_0}{c_1}$.

Proposition 2 *: There is no steady-state in the regime $H(t) > \frac{c_0}{c_1}$*

Proof 2 *: Suppose a solution with $H(t) > \frac{c_0}{c_1}$ for all t. The maximization problem is:*

$$\max_w \int_0^\infty e^{-rt} \left[aw - \frac{b}{2}w^2 \right] dt, \tag{8}$$

s.t

$$\begin{cases} \dot{H} = R - \alpha w, \\ H(0) = H_0 \end{cases}$$

The associated Hamiltonian:

$$Hamiltonian = aw - \frac{b}{2}w^2 + \lambda(R - \alpha w),$$

where λ is the adjoint variable, gives by first order conditions:

$$w(t) = \frac{a - \alpha\lambda_0 e^{rt}}{b}$$

It is not possible to maintain the groundwater greater than $\frac{c_0}{c_1}$ if $\lambda_0 \leq 0$. Note that if $\lambda_0 = 0$, condition 1 gives $\dot{H} < 0$. It is not possible to have $w \geq 0$ if $\lambda_0 > 0$.

These two propositions show that the steady-state of the optimal problem is:

$$H_{op}^{\infty} = \frac{c_0}{c_1}, \quad w_{op}^{\infty} = \frac{R}{\alpha}$$

Now to obtain the complete path we must solve first order conditions considering the Hamiltonian of the problem and taking into account the constraints.

For $H_0 < \frac{c_0}{c_1}$, the Lagrangian of the problem is:

$$L = aw - \frac{b}{2}w^2 - (c_0 - c_1 H)w + \lambda(R - \alpha w) + \mu\left(\frac{c_0}{c_1} - H\right) + \nu w, \tag{9}$$

where λ is the adjoint variable and μ and ν the Lagrange multipliers associated to the constraints $H \leq \frac{c_0}{c_1}$ and $w \geq 0$, respectively.

For $H_0 > \frac{c_0}{c_1}$, the Lagrangian of the problem is:

$$L = aw - \frac{b}{2}w^2 + \lambda(R - \alpha w) + \mu\left(H - \frac{c_0}{c_1}\right) \tag{10}$$

The time of change of regime is obtained using the continuity of the adjoint variable, the state variable and the control variable.

A.2 The Constrained Myopic Solution

The constrained myopic problem faced by the farmer is:

$$\max_{w(t)} \left[aw(t) - \frac{b}{2}w(t)^2 - \max(0,\ c_0 - c_1 H)w(t) \right] \tag{11}$$

This problem provides a feedback representation of the solution $w(H)$, under the following constraints:[20]

$$\begin{cases} \dot{H}(t) = R - \alpha w(H(t)) \\ H(0) = H_0 \ and \ H_0 \geq 0,\ H_0 \ \ given \\ H(t) \geq 0 \\ w(t) \geq 0 \end{cases}$$

Condition 2 *: We suppose that*

$$a > c_0, \quad \frac{R}{\alpha} - \frac{a - c_0}{b} > 0$$

This condition is to ensure the positivity of the steady-state and the extraction of the constrained myopic solution.

Theorem 2 *: Under condition 2, the steady-state of the constrained myopic problem is:*

$$H_{my}^{\infty} = \frac{b}{c_1}\left(\frac{R}{\alpha} - \frac{a - c_0}{b}\right), \quad w_{my}^{\infty} = \frac{R}{\alpha}$$

When $H_0 > H_{my}^{\infty}$, the constrained myopic path decreases to the steady-state.

From condition 1, we conclude that in the optimal control problem:

$$H_{my}^{\infty} < H_{op}^{\infty} \tag{12}$$

Considering the different possibilities for H ($H \ <>= \ \frac{c_0}{c_1}$), we obtain the constrained myopic extraction. We can see that if $H < \frac{c_0}{c_1}$, the resolution of the differential equation gives:

[20] The feedback representation is obtained when the solution is written according to the state variable, instead of according to time.

$$H(t) = H^{\infty}_{my} + (H_0 - H^{\infty}_{my})e^{-\frac{\alpha c_1}{b}t}, \tag{13}$$

with the steady-state that is:

$$0 < H^{\infty}_{my} = \frac{b}{c_1}\left(\frac{R}{\alpha} - \frac{a - c_0}{b}\right) < \frac{c_0}{c_1}$$

by conditions 1 and 2. However, if $H > \frac{c_0}{c_1}$, as extraction is $\frac{a}{b}$, condition 1 implies that $\dot{H} < 0$ and then, in a finite time, the trajectory enters the regime where $H < \frac{c_0}{c_1}$ and the reasoning for that regime applies.

B The Case of Multiple Agents: Game

B.1 The Social Optimum Solution

The social optimum maximization problem is given by:

$$V(H_0) = \max_{w_1(t), w_2(t)} \int_0^{\infty} e^{-rt} \sum_{i=1}^{2} \left[a w_i(t) - \frac{b}{2} w_i(t)^2 - \max(0,\ c_0 - c_1 H(t)) w_i(t) \right] dt \tag{14}$$

s.t

$$\begin{cases} \dot{H}(t) = R - \alpha(w_1(t) + w_2(t)) \\ H(0) = H_0 \ and \ H_0 \geq 0,\ H_0 \ \ given \\ H(t) \geq 0 \\ w_i(t) \geq 0 \end{cases}$$

Condition 3 *: We suppose that*

$$\frac{R}{\alpha} < \frac{a}{b}, \qquad \frac{2R\alpha c_1 + Rbr - 2a\alpha r + 2\alpha c_0 r}{2\alpha c_1 r} > \frac{c_0}{c_1}$$

As in the single agent case, this condition is designed to ensure that the steady-state of the optimal solution is $H^{\infty} = \frac{c_0}{c_1}$

Theorem 3 *: Under condition 3, the steady-state of the optimal solution is:*

$$H_{op}^{\infty} = \frac{c_0}{c_1}, \quad w_{i,\,op}^{\infty} = \frac{R}{2\alpha}$$

The optimal resource path has two regimes: it increases to this steady-state when $H_0 < \frac{c_0}{c_1}$ (decreases when $H_0 > \frac{c_0}{c_1}$) till a certain time T where $H(t) = \frac{c_0}{c_1}$ for all $t \geq T$. The optimal extraction rate follows the same trajectory towards its steady-state. It can be preceded by a null extraction regime.

B.2 The Nash Feedback solution

The Nash Feedback maximization problem for each farmer is:

$$\max_{w_i(t)} \int_0^{\infty} e^{-rt} \left[a w_i(t) - \frac{b}{2} w_i(t)^2 - \max(0,\ c_0 - c_1 H(t)) w_i(t) \right] dt \tag{15}$$

s.t

$$\begin{cases} \dot{H}(t) = R - \alpha(w_1(t) + w_2(t)) \\ H(0) = H_0 \text{ and } H_0 \geq 0,\ H_0 \ \text{given} \\ H(t) \geq 0 \\ w_i(t) \geq 0 \end{cases}$$

Condition 4 *: We suppose that*

$$Rb + 2\alpha^2 A_2 - 2\alpha(a - c_0) > 0, \quad \frac{Rb + 2\alpha^2 A_2 - 2\alpha(a - c_0)}{2\alpha(c_1 - \alpha A_3)} < \frac{c_0}{c_1}, \quad a - c_0 - \alpha A_2 > 0,$$

Where, $A_2 = \frac{(a - c_0)(-c_1 + 2\alpha A_3) - RbA_3}{-rb - 2c_1\alpha + 3A_3\alpha^2}$, *and A_3 is the solution of:* $-\frac{3\alpha^2}{2b} A_3^2 + \frac{rb + 4c_1\alpha}{2b} A_3 - \frac{c_1^2}{2b} = 0$, *with* $-c_1 + \alpha A_3 < 0$

Conditions $Rb + 2\alpha^2 A_2 - 2\alpha(a - c_0) > 0$ and $\frac{Rb + 2\alpha^2 A_2 - 2\alpha(a - c_0)}{2\alpha(c_1 - \alpha A_3)} < \frac{c_0}{c_1}$ ensure that the steady-state of the feedback path is positive and in the regime where cost is positive. Condition $a - c_0 - \alpha A_2 > 0$ ensures that extraction is always positive.

Theorem 4 *: Under condition 4, the steady-state of the feedback equilibrium is:*

$$H_f^{\infty} = \frac{Rb + 2\alpha^2 A_2 - 2\alpha(a - c_0)}{2\alpha(c_1 - \alpha A_3)}, \quad w_{i,\,f}^{\infty} = \frac{R}{2\alpha}$$

Groundwater increases to this steady-state when $H_0 < H_f^{\infty}$ (decreases when $H_0 > H_f^{\infty}$). The extraction rate follows the same trajectory towards its steady-state.

B.3 The Constrained Myopic solution

The constrained myopic problem faced by a farmer for each level of the water table is:

$$\max_{w_i(t)} \left[a w_i(t) - \frac{b}{2} w_i(t)^2 - \max(0,\ c_0 - c_1 H) w_i(t) \right] \tag{16}$$

This maximization problem also provides a feedback representation of the solution $w_i(H)$, constrained to the evolution of the water table exploited by the two symmetrical farmers:

$$\begin{cases} \dot{H}(t) = R - 2\alpha w(H(t)) \\ H(0) = H_0 \ and \ H_0 \geq 0,\ H_0 \ \ given \\ H(t) \geq 0 \\ w_i(t) \geq 0 \end{cases}$$

Condition 5 *: We suppose that*

$$a > c_0, \quad \frac{R}{2\alpha} - \frac{a - c_0}{b} > 0.$$

This condition is to ensure the positivity of the steady-state and the extraction of the constrained myopic solution.

Theorem 5 *: The steady-state of the constrained myopic problem is:*

$$H_{my}^{\infty} = \frac{b}{c_1} \left(\frac{R}{2\alpha} - \frac{a - c_0}{b} \right), \quad w_{i,\,my}^{\infty} = \frac{R}{2\alpha}$$

When $H_0 > H_{my}^{\infty}$ the constrained myopic path decreases to the steady-state.

We can conclude from conditions 3 and 4 that in the game:

$$H_{my}^{\infty} < H_{f}^{\infty} < H_{op}^{\infty} \tag{17}$$

Notice that conditions 1, 2, 3, 4 and 5 were decisive in the choice of the values of the parameters used for the experiment. A discussion of these conditions will be made in section 4.3.

C An example of how the empirical strategy works

The purpose of this appendix is to provide a precise example of an application of our empirical strategy. We follow player 58 and show all intermediate results.

Step 1: We compute the conditional MSDs in the optimal control. This gives us :

$$\begin{aligned} MSD_{my}^{c} &= 0.718 \\ MSD_{op}^{c} &= 0.011 \end{aligned} \tag{18}$$

MSD_{op}^{c} is the smallest. Extraction and conditional extraction paths of player 58 are then shown by Figure C.1.

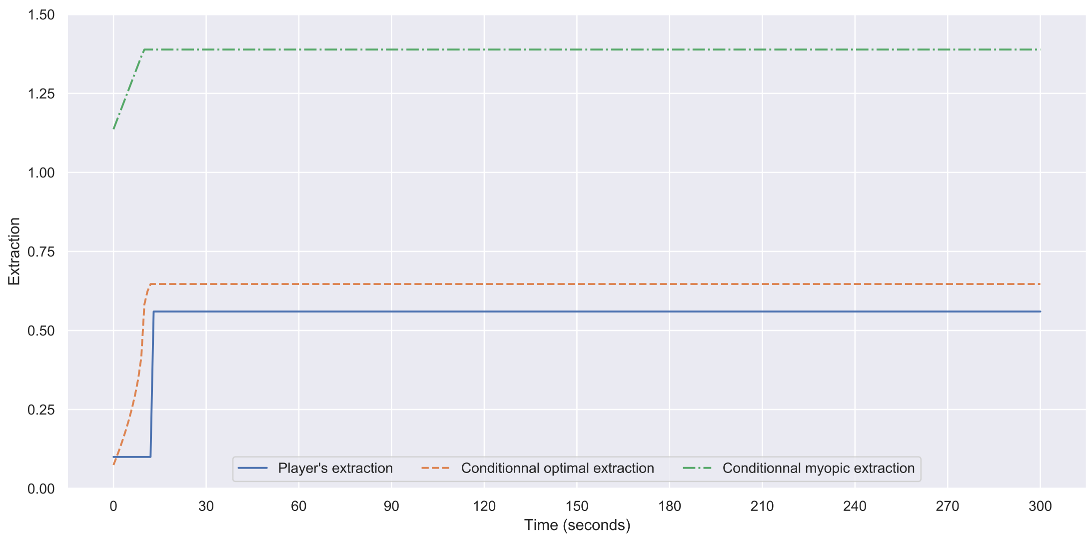

Figure C.1: Player 58's extraction path versus the conditional extraction path for the optimal control

Visual inspection confirms that player 58 is closer to the conditional optimal extraction path than to the conditional myopic extraction path.

Step 2 : Next, we regress player 58's extractions from time $t = 0$ to $t = 300$ over its conditional optimal extraction path in the optimal control. Results are shown in

Table 5.

Table 5: Player 58's extraction in the optimal control

	(1)
	$w(t)$
$w(t)^c_{op}$	1.016***
	(8.91)
Constant	-0.102
	(-1.35)
Observations	301

Newey-West standard errors with 5-period lags.

t statistics in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The coefficient is positive (1.016) and significant at 0.1%. Therefore, we consider player 58 as being significantly optimal in the optimal control.

Step 3 : Player 58 belong to group 29 in the game. We compute the conditional MSDs of the group. This gives us :

$$\begin{aligned} MSD^c_{my} &= 5.004 \\ MSD^c_{fb} &= 1.160 \\ MSD^c_{op} &= 0.070 \end{aligned} \tag{19}$$

MSD^c_{op} is the smallest. Extraction and conditional extraction paths of group 29 are shown by Figure C.2.

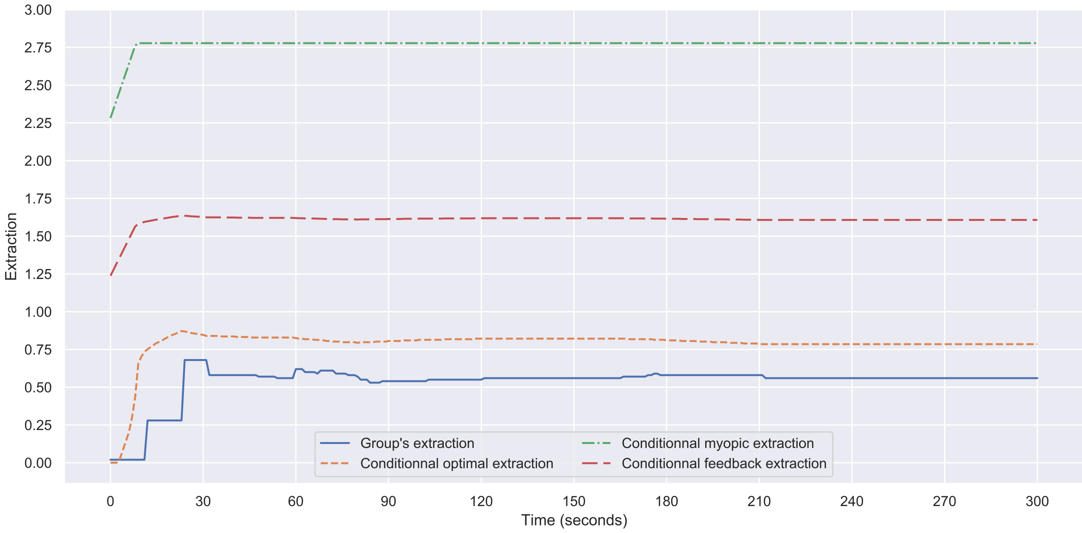

Figure C.2: Group 29's extraction path versus conditional extraction path for the game

Visual inspection confirms that group 29 is closer to the conditional optimal extraction path than to any other path.

Step 4 : Next, we regress group 29's extractions from time $t = 0$ to $t = 300$ over their conditional optimal extraction path in the game. Results are shown in Table 6.

Table 6: Group 29's extraction in the game

	(1)
	w(t)
$w(t)^c_{op}$	0.770***
	(9.11)
Constant	-0.070
	(-1.00)
Observations	301

Newey-west standard errors with 5-period lags.

t statistics in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The coefficient is positive (0.770) and significant at 0.1%. Therefore, we consider group 29 as being significantly optimal in the game.

D Instructions

Translated from French

D.1 Optimal control

You are about to participate in a decision-making experiment. We ask you to carefully read the instructions in order to better understand the experiment. An experimenter will proceed to read these instructions aloud when all participants have finished their own reading. All of your decisions will be treated anonymously. You will specify your choices using the computer in front of which you are seated. For the remainder of the experiment, we ask you to remain quiet. If you have any questions, raise your hand and an experimenter will come and speak with you privately.

This experiment includes two independent parts. Only the Part 1 instructions are included here; you will have those for Part 2 when Part 1 is over. Your payoff for the experiment will be the sum of your earnings over the two parts. Earnings in each parts are in experimental currency units (ECU). The exchange rate of ECUs into euros is specified in the instructions for each part.

Part 1

This part includes two five-minutes training phases and a five-minute experimentation phase. The payoff for the experimentation is the one considered for your remuneration for this part.

General framework

You initially have 15 resource units. At any time, you can extract between 0 and 2.8 resource units with up to two decimal points of precision. This means that you are free to choose your extraction rate as 0, 0.01, 0.02 …2.79, 2.8. You will move a slider similar to that depicted in Figure D.1 to make your choice.

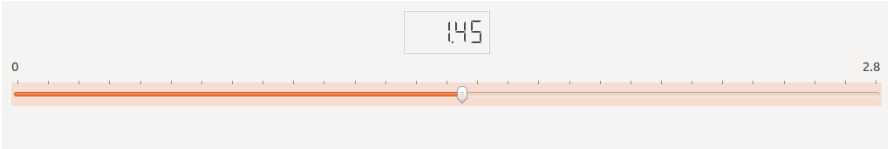

Figure D.1: Slider for decision-making

Resource dynamics

The available resource continuously evolves. Its evolution depends on two elements: (i) your extraction rate at instant t denoted E_t and (ii) a fixed rate of 0.56 automatically added at each instant t.
Thus, the resource evolves as follows:
- when your extraction rate is higher than the fixed rate, the resource decreases
- when your extraction rate is lower than the fixed rate, the resource grows
- when your extraction rate is equal to the fixed rate, the resource is stable

A graph on your screen will show you the resource's evolution in real time.

If your action is such that it brings the resource to zero, your extraction rate will be set to zero by the computer.

Payoff

When you extract the resource, you earn revenue but also incur a cost. The cost depends on the amount of the available resource: the less of the resource available, the higher the cost.

Total revenue from extraction

At the instant t, for an extraction rate E_t, the total revenue denoted REC_t is equal to:

$$REC_t = 2.5E_t - 0.9E_t^2$$

Figure D.2 below shows the total revenue according to the extraction rate.

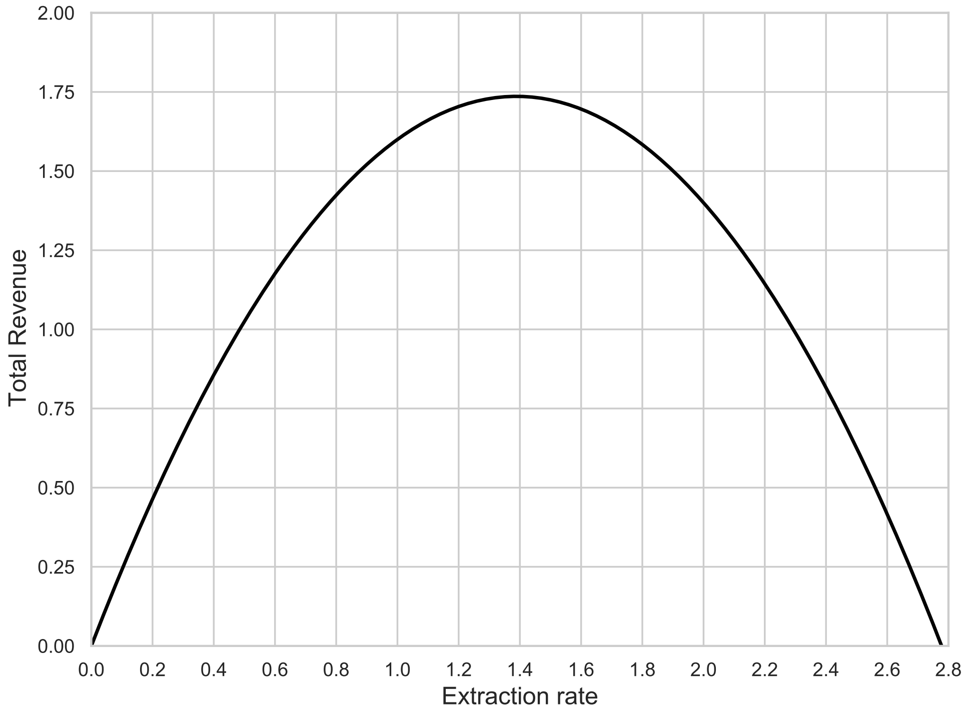

Figure D.2: Total revenue from extraction

Cost of extraction

At the instant t for an available amount of resource R_t, the unitary cost c_t is equal to:

$$c_t = \begin{cases} (2 - 0.1R_t) \text{ if } 0 \leq R_t < 20 \\ 0 \text{ if } R_t \geq 20 \end{cases}$$

Thus,

- the cost increases when the available resource decreases

- the cost is positive when the available resource is strictly lower than 20 units, and the cost is null when the available resource is greater than or equal to 20 units

Figure D.3 shows the unitary cost according to the available resource.

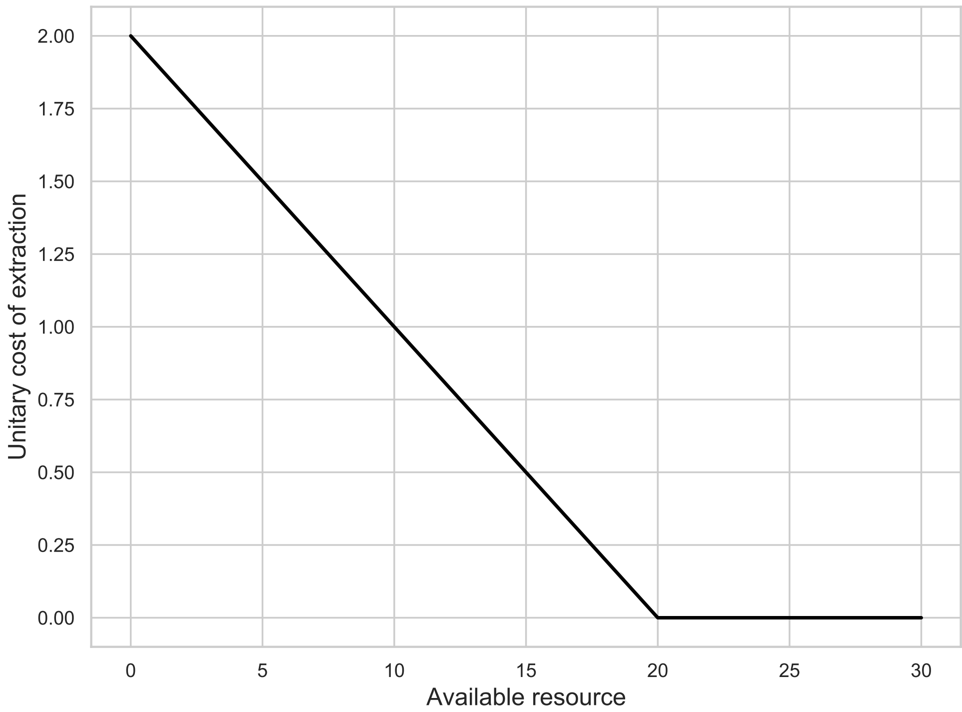

Figure D.3: Unitary cost of extraction

The total cost of extraction C_t, is equal to the extraction rate times the unitary cost, that is:

$$C_t = E_t \times c_t$$

Instant t payoff

At the instant t, payoff G_t equals the difference between benefit and cost, so that $G_t = REC_t - C_t$

Example

With $E_t = 1.4$ and $R_t = 20$, $REC_t = 1.736$ and $C_t = 0$, thus payoff is 1.736 ecus

With $E_t = 1.4$ and $R_t = 15$, $REC_t = 1.736$ and $C_t = 0.7$, thus payoff is 1.036 ecus

With $E_t = 1.4$ and $R_t = 10$, $REC_t = 1.736$ and $C_t = 1.4$, thus payoff is 0.336 ecus

With $E_t = 1.4$ and $R_t = 5$, $REC_t = 1.736$ and $C_t = 2.1$, thus payoff is -0.364 ecus

Discounted instantaneous payoff

Each instant, the instantaneous payoff (G_t) is multiplied by a discount factor, allowing us to determine the present value of the payoff perceived in the future. The discount rate equals 0.5% and concretely means that the instant t payoff is multiplied by $e^{-0.005\times t}$. Thus, the same instantaneous payoff has a different discounted value according to the instant.

Example

Let us take the same payoff $G_t = 0.5$ at 4 different instants.

At instant $t = 0$ the discounted payoff equals $0.5 \times e^{-0.005\times 0} = 0.5$

At instant $t = 1$ the discounted payoff equals $0.5 \times e^{-0.005\times 1} = 0.4975$

At instant $t = 100$ the discounted payoff equals $0.5 \times e^{-0.005\times 100} = 0.3033$

At instant $t = 300$ the discounted payoff equals $0.5 \times e^{-0.005\times 60} = 0.1116$

What one should remember from this discounting principle is that the payoffs of the first instants have a greater impact on the payoff of the experiment than those of the last instants.

Payoff for the experiment

Your payoff for the experiment includes two elements: (i) your cumulated payoff from discounted instantaneous payoffs since the beginning of the experiment (instant $t = 0$) until the present instant ($t = p$), and (ii) your "continuation payoff", which is your payoff if the experiment were to go on forever (from the present instant $t = p$ to instant $t = \infty$) with your extraction rate being fixed to the present instant p.

Your remuneration for the experiment is your payoff for the last instant of the experiment ($t = 300$). This payoff corresponds to your cumulated payoff over all the instants of the experiment, to which is added the payoff computed as if the part continued indefinitely with your extraction rate fixed at that of the last instant.

How the part works

Before the part starts you should decide on an initial extraction rate that will apply at the beginning of the experiment. Then, as soon as the experiment begins, you can, when you wish, change this rate by moving the slider on the window displayed on your screen. Once you release the slider, the value taken into account is the one displayed below the slider. When you do not move the slider, the value that is considered at each instant is the last one you set. Be careful not to click on the slider bar but to move the slider with the mouse, then release it so that the value is taken into account.

The computer performs the calculations every second, and the data displayed on your screens is also updated every second.

The decision screen includes four areas, in addition to the decision area with the slider. Three of these areas are graphic areas, and the fourth is a text area. Figure D.4 on page 57 gives you a depiction of the decision screen. Description of the areas is as follows:

- graphic at the top left is your extraction rate
- graphic at the top right is the available resource
- graphic at the bottom left is your payoff for the experiment, which, as explained previously, comprises your cumulative payoff up to the present instant, to which is added your payoff if your extraction is applied indefinitely
- text area at the bottom right contains the same information as the curves but in the form of text, namely, for each instant, your extraction rate, the available resource, your discounted instantaneous payoff, and your payoff for the experiment

Final details

The exchange rate of ECUs to euros is as follows: 10 ECUs $= 0.5$€.

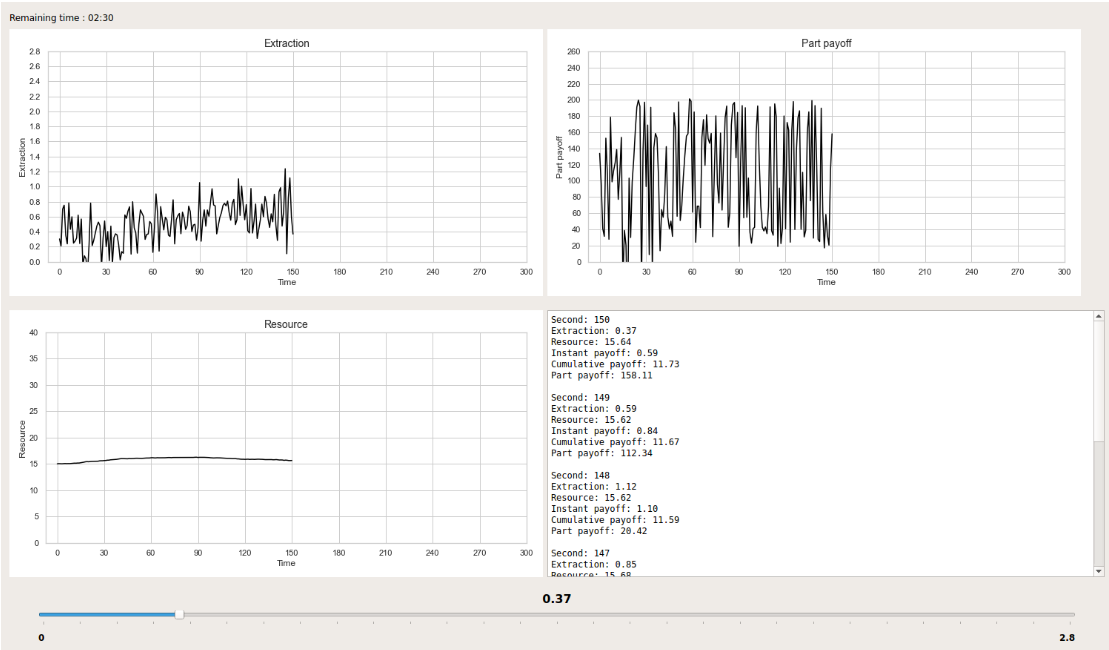

Figure D.4: Decision-making screenshot. We follow a hypothetical subject who chooses his extraction rate at random

D.2 Game

This part is identical to the previous one except that **from now on, you are two subjects who extract the same resource**. More precisely, at the beginning of the part, the central computer will randomly form pairs of 2 players. Each pair will initially have 15 units of resource, and each of the two players in the pair can at any moment extract an amount between 0 and 2.8 units.

Resource dynamics

The resource evolves continuously and this evolution depends on two elements : (i) **the total amount of resource extracted by your pair** at each instant t, and (ii) a fixed amount of 0.56 automatically added at each instant t.

If at the instant t the extraction of the pair exceeds the available resource, the extraction of each member of the pair for this instant is fixed to 0 by the computer.

Payoff

The calculation of the revenue for the extraction is identical to that in Part 1, namely $REC_t = 2.5E_t - 0.9E_t^2$, where E_t is your extraction. Thus, it does not depend on the extraction of the other player in the pair.

The calculation of the unitary cost is also identical, namely

$$c_t = \begin{cases} (2 - 0.1R_t) \text{ if } 0 \leq R_t < 20 \\ 0 \text{ if } R_t \geq 20 \end{cases}$$

Thus
- the cost increases when the amount of available resource decreases
- the cost is positive when the amount of available resource is strictly lower than 20 units and cost is null when the available resource is greater than or equal to 20 units
- **the cost depends indirectly on the total extraction of the pair from the available resource**

The total cost of extraction C_t, is equal to the extracted amount times the unitary cost, that is $E_t \times c_t$.

The instant t payoff is computed as previously by the difference between revenue and cost : $G_t = REC_t - C_t$. In the same way, the discounted instant t payoff is equal to the instant t payoff multiplied by the discount factor, that is $G_t \times e^{-0.005\times t}$.

The payoff of this part is also computed as previously: the cumulated payoff from instantaneous discounted payoffs since the beginning of the part ($t = 0$) until the present instant ($t = p$) to which is added the "continuation payoff", which is the payoff if the game went on forever (from $t = p$ to $t = \infty$) **with your extraction and the extraction of the other player in the pair** being fixed to the present instant.

The payoff used for your remuneration for this part is your total discounted payoff at the last instant ($t = 300$).

How the part works

The progress of the part is identical to that of Part 1, that is, first the choice of an initial extraction, then as soon as the part is started, the possibility of changing this extraction at any moment by moving the slider on the decision window.

The decision screen includes the same four areas as previously. **Two supplementary curves appears in the top left graphic: the other player extraction in your pair and the total extraction of your pair.**

Last details

This part includes two five-minute training phases each and also a five minutes experimentation phase. It is your payoff for the experimentation that will be considered for your remuneration in this part.

The exchange rate of ECUs to euros is as follows : 10 ECUs $= 0.5$€

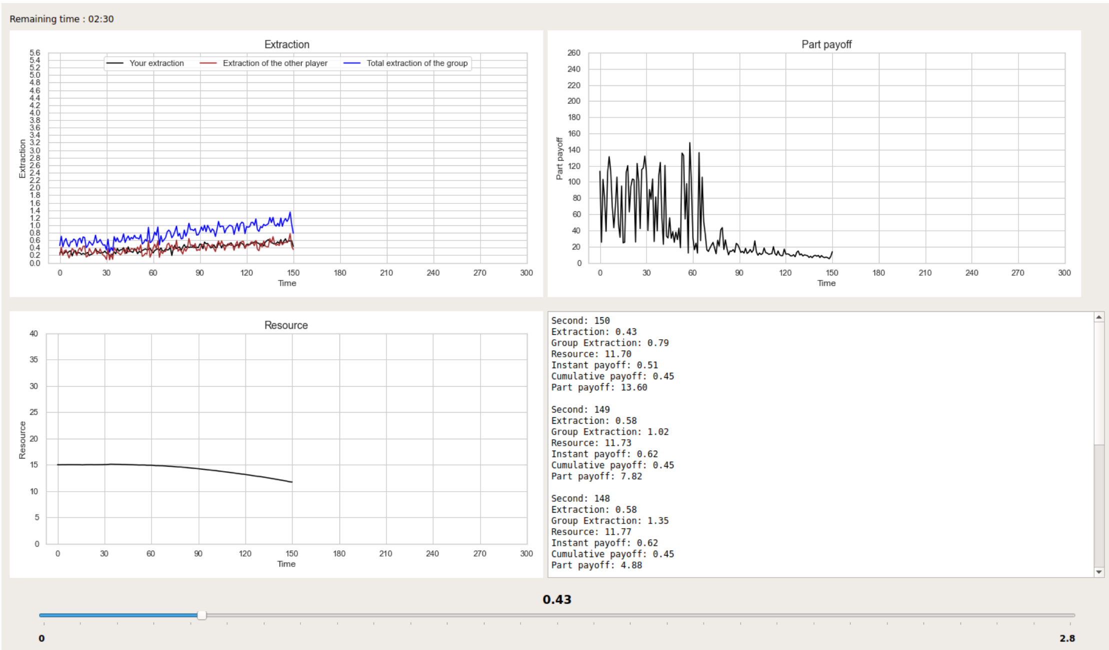

Figure D.5: Decision-making screenshot. We follow two hypothetical subjects who choose their extraction rate at random