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CEE-M
CENTER FOR ENVIRONMENTAL ECONOMICS - MONTPELLIER

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Marion Davin[1], Dimitri Dubois[1], Katrin Erdlenbruch[1], Marc Willinger[1]
[1]CEE-M, Univ Montpellier, CNRS, INRAE, Institut Agro, Montpellier, France.

Abstract

Experimenting with dynamic games raises issues about implementing discounting in experiments. Theoretical rational decision-makers evaluate payoff streams by converting them to a reference period, often "time zero." In experiments, subjects can adapt their strategy continuously. We explore individual behavior in a dynamic resource extraction experiment with two treatments: "z-discounting" (evaluating gains at time zero) and "p-discounting" (evaluating gains in present-time equivalents). Contrary to theoretical predictions, our data shows a significant positive treatment effect, indicating more substantial extraction under p-discounting. This challenges the theoretical model and prompts discussion on methodological considerations for discounting in laboratory settings.

JEL classification: C91, D90, Q20
Keywords: dynamic optimization; discounting; continuous time; laboratory experiment; time consistency.

1 Introduction

Experimenting with dynamic games raises questions about how to implement discounting. We introduce a new puzzle about the suitable reference period for discounting. We address this issue by examining, in a dynamic resource extraction experiment, how individuals behave when gains are valued at the initial point in time or when they are valued at the current time of the experimental game.

In theory, the reference period to discount is time zero: before the effective play of the game, future benefits are discounted at time zero to compute the optimal path. Dynamically consistent agents select their strategy at time zero and remain committed to it throughout. Altering their course of action as the dynamic game unfolds would prove disadvantageous. This issue was already discussed in the seminal paper of Strotz (1955) who proposed two behavioral strategies that could lead to time consistency[1]: pre-commitment and consistent planning. In contrast, in dynamic resource extraction game experiments, the subjects' task is not only to select an extraction rate for time zero, but also gradually over time. It is common to observe participants continually revising and adapting their extraction decisions in response to realized payoffs (see e.g., Benchekroun et al., 2014; Tasneem et al., 2017, 2019; Djiguemde et al., 2022a,b). But, instructing subjects about the possibility to revise their extraction rate at any point in time, raises two issues. Firstly, this is inconsistent with the theory that all decisions are to be made at time zero, and, secondly, it questions about the relevant reference period for discounting. Imposing time zero as the reference period is therefore debatable when plans can be revised as gains are realized. In this paper, we address the latter issue.

In a dynamic resource extraction game experiment, assuming that subjects behave following the theory, wherein they make an initial decision at time zero and adhere to it consistently, we show that the reference period for discounting is irrelevant if there is sole ownership of the resource. The same optimal extraction path is determined for any reference period for discounting. However if subjects do not follow a pre-established plan, but continuously adjust their decisions as time elapses, the choice of the reference period may affect their extraction path. Arguably, for such agents, the critical reference period for discounting future benefits is the present time. Indeed, alongside a dynamically consistent agent who takes decisions at time zero, an agent who continually revises takes decisions at the current time. For such an agent, what holds significance is the valuation of future benefits at the current moment.

In this paper, we investigate whether individuals playing a dynamic resource extraction game exhibit distinct behavior when benefits are assessed at the outset (time zero) compared to when they are evaluated at the current time of the experiment. Precisely, we aim to understand how subjects' behavior is affected by the informational feedback about the benefits provided in the dynamic game. We, therefore, set up an experiment in which, as the game proceeds, benefits are either converted into time zero values (z-discounting thereafter) or into present time values (p-discounting thereafter).

So far, the issue of the appropriate reference period for discounting in dynamic experimental games has been ignored. However, if plans are either non-observable or difficult to observe in the lab, as pointed out by several authors (Hey, 2002; Willinger, 2002; Bone et al., 2009; Hey and Panaccione, 2011; Hey and Knoll, 2011), the issue becomes relevant. Previous experiments on

[1]This is true even for non-standard discounting. Strotz distinguished between logarithmically linear discounting and logarithmically non-linear discounting, which may favor more proximate satisfactions.

the sole owner renewable resource model, either neglected discounting (Hey et al., 2009; Botelho et al., 2014) or relied on z-discounting (Benchekroun et al., 2014; Tasneem et al., 2017, 2019; Djiguemde et al., 2022a,b). At the same time, these experiments also allowed subjects to adjust their extraction level at any time. Therefore, valuing benefits at the present time could be an alternative and seem natural for the subjects.

Raising the issue of the appropriate reference period for discounting leads to a related issue about the implementation of infinite time in laboratory experiments. The standard implementation of an infinitely repeated game in the laboratory involves the random termination procedure of Roth and Murnighan (1978), which is considered isomorphic to discounting. The termination probability p is taken as a substitute for the discount factor δ. Discounting the period t payoff by δ^t is therefore supposed to be equivalent to ending the game with probability $p^t = \delta^t$. There are, however, several critical objections. There is indeed a small chance that the game lasts an infinite time when such a procedure is implemented, which raises an issue of credibility about the duration of the experiment[2]. From a theoretical perspective, assuming that individuals are expected utility maximizers, the equivalence between discounting and random termination is true only if agents are risk-neutral and time-consistent. From an empirical point of view, it is not obvious whether individuals treat equivalently games where future payoffs are discounted and games in which discounting is replaced by an exogenous ending probability. Evidence suggests that many people are confused about probabilities, tend to distort them (Kahneman and Tversky', 1972; Tversky and Kahneman, 1973) and revise them in a biased way (Zimmermann, 2020). Even when they are familiar with the concept, they might neglect small continuation probabilities (Selten et al., 1997). Furthermore, it is unlikely that subjects believe that the probabilities given by the experimenter are credible, because "the server may crash, or there may be an earthquake" (Dal Bó and Fréchette, 2018), suggesting that probabilities are transformed subjectively. In addition, from a practical point of view, random termination methods lead to heterogeneous observations with respect to game length, because of uncontrolled termination dates (Dal Bó and Fréchette, 2018).

The previous reasons plead in favor of relying on discount factors rather than on termination probabilities for designing experiments on dynamic games. Providing feedback to subjects about discounted gains seems also more in line with the spirit of dynamic games when there is no uncertainty. A mixed option, consisting of a combination of discounting and random termination, was proposed by some researchers (see Sabater-Grande, 2002; Cabral et al., 2014; Vespa, 2020). Discounting is implemented during a fixed number of periods of an initial sequence, followed by a sequence with a random termination procedure during which discounting is replaced by termination probabilities. The problem with this comes from the fact that each possible combination of discounting sequences with random ending sequences, provides specific incentives to subjects. Frechette and Yuksel (2016) compared four (theoretically) equivalent methods and concluded that ".. systematic behavioral differences in repeated interactions with payoff discounting versus random continuation can have important implications for the application of the theory of infinitely repeated games to these different environments." In addition, the "random round payment" method, which is often used in combination with the random termination procedure, tends to distort the discount factors (Sherstyuk et al., 2013; Chandrasekhar and Xandri, 2023), in a way that puts lower weights on future periods.

[2] Many experiments using random termination (e.g., Roth and Murnighan (1978), Fréchette and Yuksel (2017)) have a credibility issue about the possibility of infinitely long experimental duration. In most cases, what happens in the case of a very long repetition of the game is not discussed in the instructions. A notable exception is Lei and Noussair (2002) who considered in detail all the possible outcomes.

Given the above limitations of the standard practice of implementation of infinite horizons in the lab, we chose to rely on an alternative method that avoids random termination but keeps the infinite horizon fully credible. In addition, this method is fully consistent with discounting. Indeed, we use the "continuation payoff" method, which corresponds to the discounted payoffs from the termination time of the experiment up to infinity (see Tasneem et al., 2017[3], Djiguemde et al., 2022a,b). When the experiment reaches the time limit, which is announced at the beginning of the experiment, subjects are aware that their final extraction rate will be used to calculate the "continuation payoff". Practically, this long-term gain is computed at any instant p of the game and included in the total gains of the play. In the instructions, this value was defined as the long-term gain and phrased as follows: "Your long-term gain at date p is equal to the potential gain that you could realize if the game continued indefinitely and your extraction remained fixed forever at the level of the present moment."

We investigate the role of the reference period by comparing time zero discounting (z-discounting) and present-time discounting (p-discounting), in a continuous time CPR game in which we implemented the continuation payoff method. Participants were involved in a continuous extraction game of a renewable resource R. R had a constant growth rate and was decreasing in total instantaneous extraction (E). The subjects' task was to choose the level of extraction, which could be adjusted at any time. Chosen extractions induced benefits and costs (depending on the scarcity of the resource) in each period and gave rise to instantaneous and long-term gains. Both gains were either z-discounted or p-discounted. The sum of instantaneous gains and long-term gains gave rise to the overall gains of the play (G). Participants received instantaneous feedback about the levels of R, E, and G. This information was displayed permanently allowing participants to see how their decisions affected their overall gains.

The experiment consisted of two treatments: In the baseline treatment (z-discounting) gains are measured in terms of time $t = 0$ equivalents; in the test treatment (p-discounting) gains are measured in present time $t = p$ equivalents. Besides the main task, we implemented several control tasks. We elicited subjects' impatience using a mini-version of the Convex Time Budget method (Andreoni and Sprenger, 2012) and their risk-tolerance based on the Bomb Risk Elicitation Task proposed by Crosetto and Filippin (2013). Impatience is likely to strongly affect subjects' extraction rates (see e.g., Fehr and Leibbrandt, 2011). It is less obvious whether risk tolerance also plays a role, but we may think about subjects who have a poor understanding of the dynamics of the game being more cautious about their extraction rates. We also collected demographic data (age, education level, gender) to take into account usual behavioral control factors.

Our predictions rely on a standard sole owner dynamic extraction game, with either exponential z-discounting or exponential p-discounting. The model predicts that z-discounting and p-discounting lead to the same optimal path, as the total discounted gains only differ by a multiplicative factor between the two reference periods. This property implies that there is no ground for predicting that subjects will be more likely to follow the optimal extraction path under one reference period than under the other. Furthermore, this dynamic adaptation does not impede subjects with a pre-existing plan from endeavoring to stick to it throughout their actions. However, from a behavioral point of view, under p-discounting, subjects' perception of the game could be different from that of standard z-discounting, because current gains are multiplied by a positive constant that increases over time. Past gains have therefore higher weights than future gains. Intuitively, because of the larger magnitude of the gains under p-discounting,

[3] An earlier version of this paper is Benchekroun et al. (2014)

p-discounters could be expected to play more accurately because they would have a better sense of the evolution of marginal gains than the z-discounters[4].

We find that extraction rates are generally larger under p-discounting than under z-discounting. Furthermore, the extraction path deviates substantially more from the optimal extraction path under p-discounting, as compared to z-discounting. Although z-discounters seem to follow a nearly optimal path "on average", few of them can be categorized as *optimal players* (19 percent, compared to 16 percent for p-discounters). Hence, our treatment effect is primarily influenced by non-optimal subjects who substantially deviate from the optimal path, as the effect is absent among optimal players. Moreover, we analyze the behavior of subjects categorized as *planners* and *non-planners*, depending on whether they declared, before starting the game, having a plan about how to extract the resource over the whole time horizon, and taking into account the continuation payoff. We show that planners are on average closer to the optimum path than non-planners, who exhibit a much more erratic extraction behavior. However, both planners and non-planners exhibit a positive correlation between their extraction behavior and p-discounting. We suggest that plausible explanations, such "money illusion" (Fehr and Tyran, 2001; Petersen and Winn, 2014) or the magnitude effect (Andersen et al., 2013; Noor, 2011; Ballard et al., 2017; Sun and Potters, 2022), have poor explanatory power.

The remainder of the paper is organized as follows. In section 2 we introduce the model and its parametrization, compute the optimal solution, and show the equivalence between the p-discounting and z-discounting approach. In section 3, we discuss some important issues of the experimental design and describe the different parts of the experimental setting. In section 4, we present the results. We discuss our findings in section 5, and conclude in section 6.

2 Theoretical Considerations

2.1 The underlying resource model

We base our work on a dynamic continuous-time model of resource extraction and concentrate on the sole ownership case, as in Gisser and Sánchez (1980). The demand for the extracted resource, E_t is linear in its price, P: $E_t = g + kP$ where $k < 0$ and $g > 0$ and gives rise to the benefits from resource use. The cost to extract one unit of resource is linearly decreasing with the resource stock level R_t:

$$C(R_t) = \max\{C_0 - C_1 R_t; 0\} \quad \text{with} \;\; C_0 > 0, C_1 > 0.$$

The cost is thus strictly positive for $R_t < C_0/C_1$.
Agents' benefit is given by the surface underneath the inverse demand function:

$$B(E_t) = \int_{E_t} P(x)dx = \int_{E_t} \left(\frac{x}{k} - \frac{g}{k}\right) dx = \frac{1}{2k}E_t^2 - \frac{g}{k}E_t.$$

The equation of motion for the renewable resource is:

$$\dot{R} = \alpha - (1-\gamma)E_t$$

with $\alpha > 0$ the exogenous natural recharge, and γ a return flow coefficient associated with extraction levels, with $0 \leqslant \gamma \leqslant 1$.

[4] We thank François Salanié for suggesting this idea during a conference presentation.

2.2 The optimal control solution

The social planner, or the sole owner, solves an infinite-horizon dynamic optimization problem. He applies the discount factor $e^{-\rho(t-s)}$ to discount the gains, where $\rho \in (0,1)$ is the discount rate. We denote s as the reference date for discounting. While $s=0$ is the usual reference date for dynamic optimization problems, other reference dates are conceivable. In particular, in laboratory experiments where subjects can continuously update their extraction rate, discounting at the present time, i.e. setting $s=p$, might be more relevant for choosing their extraction rates. However, as shown below, whatever the value of $s \in [0;t[$, the optimum extraction path is the same. Therefore, in agreement with our theoretical framework, subjects seeking to achieve the optimum path in a dynamic resource extraction experiment should not be affected by the value chosen for s.

The optimal extraction plan is obtained by maximizing the following program:

$$\max_{E_t \geqslant 0} \int_0^{\infty} G(E_t, R_t) e^{-\rho(t-s)} dt$$

$$s.t \quad R_0 \quad \text{given and} \quad \dot{R} = \alpha - (1-\gamma)E_t.$$

with the gains:

$$G(E_t, R_t) = \frac{1}{2k}E_t^2 - \frac{g}{k}E_t - (C_0 - C_1 R_t)E_t.$$

The optimal solution consists of a monotonic transition path towards the steady state $(R_\infty^*; E_\infty^*)$, for resource and extraction:

$$R_\infty^* = \frac{kC_1\alpha + \rho\,(g + kC_0) - \rho\alpha(1-\gamma)}{k\rho C_1} \;;\; E_\infty^* = \alpha/(1-\gamma).$$

Note that some conditions on the parameters have to be satisfied to keep the steady state of the resource positive:

$$kC_1\alpha + \rho\,(g + kC_0) - \rho\alpha(1-\gamma) > 0.$$

Both the optimal extraction paths for R_t^* and E_t^* and the steady state (R^*, E^*) do not depend on s, meaning that the time at which the gains are discounted is without consequences. As the planner discounts all future gains at a constant rate of interest, he adopts a time-consistent plan.

An alternative way to highlight the dynamic consistency of the plan or its independence from the discount factor, consists of decomposing the stream of gains associated with this plan. Denote the total gains of the plan at time p by GP_p^T, with $T = \{Z, P\}$ for z-discounting or p-discounting. We decompose GP_p^T into instantaneous gains, GC_p^T, and long-term gains, GLT_p^T (see also instructions in the appendix A). We note $t > p$ the time from p onwards (in the experience, time is measured in seconds, and we switch from t to $t = p+1$). We thus have:

$$GP_p^T = \underbrace{\int_{t=0}^{p} e^{\rho(p-t)} G(R_t, E_t) dt}_{GC_p^T} + \underbrace{\int_{t>p}^{\infty} e^{-\rho(t-p)} G(R_t, E_t) dt}_{GLT_p^T}.$$

To see that both discounting references dates, i.e. z and p, lead to the same time-consistent plan, let us substitute T by Z and by P, respectively to obtain the corresponding gains:

$$\begin{aligned} GP_p^Z &= GC_p^Z + GLT_p^Z \\ &= \int_{t=0}^{p} e^{-\rho t} G(E_t, R_t) dt + \int_{t>p}^{\infty} e^{-\rho t} G(E_t, R_t) dt. \\ GP_p^P &= GC_p^P + GLT_p^P \\ &= \int_{t=0}^{p} e^{\rho(p-t)} G(E_t, R_t) dt + \int_{t>p}^{\infty} e^{-\rho(t-p)} G(E_t, R_t) dt. \end{aligned}$$

Define $G(R_t, E_t) \equiv G_t$, these two equations become:

$$\begin{aligned} GP_p^Z &= \int_{t=0}^{p} e^{-\rho t} G_t dt + \int_{t>p}^{\infty} e^{-\rho t} G_t dt. \\ GP_p^P &= \int_{t=0}^{p} e^{\rho(p-t)} G_t dt + \int_{t>p}^{\infty} e^{-\rho(t-p)} G_t dt. \end{aligned}$$

We note the equivalence:

$$GP_p^P = \int_{t=0}^{p} e^{\rho(p-t)} G_t dt + \int_{t>p}^{\infty} e^{-\rho(t-p)} G_t dt = GP_p^Z e^{\rho p}.$$

In other words, total discounted gains only differ by a multiplicative factor $e^{\rho p}$ between the two reference periods. There is a nominal difference in gains between the two configurations. As this difference is independent of the individual's choices, the optimal solution remains unchanged. For a given discount rate, future benefits are consistently discounted to their present value, regardless of the specific date at which the discounting occurs.

2.3 Numerical analysis

For the sake of the experiment, we assigned values to the model parameters. We calibrated the model in a way that an optimally managed resource converges close to the steady state within 5 minutes (300 seconds). The parameterization below allows to reach this target. We also selected values that can be easily imagined by subjects, such as a resource stock of 700 units or an extraction between 0 and 50 units. The discount rate of one percent did have the advantage not to extremely distort the sum of gains. In addition, we were careful to have instantaneous and total gains in an order of magnitude that remained easily understandable to subjects. The chosen parameter values are summarized in Table 1.

Table 1: Description of the model parameters

Parameter	**Description**	**Calibrated values**
R_0	initial resource stock	700
C_0	maximum average cost of extraction	550
C_1	sensitivity of cost to the resource level	0.5
k	parameter in the benefit function	-0.097
g	parameter in the benefit function	44
α	natural recharge	3.6
γ	return flow coefficient	0
ρ	discount rate	0.01

With these values, the steady state is defined by $(R^*; E^*) = (627.01; 3.6)$ and the optimal extraction paths are given by (values are rounded) by the following equations:

$$R_t^* = 72.99e^{-0.0176t} + 627.01,$$
$$E_t^* = 1.28e^{-0.0176t} + 3.6$$

Different types of gains can be computed, namely instantaneous gains, which can be evaluated at any second, and total gains, which are the sum of instantaneous gains and long-term gains. Of particular relevance is the long-term gain at the last instant of the game. Numerical model outputs for gains are given in Table 2. We depict instantaneous gains at time 300 (the end of the game), and corresponding total gains, under the assumption of an optimal extraction strategy, for both z-discounting and p-discounting. Observe that the magnitude of gains is about 20 times greater under p-discounting than under z-discounting, both for the instantaneous gain at $t = 300$ and for the gains of the play, including the long-term gains.

Table 2: Numerical model results (values rounded)

Parameter	Description	Optimal values
GC_{300}^Z	Instantaneous gains at time 300 for z-discounting	36
GC_{300}^P	Instantaneous gains at time 300 for p-discounting	717
GP_{∞}^Z	Total gains of the play including long-term gains for z-discounting	85 468
GP_{∞}^P	Total gains of the play including long-term gains for p-discounting	1 716 662

3 Experimental design

We set up a dynamic continuous-time model following previous work by Benchekroun et al. (2014), Tasneem et al. (2017, 2019) and Djiguemde et al. (2022b). Our protocol is closest to the one of Djiguemde et al. (2022b), see the appendix in section 6. In subsection 3.1, we first discuss the two key design issues raised in the introduction, i.e. continuous time and infinite horizon, before introducing our experimental design features in subsection 3.2.

3.1 Key design issues for the extraction game

3.1.1 Continuous-time

Our approach to implementing continuous time is similar to that of Tasneem et al. (2017) and Djiguemde et al. (2022a,b), which is based on real-time. Specifically, the elapsed time between two instants of the game was set to one second. Therefore, the computer program calculated the subject's resource and gain every second, taking into account their extraction at the corresponding second. The graphs displayed on the players' screens were also updated every second. As detailed in Djiguemde et al. (2022a,b), this time interval between two instants of the theoretical model facilitates the understanding of the instructions by the subjects and ensures technical precision in the calculations and data exchanges over the network between the server and the subjects' stations.

In practical terms, the subjects had a horizontal cursor on their screen to set their extraction level, which they could move during play. The cursor value was sent to the server every second and used to perform calculations (resource stock and gains). The updated information was then sent back to the player's computer, where the graphs and displayed information were updated accordingly. If a subject did not move the cursor, the standing value was used for the calculation of the next extraction level. Throughout the experiment, the resource level evolved continuously, while the player's decision remained constant between two instants. This allowed for calculations to be performed in continuous time, while the displayed information was updated every second.

3.1.2 Infinite horizon

The standard method for implementing infinite time in an experiment involves the random termination procedure (RTP thereafter) introduced by Roth and Murnighan (1978). For instance, RTP has been used by Suter et al. (2012) and Vespa (2020) in the case of dynamic CPR extraction games. RTP has several drawbacks already discussed in the introduction. First, there is a credibility issue about the real duration of the experiment (Selten et al., 1997; Dal Bó and Fréchette, 2018), second, variable endings across sessions and/or individuals complexify the analyses, and third discount factors are distorted if RTP is combined with the random round payment method (Sherstyuk et al., 2013; Chandrasekhar and Xandri, 2023). In addition, the usual argument that discounting and random termination are isomporphic, holds true in the expected utility framework only if agents are risk-neutral and time-consistent. An alternative approach is to use the continuation payoff method (CPM thereafter) as in Tasneem et al. (2019) and Djiguemde et al. (2022a). The CPM consists in calculating the discounted payoff for all future periods, up to infinity, assuming that the player keeps his extraction effort at the current level forever. CPM offers two advantages. Firstly, players can monitor their gains at the infinite horizon at any time, irrespective of the actual game end date. Secondly, they gain an understanding of the long-term consequences associated with their current extraction choices. Additionally, this approach ensures that all players play for the same effective duration, as set by the experimenter, making data more easily comparable and facilitating analysis.

Formally, the continuation payoff at time p for level of extraction E_p is defined as follows:

$$GLT_t^T(p) = \sum_{t=p+1}^{\infty} e^{-\rho(t-s)} G(E_p, R_t). \tag{1}$$

As a result, we define the subject's payoff for the game at time p as:

$$GP_p^T = \sum_{t=0}^{p} e^{-\rho(t-s)} G(E_t, R_t) + \sum_{t=p+1}^{\infty} e^{-\rho(t-s)} G(E_p, R_t). \tag{2}$$

with $T = \{Z, P\}$ and $s = \{0, p\}$. The first term in equation (2) is the discounted current payoff and the second one the continuation payoff.

3.2 Experimental settings

The experiment consisted of four parts, plus a socio-demographic questionnaire. In the first part, the subjects played the dynamic extraction game alone (optimal control), they played the same game in pairs in the second part. The third part aimed at measuring the subject's impatience, with the Convex Time Budget method (Andreoni and Sprenger, 2012), and the fourth part their risk attitude based on the Bomb Risk Elicitation Task (Crosetto and Filippin, 2013). The four parts and the questionnaire were computerized, they were developed with the oTree platform (Chen et al., 2016). Participants were informed of the number of games, and also that their payoff for the experiment would consist of either part 1 or part 2 plus either part 3 or part 4, based on random selections made by the computer program. The rest of the section details the different parts.

3.2.1 Presentation of the experiment

After a silent reading of the instructions by subjects, an experimenter read the instructions aloud, and participants could ask questions (in private). After reading the instructions, subjects had to answer 5 comprehension questions. Written explanations for each answer were shown once all questions were answered.

3.2.2 Part 1: individual extraction task

In part 1 the subjects played the extraction game as a single owner for two rounds. The first round was a training round that did not count for the payoff of this part. Participants could get used to the information displayed on the computer screen (extraction, resource level, and total gains of the play, including the continuation payoff) and observe the impact of their behavior on these indicators.

Each round lasted exactly 5 minutes (300 seconds). Before the start of a round, subjects had to choose an initial extraction level for instant $t = 0$. Once all the subjects in the room had finished, the countdown (300 seconds) started and subjects could change their extraction level at any time by moving a cursor on a slider. Appendix A displays a picture of the screen that showed the 300 seconds of play of the dynamic game. The possible extraction values ranged from zero to 50 units. This wide range was chosen to avoid inducing extraction behavior close to the optimal values, i.e. 4.88 units at time zero and 3.6 units in the steady state.[5] Every second the subject's computer sent the current extraction on the slider to the server, and the latter made computations to establish the resource stock and the player's payoff, and sent back the updated values to the subject's computer which updated the graphs: the extraction level, the resource stock and the payoff for the part.

3.2.3 Part 2: two player CPR extraction game

The second part of the experiment consisted of three rounds of the dynamic game played by pairs of subjects. At the beginning of each round, new pairs were formed randomly, making sure that two players could not meet more than once. The conditions were exactly the same as in the first part, except that two players extracted the same resource. On the players' screen a curve was added to the extraction graph, this curve reported the extraction level chosen by the other player of the pair. The data collected in this second part of the experiment will not be analyzed in this paper, which focuses on the issue of discounting when the subject is alone in extracting the resource.

[5] We also wanted to include values leading to the maximum of the benefit function (at 44 units) as shown in the appendix A.

3.2.4 Part 3: time preferences

Common pool resource is intertemporal in nature, individual time preferences are therefore a key ingredient to examining extraction behaviors. Subjects' time preferences are likely to affect their extraction decisions. For example, impatient individuals may choose higher extraction rates and deplete the resource faster than patient individuals. Classical economic theory teaches that a lower rate of time preference, characterized by a lower discount on future payoffs, implies that the agent puts a higher value on the future. In the context of dynamic CPR, this entails that the patient individual extracts more sustainably because under-extraction in the present time is a way to increase the availability of resources in the future. This view is supported by the field experiment of Fehr and Leibbrandt (2011) with Brazilian Fishermen. However, Javaid et al. (2016) found the opposite result in Indian fishermen, suggesting a more complex relationship between time preference measures and CPR exploitation. To capture the level of patience of individuals we rely on the Convex Time Budget (CTB hereafter) method proposed by Andreoni and Sprenger (2012). With this method, we can establish that the more a subject allocates to the sooner date, the more impatient they are. We ask each subject to make three allocations for a given pair of dates, by changing the interest rate (1.1, 1.25, 1.5), to check for consistency (the allocation at the sooner date should be non-increasing in the interest rate). We take the average allocation at the later date for the three interest rates as an index of patience.

3.2.5 Part 4: risk preferences

Subjects' risk attitude is measured with the Bomb Risk Elicitation Task (BRET hereafter) proposed by Crosetto and Filippin (2013). In this task the subject chooses the number of boxes they want to open, knowing that one box contains a bomb. Each box opened was worth 0.5 euros. If the box that contains the bomb is opened the subject loses all their payoff and earns 0 euros.

3.2.6 Questionnaire on extraction strategies

In 7 test sessions (over 15, 4 in treatment z-discounting and 3 in treatment p-discounting), we added a questionnaire on extraction strategies before and after part 1. After having read the instructions, and before part 1, subjects had to answer several questions (on top of the existing understanding questions) about their extraction strategies: whether they had a precise idea about the way they would extract the resource, which indicator variables (resource, extraction, gains) they intended to follow, whether they would extract more in the beginning or the end, in a constant way or using spikes, etc. what particular resource level they aimed at and whether they had an idea about the total gains they could obtain. After having played the extraction experiment in part 1, we asked subjects whether they had followed their initial extraction strategy and if not, why. Several open and closed questions were dedicated to this issue. The test sessions were designed to gain a better understanding of the subjects' way of dealing with a dynamic extraction game in continuous time. For these sessions, we skipped part 2 of the experiment (the game with pairs of subjects), but subjects performed part 3 (time preferences) and 4 (risk preferences) and answered the socio-demographic questionnaire. The implementation of the questionnaire on extraction strategies in certain sessions might have influenced the behavior of subjects; however, evidence presented in section 4.1 indicates that this was not the case.

4 Results

In this section, we present our main results. In subsection 4.1 we first explore whether subjects took into account the dynamic nature of the game. In subsection 4.2, we analyze average extraction paths and the resulting evolution of resource stocks depending on the discounting treatment. In subsection 4.3 we characterize the efficiency of extraction depending on the treatment. Finally, in subsection 4.4 we explore two behavioral strategies that could account for the treatment effect of discounting: optimality of play and planning strategy.

Table 3 reports summary statistics about the participants ($N = 160$), in total and the two treatments.[6]

	Total	z-discounting	p-discounting	Difference	p-value
Participants	160	90	70		
TQ=0 | TQ=1	79 | 81	42 | 48	37 | 33		
Gender (Male)	0.44	0.52	0.33	0.19	0.022**
Age	23.21	22.66	23.93	-1.27	0.026**
Student	0.84	0.88	0.80	0.08	0.261
Studied discipline					
Economics and management	0.44	0.43	0.46	-0.03	
Human sciences	0.18	0.20	0.16	0.04	
Science and engineering	0.19	0.22	0.16	0.06	0.329
Health	0.05	0.02	0.09	-0.07	
Other	0.13	0.12	0.14	-0.02	
Study level	3.01	2.76	3.34	-0.58	0.038**

χ^2 tests were performed for variables Gender, Student, Studied discipline and Study level.
Mann-Whitney test was performed for the variable Age.

Table 3: Statistics about participants

4.1 The dynamic nature of the experiment

Before proceeding with the analysis of the whole sample, we tested whether the dynamic nature of the experiment was taken into account by the participants. 81 subjects participated in these test sessions. Based on their answers to the questionnaire on extraction strategies, we created two binary variables. The first one is "playing a dynamic game" which is equal to 1 if a subject declared that the continuation payoff had an impact on her extraction behavior. The second one is "having a dynamic extraction strategy" equal to 1 if a subject declared that they had a plan for how to extract the resource over the 300 instants and that the continuation payoff had an impact on his extraction behavior. 75 percent of the participants of the test sessions stated that they are "playing a dynamic game" and 53 percent declared"having a dynamic

[6]Note that 180 subjects participated in our experiment. However, 20 of them ended part 1 with a negative payoff, indicating a misunderstanding of the game dynamics. As subjects knew they could not lose money, retaining their data would be challenging since they lacked any incentive to conserve resources. It is worth noting that these 20 subjects are evenly distributed between the two treatments, with 12 from the z-discounting treatment and 8 from the p-discounting treatment. Moreover, we observed that these 20 subjects exhibited a higher frequency of errors in the understanding questionnaire, with an average of 1.75 faults (sd=1.25), compared to the other participants averaging 1.03 faults (sd=0.94). This discrepancy in performance between the two groups is statistically significant, as indicated by the Mann-Whitney test (p-value = 0.010).

extraction strategy" at the beginning of the play.[7] Regressions show that having a high score in the understanding questionnaire is positively related to both these strategies, independently of the treatment (see Table 4).[8] We examined additional control variables, as presented in Table 3, but none of them exhibited a significant impact on the responses to these questions. To ensure that this additional questionnaire did not affect participants' extraction behavior, we define the control variable *'Questionnaire'* which is equal to 0 for participants in sessions without the questionnaire and 1 for the others. Mann-Whitney U-tests and OLS regression of extraction on *'Questionnaire'* show that there is no significant effect of this variable, on extraction behavior. Consequently, we view the data as a cohesive entity for the forthcoming analysis. In essence, any significant difference between treatments can be solely attributed to them.

"Playing a dynamic game"

	dy/dx	Std error	z	$Prob > \|z\|$	95% Conf. Interval	
Treatment	0.085	0.096	0.88	0.377	-1.034	0.275
Gender	0.106	0.095	1.11	0.269	-0.081	0.293
Understanding	0.148	0.051	2.89	0.004	0.048	0.248
Prob(predicted):	0.786					
N=81						

"Having a dynamic extraction strategy"

	dy/dx	Std error	z	$Prob > \|z\|$	95% Conf. Interval	
Treatment	0.013	0.126	1.10	0.921	-2.333	0.259
Gender	0.181	0.118	1.53	0.126	-0.051	0.412
Understanding	0.180	0.070	2.56	0.011	0.042	0.317
Prob(predicted):	0.533					

N=81. dy/dx: discrete change for dummy from 0 to 1

Table 4: Marginal effects of logit regression explaining participants' dynamic extraction strategies.

4.2 Average extraction and resource stock

4.2.1 Average extraction and resource paths

Figure 1 shows the evolution of the average extraction and resource stock for both treatments, with discounting at time zero (blue) and present time (orange). The optimal extraction path, which is common to both treatments, is indicated by the black dashed line. We can see that the extraction paths are quite similar in both treatments until halfway through the game, at which point the extraction level in the p-discounting treatment becomes higher than in the z-discounting treatment (instant 138). As a consequence, the average resource stock drops sharply and ends up at a much lower level in the p-discounting treatment (see the resource graph at the bottom of Figure 1). This visual trend is confirmed by the average extraction and resource levels

[7] Specifically, of the 54 participants who acknowledged "playing a dynamic game", 24 also reported "having a dynamic extraction strategy", while the remaining 30 did not. In contrast, among the 27 participants who denied "playing a dynamic game" 18 similarly reported "not having a dynamic extraction strategy", whereas 9 reported the contrary.

[8] Beforehand, we checked that the score in the understanding questionnaire was not influenced by the treatment.

by minute, provided in Table 5. Statistical support is provided by the estimates of a mixed linear model that considers both inter-individual and intra-individual variability, reported in Table 6.

4.2.2 Individual heterogeneity in extraction paths

We can also look at individual explanatory factors for the above paths. First, note that there is more heterogeneity among players in the p-discounting treatment than in the z-discounting treatment, as shown in Figure 2, which displays the distribution of the average individual extractions minute by minute in both treatments. Moreover, Table 11 in the appendix shows the impact of the treatment on extractions in different mixed linear models, when considering additional control variables.

4.2.3 Mean squared deviation from the optimal path

Additionally, we compute the mean squared deviation from the theoretical optimal resource path, per participant, in the two treatments. Table 7 reports results for periods incremented by 60 instants. The mean squared deviation exhibits a significant positive difference between the z-discounting and the p-discounting treatment in the first minute. Then, the difference becomes significantly negative. This is in line with resource trends depicted in Figures 1 and confirms that when gains are measured at present time, players' behavior moves away from the optimal resource evolution path.

Taken together, the data reported in the figures and the tables clearly indicate a significant treatment effect, which is particularly evident in the later stages of the game. To the extent that it is optimal to adopt the same strategy in both treatments, this result highlights that players, in at least one of the two treatments, do not behave optimally.

	Extraction		Resource	
	z-discounting	p-discounting	z-discounting	p-discounting
t=0 to t=59	4.82	4.55	648.26	659.20
t=60 to t=119	3.35	3.54	638.88	651.42
t=120 to t=179	3.68	4.11	646.23	642.03
t=180 to t=239	3.46	4.18	647.58	603.14
t=240 to t=300	3.87	4.39	646.88	566.22

Table 5: Average extraction and resource per treatment and minute.

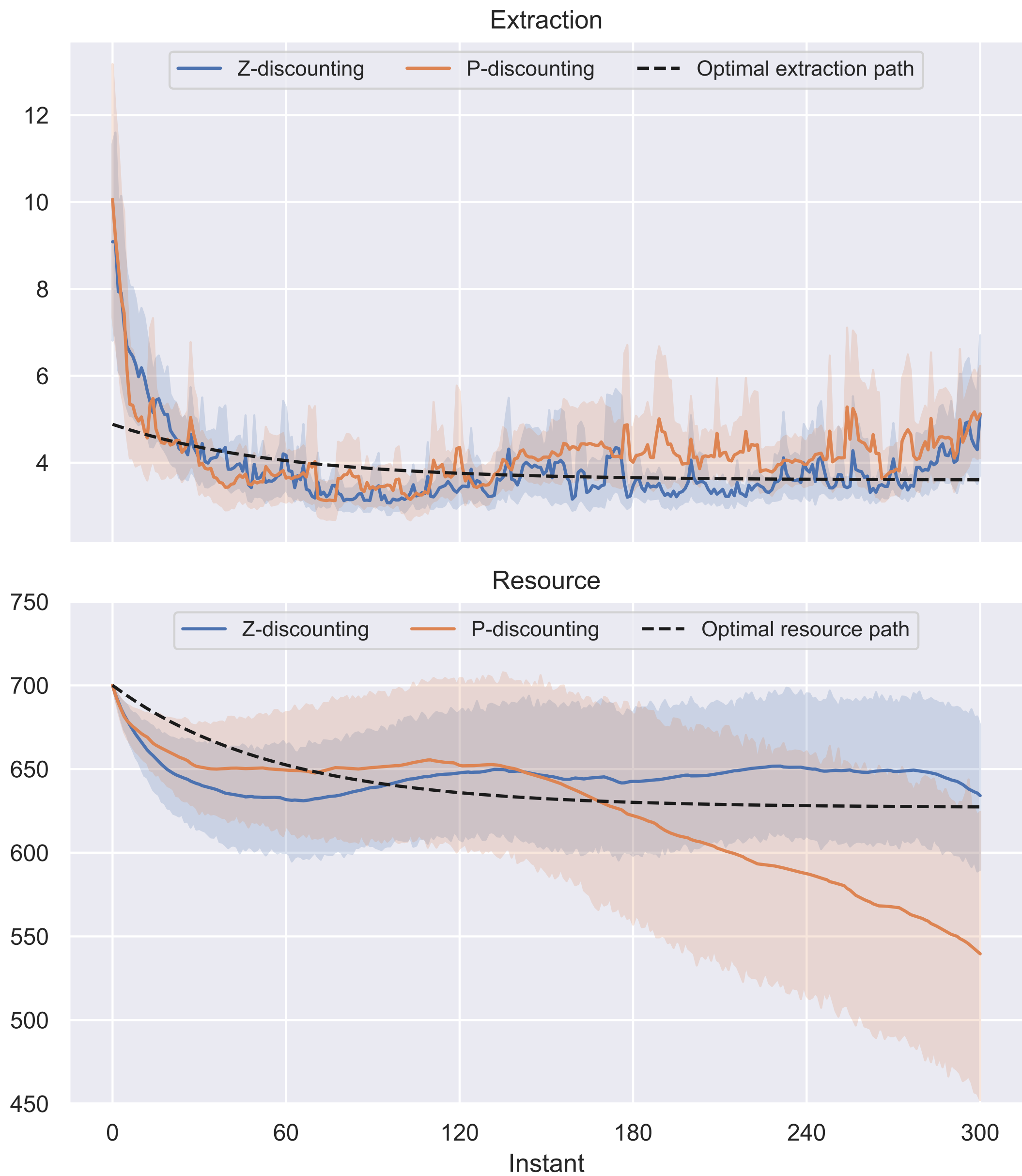

Figure 1: Evolution of the average extraction (top) and resource stock (bottom). *Shaded areas represent 95% confidence intervals around the mean.*

4.3 Efficiency

Dividing the player's final payoff by the predicted optimal payoff, we obtain a simple measure of relative efficiency. Given the high over-exploitation of the resource under p-discounting, we expect higher efficiency losses under this treatment. We assess these losses by looking at the relative efficiency reached in each treatment. The average relative efficiency is equal to 0.83

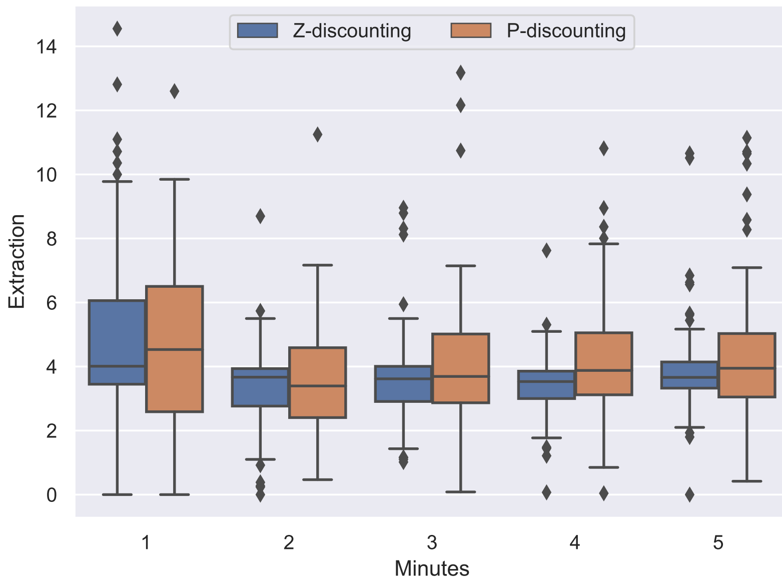

Figure 2: Individual average extraction distribution per treatment and minute

(sd = 0.23) for the z-discounting treatment and 0.79 (sd = 0.18). Although the difference is relatively modest, it is significant (Mann Whitney U-Test, p-value=0.001). To illustrate the difference, Figure 3 displays the cumulative distribution of the relative efficiency for the two treatments. A Kolmogorov-Smirnov two-sample test rejects the null hypothesis that the two distributions are identical (p-value = 0.004).

4.4 Behavioral strategies

To better understand the reasons for the treatment effect of the reference period for discounting, we explore different behavioral patterns. We analyze subjects' stated behaviors according to the questionnaire on extraction strategies (planned behavior) and their reactions to the level of stock of the resource (optimal behavior).

4.4.1 Optimal players

A plausible reason for the discrepancy in terms of efficiency between the two treatments is the likelihood that subjects react optimally to the prevailing level of resource stock. Because the magnitude of the gains is amplified under p-discounting, we expected players involved in the p-discounting treatment to be more sensitive to variations in their payoffs and the stock of available resources. Therefore, we identify subjects' reactions to variations of the resource stock, by estimating the following model $E_t = \beta_0 + \beta_1 E_t^c$ for each subject.[9] E_t^c represents the optimal extraction conditional on the current stock of resources. A player who behaves optimally is expected to increase her extraction when the (conditional) optimal extraction increases. We

[9]This method was proposed by Djiguemde et al. (2022a) who showed that the linear regression provides a better categorization than the former method proposed by Suter et al. (2012).

	Extraction	Resource
(Intercept)	4.82^{***}	648.26^{***}
	(0.13)	(19.80)
p-discounting	-0.27	10.94
	(0.17)	(29.94)
minute2	-1.47^{***}	-9.38^{***}
	(0.13)	(2.03)
minute3	-1.14^{***}	-2.03
	(0.13)	(2.03)
minute4	-1.36^{***}	-0.67
	(0.13)	(2.03)
minute5	-0.95^{***}	-1.38
	(0.13)	(2.03)
p-discounting:minute2	0.46^{***}	1.60
	(0.10)	(3.02)
p-discounting:minute3	0.69^{***}	-15.14^{***}
	(0.10)	(3.02)
p-discounting:minute4	0.98^{***}	-55.38^{***}
	(0.10)	(3.02)
p-discounting:minute5	0.79^{***}	-91.60^{***}
	(0.10)	(3.00)
AIC	257293.93	584840.39
BIC	257408.10	584954.56
Log Likelihood	-128633.97	-292407.20
Num. obs.	48160	48160
Num. groups: instant	301	301
Num. groups: participant	160	160
Var: instant (Intercept)	0.34	4.68
Var: participant (Intercept)	0.89	35115.00
Var: Residual	11.97	10753.80

$^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6: Treatment effect by minute

	z-discounting	p-discounting	Diff	Prob > $\|z\|$
t=0 to t=59	14913.02	11904.06	3008.96	0.0000
t=60 to t=119	29322.36	34764.15	-5441.69	0.0000
t=120 to t=179	40744.24	56034.17	- 50287.08	0.0000
t=180 to t=239	42955.59	85819.24	-15289.93	0.0000
t=240 to t=300	44238.36	114613	-70374.64	0.0000

We applied a Mann-Whitney U-test to test for the difference between the two treatments.

Table 7: Mean Squared Deviation from the optimal resource path per treatment and minute.

therefore classify subjects into two groups depending on whether their β_1 value is significantly different from zero and positive, or not. We categorize a subject as having behaved optimally in the experiment if $\beta_1 > 0$ and is statistically significant.

We found that 18.89% of the subjects behaved optimally in the z-discounting treatment and

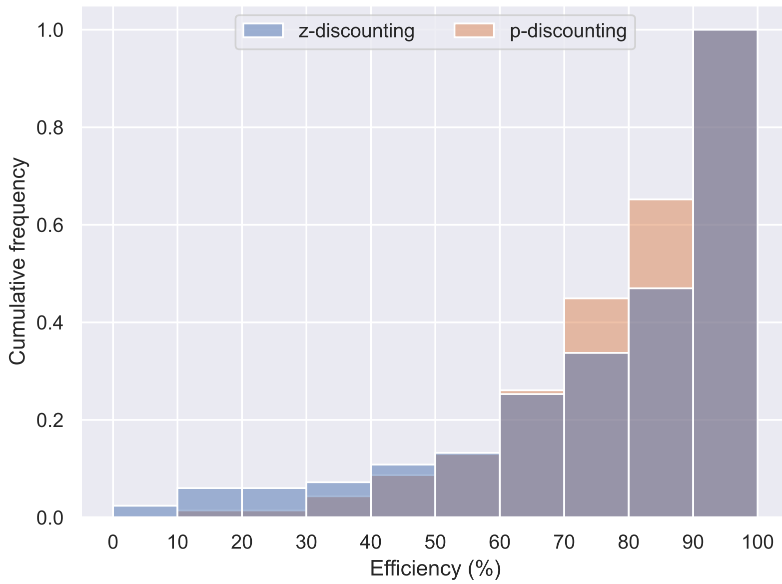

Figure 3: Cumulative distribution of the efficiency at the last instant of play (part payoff / theoretical part payoff).

15.71% in the p-discounting treatment, with no significant difference (Chi-squared test, p-value = 0.753). Additionally, Table 8 reports the results of a logit model where the dependent variable is "behaving optimally" (equal 1 if the subject is categorized as optimal). The absence of a treatment effect is confirmed by the model. The only control variable with a significant effect is stated risk aversion which has a positive effect on optimal extraction behavior. Figure 4 illustrates the path of gains for optimally behaving players and non-optimally behaving players in the z-discounting (left) and p-discounting (right) treatments. It reveals that optimal players closely align with the optimal gain paths in both treatments.

In Table 9 and Figure 5, we decompose our analysis depending on the optimality behavior. The analysis in Table 9 highlights the fact that the significant treatment effect is driven by non-optimal players, whereas among optimal players, the treatment effect is not significant. This confirms the consistency of our strategy to identify optimal players, as theory suggests that optimal players are expected to employ the same extraction strategy in both treatments. Figure 5 illustrates the average MSD between the observed resource path and the theoretical resource path, for both the z-discounting (left) and the p-discounting (right) treatments and optimally or non-optimally playing subjects. In each treatment, the average MSD for players deemed optimal is significantly lower than that for non-optimal players. This discrepancy is statistically significant in both instances, as indicated by Mann-Whitney tests, with p-values falling below the 0.05 threshold.

4.4.2 Planners

In this subsection, we investigate whether planners' instantaneous extractions are closer to the optimal extraction path than those of non-planners. Remember that 81 subjects answered a detailed questionnaire about their extraction strategies. We categorized a subject as a planner

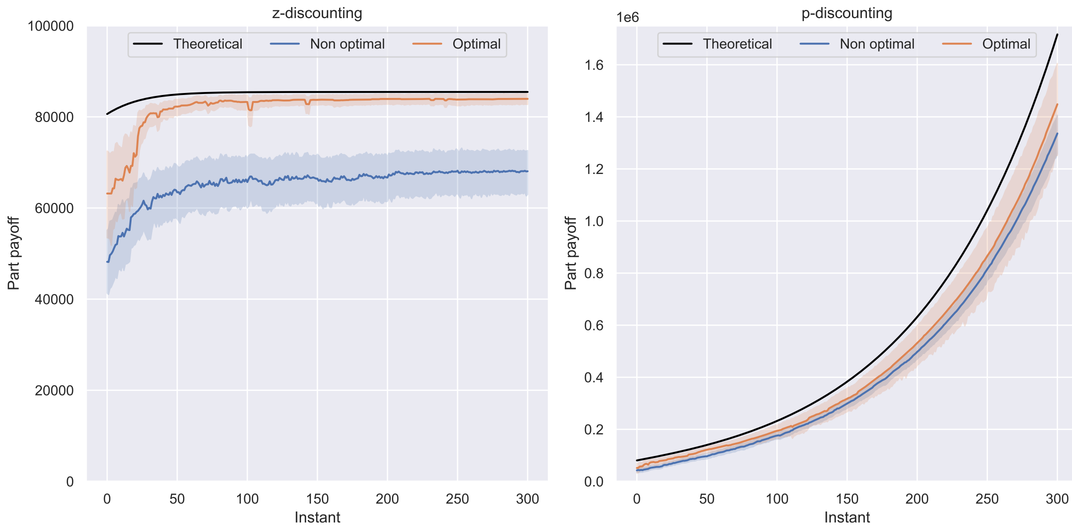

Figure 4: Path of gains for optimally and non-optimally playing subjects in the two treatments.

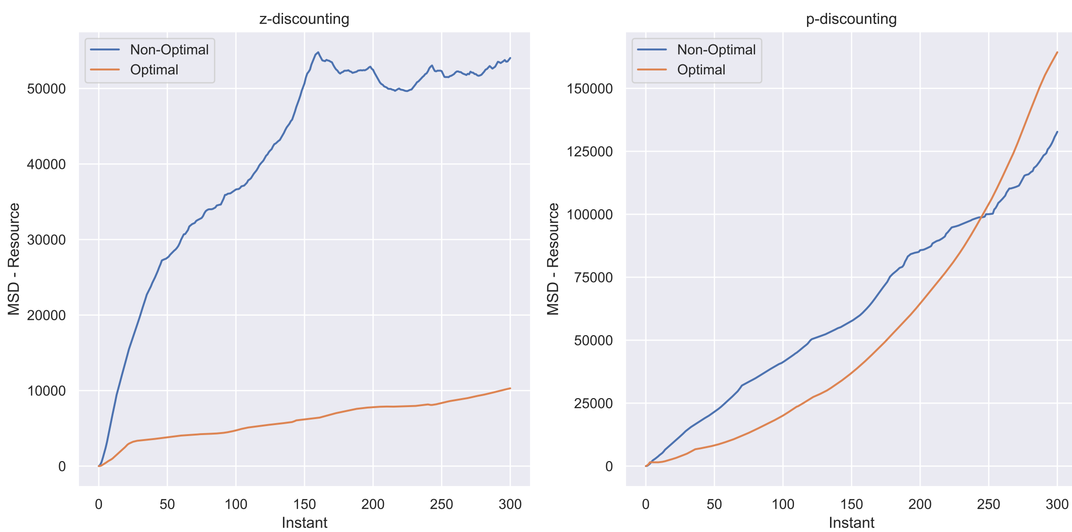

Figure 5: Mean Squared Deviation from the Resource theoretical path for optimal and non-optimal players in the two treatments.

Dep. Variable:	Optimal ($\beta > 0$)	No. Observations:	160
Model:	Logit	Df Residuals:	150
Method:	MLE	Df Model:	9
converged:	True	Pseudo R-squ.:	0.04528
Covariance Type:	nonrobust	Log-Likelihood:	-70.837
		LL-Null:	-74.196
		LLR p-value:	0.6664

	coef	std err	z	P> |z|	[0.025	0.975]
Const.	-2.9708	1.496	-1.986	0.047**	-5.902	-0.040
P-discounting	-0.2346	0.456	-0.514	0.607	-1.129	0.660
Understanding faults	0.0953	0.236	0.404	0.686	-0.367	0.557
Patience (CTB)	0.0178	0.027	0.667	0.505	-0.035	0.070
Risk (BRET)	-0.0036	0.010	-0.349	0.727	-0.024	0.016
Risk (declared)	0.2449	0.117	2.096	0.036**	0.016	0.474
Patience (declared)	-0.0447	0.083	-0.540	0.589	-0.207	0.118
Gender (Male)	-0.7011	0.489	-1.433	0.152	-1.660	0.258
Age	0.0078	0.057	0.137	0.891	-0.103	0.119
Study level	0.0155	0.141	0.110	0.912	-0.261	0.292

$^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 8: Logistic Regression Analysis of Factors Influencing Optimal Behavior.

if he answered positively to the two questions: (i) whether she had a strategy for extracting the resource over the 300 instants of the experiment, and (ii) whether she thought that the continuation payoff had an impact on their extraction behavior. Based on this definition, 43 of the 81 subjects were categorized as planners and 38 as non-planners. We examined the potential correlation between being a planner and patience. Individuals with greater patience might demonstrate a heightened awareness of the dynamic aspects of the game and the implications of continuation payoffs. However, our analysis did not reveal any significant association between being a planner and patience, either in terms of self-reported patience (p-value = 0.605) or in terms of elicited patience (p-value = 0.241) through the CTB method.[10] This findings suggest that being a planner is more likely be related to cognitive factors than to time-preferences. We also checked whether the relative frequency of planners varied across treatments. Still, no significant differences were observed (52% and 55% of the participants involved in the questionnaire sessions were identified as planners in the p-discounting and z-discounting treatments, respectively).

The regression results reported in Table 10 show that p-discounting increases significantly the level of extractions, both for planners and non-planners. Figure 6 reports the extraction and resource paths for planners and non-planners. One can see that planners are on average closer to the (unconditional) optimum path. However, looking at MSDs, there is no significant difference between the chosen and the optimal level of extraction, neither under z-discounting (p-value = 0.820) nor under p-discounting (p-value = 0.814). Figure 7 shows that the discrepancy is mainly related to the p-treatment. Under z-discounting both planners and non-planners are closer to the (unconditional) optimum path than in the p-treatment. In addition, extraction rates are more noisy in the p-treatment, especially for the non-planners.

[10] p-values are based on a logit regression with dependent variable "being a planner".

	Extraction Non-optimal players	Extraction Optimal players
(Intercept)	5.06^{***}	2.89^{**}
	(0.58)	(1.06)
P-discounting	0.51^{**}	-0.21
	(0.17)	(0.33)
Patience (CTB)	-0.01	0.01
	(0.01)	(0.02)
Patience (declared)	-0.08^{*}	0.23^{***}
	(0.03)	(0.06)
Risk (BRET)	-0.00	-0.01
	(0.00)	(0.01)
Risk (declared)	0.06	-0.11
	(0.04)	(0.08)
Gender (Male)	-0.16	0.13
	(0.18)	(0.40)
Age	-0.04	0.01
	(0.02)	(0.04)
Study level	0.06	-0.03
	(0.06)	(0.08)
AIC	218503.44	33032.29
BIC	218606.52	33116.76
Log Likelihood	-109239.72	-16504.14
Num. obs.	39732	8428
Num. groups: instant	301	301
Num. groups: participant	132	28
Var: instant (Intercept)	0.52	0.49
Var: participant (Intercept)	0.85	0.59
Var: Residual	13.97	2.71

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 9: Mixed Linear Models - Extraction of non-optimal and optimal players.

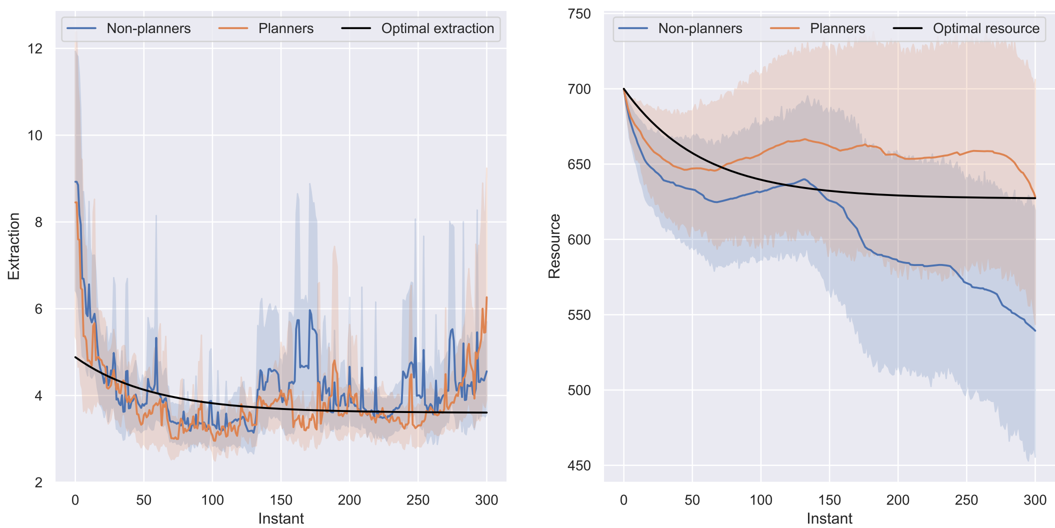

Figure 6: Average extraction (left) and resource (right) for planners and non-planners

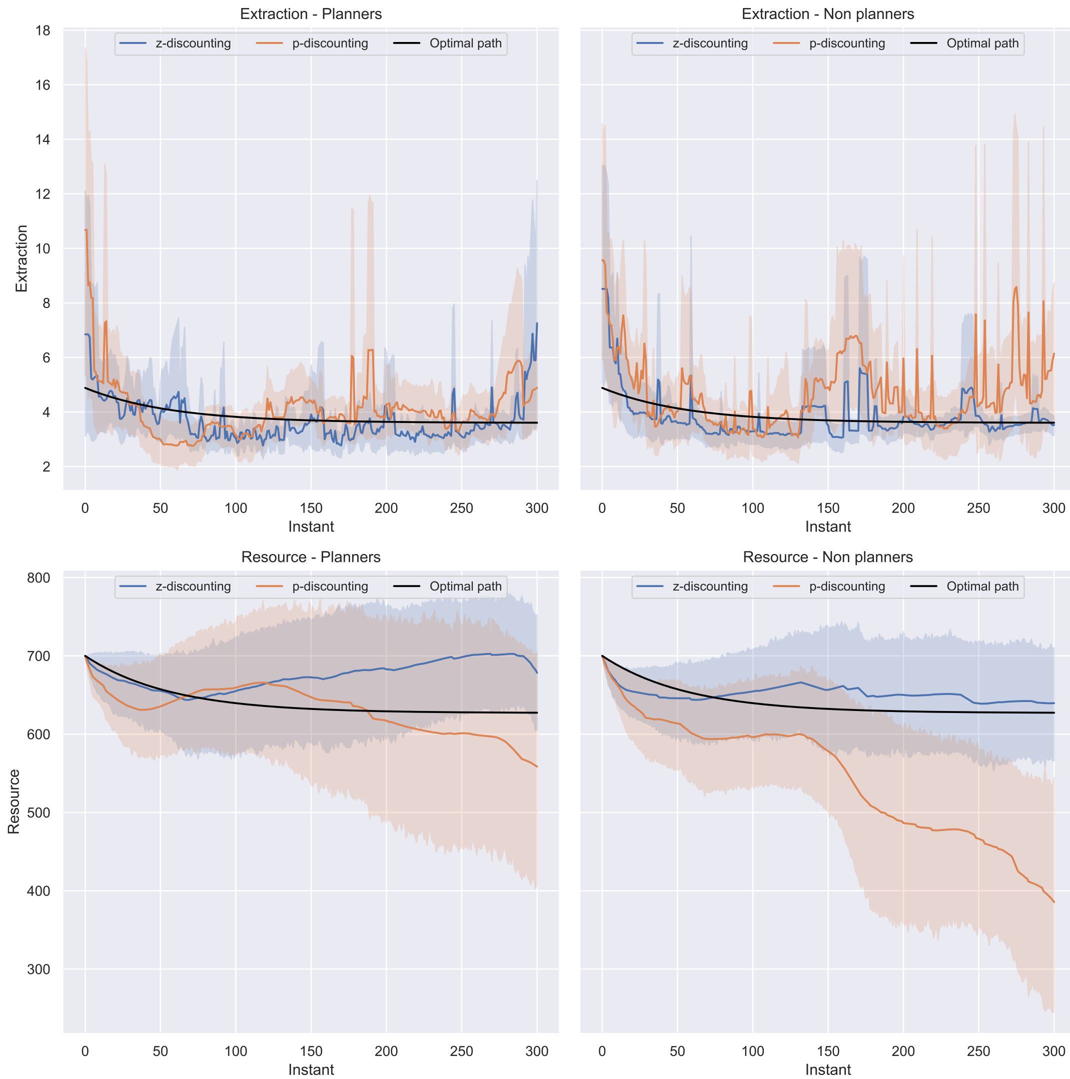

Figure 7: Paths for planners and non-planners by treatment

	Extraction Non-planners	Extraction Planners
(Intercept)	4.25^{**}	5.40^{***}
	(1.53)	(1.04)
P-discounting	0.86^{**}	0.81^{*}
	(0.32)	(0.33)
Patience (CTB)	0.00	-0.01
	(0.02)	(0.01)
Patience (declared)	-0.05	-0.08
	(0.06)	(0.07)
Risk (BRET)	0.00	-0.01
	(0.01)	(0.01)
Risk (declared)	0.09	-0.01
	(0.07)	(0.07)
Gender (Male)	-0.34	0.29
	(0.30)	(0.32)
Age	-0.04	-0.04
	(0.06)	(0.04)
Study level	0.11	-0.00
	(0.11)	(0.08)
AIC	61042.20	68065.71
BIC	61130.34	68155.33
Log Likelihood	-30509.10	-34020.86
Num. obs.	11438	12943
Num. groups: instant	301	301
Num. groups: participant	38	43
Var: instant (Intercept)	0.51	0.36
Var: participant (Intercept)	0.62	0.75
Var: Residual	11.70	10.87

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 10: Mixed Linear Models - Extraction of planners and non-planners.

5 Discussion

We report a sharp treatment effect of the reference period for discounting gains in a continuous infinite time CPR extraction game. On average, extraction levels are larger under p-discounting than under z-discounting. Furthermore, average extractions are closer to the optimum path under z-discounting. Over time, following an initial time interval during which average extraction trajectories of both treatments are close, a sharp drop in the resource is observed under p-discounting. Our different analyses seem to converge to the conclusion that participants are less efficient when their gains are discounted in the present time.

However, this conclusion is nuanced when we split the sample of participants into optimizers and non-optimizers. Recall that an optimizing agent is defined as a participant who adjusts her current extraction level towards her optimal conditional level of extraction. We found that optimizers' extraction levels are independent of the discounting reference period, whereas non-optimizers are positively influenced under p-discounting. This observation suggests that participants who fail to realize what their best contemporary extraction strategy is, are influenced by the perception of the gains. Nevertheless, upon segregating the subset of participants who responded to a comprehensive questionnaire regarding extraction strategies, we discern no distinction between planners and non-planners in terms of how these individuals are impacted by the discounting reference period. Both planners and non-planners exhibit a positive correlation between their extraction behaviors and p-discounting; in other words, extractions are greater under p-discounting compared to z-discounting for both categories.

Another reason for the deviant extraction behavior of non-optimizers could be related to the complexity of the extraction game, because of the temporal dimension. According to Enke et al. (2023), intertemporal decisions entail intrinsic complexity, which could influence players' decision-making strategies: intertemporal tradeoffs appear to generate behavioral distortions in large part because they require a great deal of costly cognitive information processing. Subjects respond to this complexity by substituting from costly rational procedures for evaluating tradeoffs to less costly noisy or heuristic alternatives that are relatively inelastic to time intervals, generating systematic departures from time consistency."

The inherent complexity of the dynamic task may have led many subjects to adopt strategies not aligned with their best interests, at various points in time. These subjects might have opted for extraction levels that prioritized short-term gains, even if such strategies were suboptimal in the long run. The question then becomes whether the complexity of the game is more significant in the p-treatment. The comprehension questionnaire does not reveal any differences in the understanding of the game between the two treatments. However, this questionnaire only captures a limited aspect of the player's perception of complexity and cannot be used as a relevant indicator of the game's complexity. However, the perceived complexity of the game is likely to have been greater under p-discounting because the discount factor evolves throughout the game, while under z-discounting instantaneous gains at any given instant t remain constant throughout the entire game. Precisely, under z-discounting the instantaneously discounted gain at instant t is $e^{-\rho t}G(E_t, R_t)$, while under p-discounting it becomes $e^{-\rho(t-p)}G(E_t, R_t)$. It is easy to perceive that the introduction of this second alternative added increased complexity, leading to potentially heightened confusion in participants' comprehension of the game. Indeed, the notion that p-discounting introduces a *sliding reference date* may have confused participants' minds. However, the relative frequency of planners in the two treatments was not affected by the apparent complexity of the instructions (Chi-squared test, p-value = 1).

Were our participants under p-discounting exposed to a magnitude effect? Several experimental studies have highlighted the importance of the magnitude of the gains in temporal allocation tasks (see e.g., Raineri and Rachlin, 1993; Andersen et al., 2013; Sun and Potters, 2022). Under p-discounting, gains were multiplied by the factor $e^{\rho p} > 1$, where p is the current period. This factor, which increases over time, may have mistakenly led subjects to believe that their current and future wealth was being amplified, leading them to over-extract. However, our data indicates rather a negative magnitude effect. Subjects in the p-treatment behaved as if the magnified gains they observed prompted them to act more "impatiently" in their extraction decisions compared to those in the z-discounting treatment.

Finally, could our subjects be susceptible to a form of "money illusion" effect? Harrison (1989)[11] argued that increasing the nominal value of the gains can affect the perceived opportunity cost of misbehavior. If this argument applied to our subjects, we would have expected to observe greater consistency under p-discounting, which is not the case. Our claim of the absence of money illusion in our individual optimization experiment is further supported by the findings of Fehr and Tyran (2001) who demonstrated that subjects exhibit less susceptibility to money illusion when interacting with a computer program that optimally best responds, compared to playing against a human opponent[12]. In addition, Drichoutis et al. (2015) provided clean evidence against a money illusion effect in a second price auction experiment, by manipulating the conversion rate: whether subjects are incentivized in Euros or Ecus (with conversation rates ranging from 10:1 to 25:1), did not affect their bidding strategies.

6 Conclusion

We implemented a single-owner resource extraction game in the lab, to study the possible impact of the discounting reference period. We found that subjects' extraction levels are affected by the discounting reference period. We observed higher extraction levels under p-discounting than under z-discounting. This is not in accordance with the theory, as subjects' extraction levels should not be affected by the reference period. From a theoretical point of view, the optimum extraction path is independent of the discount factor.

In a sub-sample, we confirmed subjects' comprehension of the dynamic game, with the majority employing dynamic extraction strategies. Utilizing various models, we identified a significant positive treatment effect, indicating overall higher extraction under p-discounting than z-discounting. Further, we identified subjects adopting optimal extraction paths by comparing strategies to optimal conditional ones based on past behavior. The treatment effect did not influence subjects following optimal paths, in line with theory. We controlled for socio-economic variables, game understanding, impatience, and risk attitude.[13]

Continuous-time dynamic game experiments are still in their early stages but are gaining traction among experimental economists. Knowing how to best implement this type of game in the laboratory is a key aspect of good experimental practice. Based on our findings we suggest using z-discounting rather than p-discounting. We also recommend relying on the continuation

[11]This paper led to a controversy about proper incentives in auction experiments, see Kagel and Roth (1992) and Harrison (1992).

[12]Yamamori et al. (2018) report a sharp money illusion effect in an experiment based on an inter-temporal consumption model (without discounting). However, their experiment involved random price fluctuations, which could have induced a loss aversion effect in consumption rather than a money illusion effect.

[13]Only declared general risk aversion significantly impacted optimal extraction behavior.

payoff method, rather than on the random termination method, to implement infinite horizon in the lab.

Conflict of Interest Statement

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

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A Instructions of part 1 (optimal control)

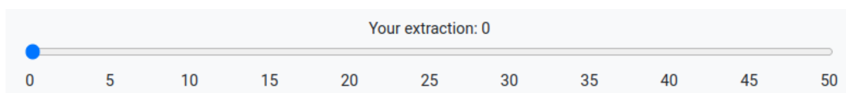
Instructions

Translated from french
[instructions of the z-discounting treatment]

General Framework

In this part, payoffs will be expressed in ECU (Experimental Currency Unit). The conversion rate of ECUs to Euros will be specified at the end of these instructions.

You initially have a resource of 700 units. At any time, you can extract an amount between 0 and 50 units from this resource. You are free to choose the amount you wish to extract, with a decimal precision, that is 0, 0.1, 0.2, …, 49.8, 49.9, 50. To make your choice, you must move a slider similar to the one below. For more precision, you can use the arrows on your keyboard.



Between two decisions, you can take as much time as you need to think. If you do not touch the slider, your extraction is maintained at the last level you chose.

Resource Evolution

Throughout the experiment, time will be measured in seconds, meaning that exactly one second will elapse between two consecutive instants t and t+1. The quantity of available resource evolves according to two elements: (i) the amount you extract at each instant t, noted E_t, and (ii) a fixed quantity of 3.6 units, added automatically at each instant t. Denoting R_t as the quantity of resource available at each instant t, the evolution of the resource is described by the relation:

$$R_{t+1} = R_t - E_t + 3.6$$

In other words, the resource available at instant t+1 (R_{t+1}) is equal to the resource available at t (R_t) minus the amount you extracted at t (E_t) plus the amount that adds automatically (3.6).

If at instant t your extraction exceeds the available resource, your extraction for that instant will be automatically set to 0 by the computer.

<u>Example 1</u>: Let's assume that at instant t, the quantity of available resource is 500 units and that your extraction is 3 units. At instant t+1, the quantity of available resource will then be equal to: R_{t+1} = 500 - 3 + 3.6 = 500.6 units.

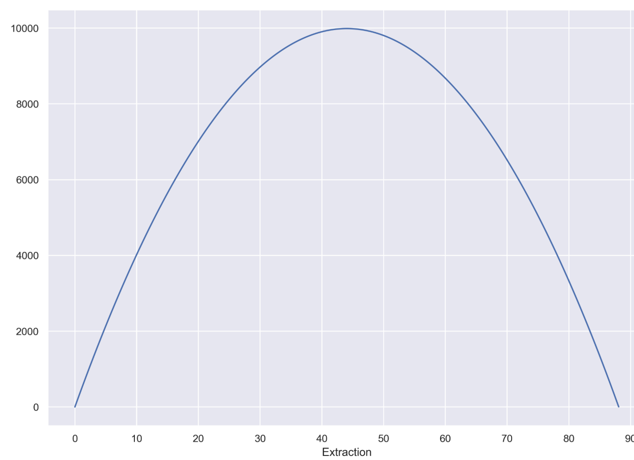
Example 2: Let's assume that at instant t the quantity of available resource is 37 units. You decide to extract 42 units. The computer will automatically set your extraction level to 0. Of course, you can choose a new quantity immediately after.

Gain from extraction

Your total gain for the game depends on the gain from extraction at each instant. Your gain at instant t is the difference between the revenue from extraction at instant t and the cost of extraction at instant t.

Extraction Revenue

Your revenue depends on your extraction at instant t as illustrated by the figure below.



In the first instance, the higher your extraction, the higher your revenue. This is true as long as your extraction is less than 44 units. In the second instance, the higher your extraction, the lower your revenue will be. This occurs if the extraction exceeds 44 units. Specifically, at instant t, for an extracted quantity E_t, the revenue from extraction at moment t, noted REC_t, is equal to RECt = $453.61\ E_t - 5.15\ E_t^2$.

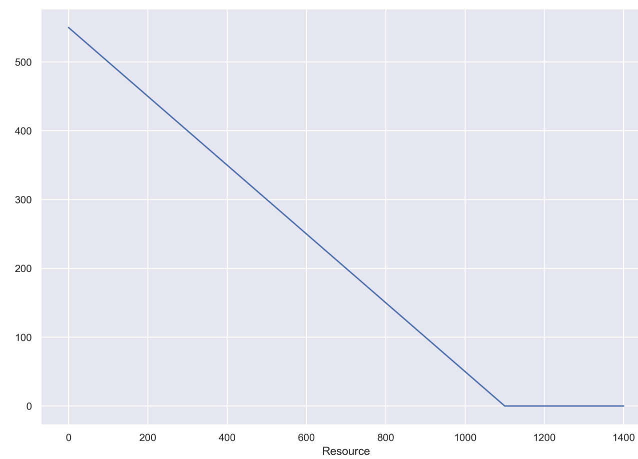
Extraction Cost

The extraction of the resource generates a cost that differs for each extracted unit. The unit cost of extraction at instant t depends on the quantity of the resource:

- The higher the quantity of available resource, the lower the extraction cost.

- The extraction cost becomes null when the quantity of the resource is equal to or greater than 1100 units.

The figure below graphically represents the unit cost according to the quantity of available resource. Specifically, when the resource is less than 1100 units, the unit cost of extraction, c_t, evolves according to the following relation: $c_t = 550 - 0.5R_t$. The cost of extraction at instant t, C_t, is equal to the extracted quantity multiplied by the unit cost of extraction, that is: $C_t = E_t \times c_t$.



Gain at Instant t

The gain at instant t (G_t) is equal to the difference between the revenue from extraction and the cost of extraction, that is: $G_t = REC_t - C_t$.

Example 3: At instant t the quantity of available resource is $R_t = 500$ units. Your extraction at instant t is $E_t = 5$ units. The unit cost of the extraction is equal to 300 ECUs. The total cost is therefore equal to 1500 ECUS and the revenue to 2241.48 ECUs = 453.61 x 5 - 5.15 x 5^2. Your gain at instant t is equal to 741.48 ECUs = 2241.48 - 1500.

Example 4 : The table below illustrates with examples several possible situations. The first row corresponds to example 3.

Ressource R_t	Extraction E_t	Coût unitaire c_t	Coût C_t	Recette REC_t	Gain de l'instant G_t
500	5	300	1500	2241.48	741.48
400	5	350	1750	2241.48	491.48
200	5	450	2250	2241.48	-8.52

Gain for the game at Instant t

At any instant t, the computer will calculate the gain for the game. This gain will be displayed on your screen at each instant. It is calculated based on two elements:

1. Your cumulative gain from all instants since the beginning of the game.
2. Your long-term gain.

1. Your cumulative gain from the beginning of the game
This is the capitalized sum of gains made since the beginning of the game (t=0) until the present instant (t=p). All the gains you have obtained between the present instant p and the beginning of the game are converted into gains of the instant p *[instant 0]*. To do this, the gains made before instant p *[after instant 0]*, are updated at a rate of 1%. Concretely, the gain of instant t<p is multiplied by $e^{-0.01(p-t)}$. *[of instant t>0 is multiplied by* $e^{-0.01t}$*]*

<u>Example 5</u>: Imagine the instant p=60 in the game, and consider a gain G_t = 100 realized at three distincts instants before p.

- at instant p=60, this gain of 100 ECUs obtained in t=0 will be multiplied by 1.82 (100 x $e^{0.01x60}$ = 100 x 1.82 = 182)
- at instant p=60, this gain of 100 ECUs obtained in t=10 will be multiplied by 1.65 (100 x $e^{0.01x50}$ = 100 x 1.65 = 165)
- at instant p=60, this gain of 100 ECUs obtained in t=60 will be multiplied by 1 (100 x $e^{0.01x0}$ = 100 x 1 = 100)

[

- *at instant p=60, this gain of 100 ECUs obtained in t=0 will be multiplied by 1 (100 x* $e^{0.01x0}$ *= 100 x 1 = 100)*
- *at instant p=60, this gain of 100 ECUs obtained in t=10 will be multiplied by 0.9 (100 x* $e^{0.01x10}$ *= 100 x 0.9 = 90)*
- *at instant p=60, this gain of 100 ECUs obtained in t=60 will be multiplied by 0.55 (100 x* $e^{0.01x60}$ *= 100 x 0.55 = 55)*

]

What should be understood from this principle is that the older past gains have a greater impact on the game's overall gain than the more recent past gains. The sum of these capitalized past gains constitutes your gain of past instants, GC_p.

$$GC_p = \sum_{t=0}^{p} e^{0.01(p-t)} G_t$$

$$[GC_p = \sum_{t=0}^{p} e^{0.01t} G_t]$$

2. Your long-term gain
This is your gain for all future moments relative to instant p. It is calculated based on your extraction at instant p. Your long-term gain at date p is equal to the potential gain you could achieve if the game continued indefinitely (from t=p to t=∞) and your extraction remained fixed forever at the present instant level ($E_t = E_p$). Your future gains are converted into gains

of instant p *[instant 0]*. To do that, the long-term gain for instant p is obtained by updating the future gains at the rate of 1%. More precisely, it means that the gain of instant t is multiplied by $e^{-0.01x(t-p)}$ *[by $e^{-0.01t}$]*. The long-term gain is therefore equal to:

$$GLT_p = \sum_{t=p+1}^{\infty} e^{-0.01x(t-p)} G_t$$

$$[GLT_p = \sum_{t=p+1}^{\infty} e^{-0.01t} G_t]$$

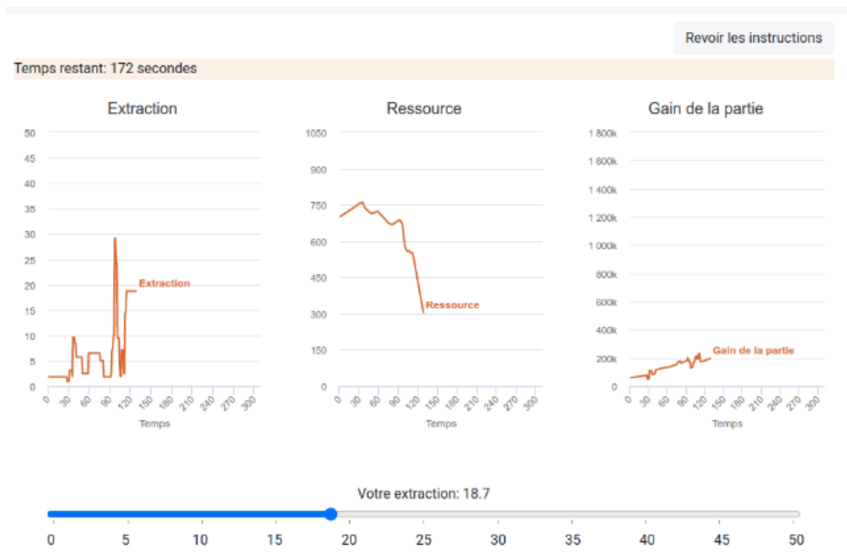
The game gain at moment p is therefore equal to the sum of your cumulative gain from all past moments and your long-term gain: $GP_p = GC_p + GLT_p$.

The gain that will be paid to you at the end of the experiment for this game is your gain calculated at the last moment of the game, that is at p=300.

Unfolding of the game

Before the game starts, you will need to choose an initial extraction level, which will apply at the beginning of the game (t=0). Then when the game starts, you can change your extraction level every second if you wish. To do this, select the slider and move it to the desired extraction level. The last chosen extraction level will be applied as long as no new extraction level is chosen. The decision screen includes three charts, in addition to the decision area with the slider.

- On the left: the evolution of your extraction.
- In the center: the evolution of the resource.
- On the right: the evolution of your gain for the game.



[Scale of the game gain graphic (right-side) range from 0 to 100k]

Final Details

This game consists of 2 rounds. The first round is a trial round and does not count for your gain for this game. The conversion rate of ecus to euros is 75000 ECUs = €1.00 *[7500 ECUs = €1]* if your game gain is positive. If your game gain is negative, the conversion rate is null.

B Understanding, pre-game and post-game questionaires

Understanding questionnaires

z-Discounting

1. Text: The quantity of available resource is updated every second.
Options: true, false
Solution: true
Explanation: Every second, the resource is decreased by the quantity you have extracted and increased by 3.6.

2. Text: If your extraction at each instant is 50 units, the quantity of resource decreases over time and becomes zero before the instant t=300.
Options: true, false
Solution: true
Explanation: If your extraction is 50, as a fixed quantity of 3.6 units is added automatically at each instant, the quantity of resource decreases by 46.4 units each instant. In less than 20 seconds, the initial 700 units of resource are exhausted.

3. Text: The gain at each instant of the game depends on the quantity of available resource.
Options: true, false
Solution: true
Explanation: The gain at instant t is the difference between the revenue and the cost at instant t. The revenue depends only on the extracted quantity (see figure 2 of the instructions), but the cost depends on the quantity of available resource. The unit cost or the total cost (unit cost x extracted quantity) increases as the resource decreases but is zero once the quantity of available resource is equal to or greater than 1100.

4. Text: At the instant 60 of the game, which of the following gains contributes the most to the game's gain?
A) a gain of 10 obtained at instant 5,
B) a gain of 10 obtained at instant 10,
C) a gain of 10 obtained at instant 50
Options: A, B, C
Solution: A
Explanation: The gain obtained at instant 5 will be capitalized over a longer duration than the gains obtained at instants 10 or 50. Since the present instant is 60, the gain obtained at instant 5 will be capitalized for 55 seconds, the one obtained at instant 10 for 50 seconds, and the one obtained at instant 50 for 10 seconds.

5. Text: The gain of the game at the instant t=p is composed of two elements:
(i) the sum of the (capitalized) gains of each instant between t=0 and t=p, and
(ii) the gain calculated from the instant t=p to infinity assuming that the extraction level is maintained at that of instant t=p
Options: true, false
Solution: true

Explanation: At each instant, the computer gives you the gain of the game if it stopped immediately, with therefore the two mentioned elements: (i) the instantaneous capitalized gain from the initial instant (t=0) to the present instant, and (ii) the gain from the present instant to infinity assuming that the resource continues to evolve according to the defined rule but that you no longer change your extraction level. Your gain from the experience, for this part, is therefore your gain of the game at the last instant of play, namely at instant t=300.

6. Text: The decision screen shows the game's gains (3rd chart on the right). In your opinion, what is the maximum level of gains that you can obtain at the end of the game (by applying the best possible extraction strategy)?
Options: 207,000, 172,000, 103,000, 86,000, 43,000, 30,000
Solution: 86,000
Explanation: This is the result that can be obtained by choosing extractions optimally, in order to maximize the sum of the capitalized gains of the game.

7. Text: Imagine that you are at the instant t=10. At this instant, the gain you realize:
A) is not updated because it corresponds to the instant when you make your decision,
B) is not updated because all gains are converted into gains of the instant t=0,
C) is updated because all gains are converted into gains of the present instant
Options: A, B, C
Solution: C
Explanation: The gains of each instant are converted into the gain of the instant t=0.

8. Text: At the last instant, you realize an instant gain of 100. This gain increases your total gain by an amount:
A) equal to 100 x e^(-0.01 x 300),
B) less than 100 x e^(-0.01 x 300),
C) more than 100 x e^(-0.01 x 300)
Options: A, B, C
Solution: C
Explanation: Your extraction at each instant contributes not only to your cumulative gain of past instants but also to your long-term gain.

9. Text: At the instant t=60, which of the following gains is not updated:
A) a gain of 10 obtained at t=0,
B) a gain of 10 obtained at t=60
Options: A, B
Solution: B
Explanation: All gains are converted into the gain of the present instant (t=p), so only the gain obtained at t=60 is not updated.

p-Discounting

1. Text: The quantity of available resource is updated every second.
Options: true, false
Solution: true

Explanation: Every second, the resource is decreased by the quantity you have extracted and increased by 3.6.

2. Text: If your extraction at each instant is 50 units, the quantity of resource decreases over time and becomes zero before the instant t=300.
Options: true, false
Solution: true
Explanation: If your extraction is 50, as a fixed quantity of 3.6 units is added automatically at each instant, the quantity of resource decreases by 46.4 units each instant. In less than 20 seconds, the initial 700 units of resource are exhausted.

3. Text: The gain at each instant of the game depends on the quantity of available resource.
Options: true, false
Solution: true
Explanation: The gain at instant t is the difference between the revenue and the cost at instant t. The revenue depends only on the extracted quantity (see figure 2 of the instructions), but the cost depends on the quantity of available resource. The unit cost or the total cost (unit cost x extracted quantity) increases as the resource decreases but is zero once the quantity of available resource is equal to or greater than 1100.

4. Text: At the instant 60 of the game, which of the following gains contributes the most to the game's gain?
A) a gain of 10 obtained at instant 5,
B) a gain of 10 obtained at instant 10,
C) a gain of 10 obtained at instant 50
Options: A, B, C
Solution: A
Explanation: The gain obtained at instant 5 will be capitalized over a longer duration than the gains obtained at instants 10 or 50. Since the present instant is 60, the gain obtained at instant 5 will be capitalized for 55 seconds, the one obtained at instant 10 for 50 seconds, and the one obtained at instant 50 for 10 seconds.

5. Text: The gain of the game at the instant t=p is composed of two elements:
(i) the sum of the (capitalized) gains of each instant between t=0 and t=p, and
(ii) the gain calculated from the instant t=p to infinity assuming that the extraction level is maintained at that of instant t=p
Options: true, false
Solution: true
Explanation: At each instant, the computer gives you the gain of the game if it stopped immediately, with therefore the two mentioned elements: (i) the instantaneous capitalized gain from the initial instant (t=0) to the present instant, and (ii) the gain from the present instant to infinity assuming that the resource continues to evolve according to the defined rule but that you no longer change your extraction level. Your gain from the experience, for this part, is therefore your gain of the game at the last instant of play, namely at instant t=300.

6. Text: The decision screen shows the game's gains (3rd chart on the right). In your opinion, what is the maximum level of gains that you can obtain at the end of the game (by applying the best possible extraction strategy)?
Options: 2,070,000, 1,720,000, 1,030,000, 860,000, 430,000, 300,000
Solution: 1,720,000
Explanation: This is the result that can be obtained by choosing extractions optimally, in order to maximize the sum of the capitalized gains of the game.

7. Text: Imagine that you are at the instant t=10. At this instant, the gain you realize:
A) is not updated because it corresponds to the instant when you make your decision,
B) is not updated because all gains are converted into gains of the instant t=0,
C) is updated because all gains are converted into gains of the present instant
Options: A, B, C
Solution: A
Explanation: The gain of the present instant does not need to be updated at the time of the decision (i.e., at the present instant). It will be, however, from the next instant onwards.

8. Text: At the last instant, you realize an instant gain of 100. This gain increases your total gain by an amount:
A) equal to 100 x e^(-0.01 x 300),
B) less than 100 x e^(-0.01 x 300),
C) more than 100 x e^(-0.01 x 300)
Options: A, B, C
Solution: C
Explanation: Your extraction at each instant contributes not only to your cumulative gain of past instants but also to your long-term gain.

9. Text: At the instant t=60, which of the following gains is not updated:
A) a gain of 10 obtained at t=0,
B) a gain of 10 obtained at t=60
Options: A, B
Solution: B
Explanation: All gains are converted into the gain of the present instant (t=p), so only the gain obtained at t=60 is not updated.

Pre-game questionnaire

1. Do you have an idea of your extraction plan for the 300 instants?
Options: Yes, absolutely | Yes, more or less | No, I will see as it goes | No, no idea
2. Can you describe this plan in two or three sentences? Leave blank if you do not have a plan.
3. The decision screen shows the level of extraction (on the left), the resource (in the middle), and the game's gains (on the right) over time. Which information do you plan to follow primarily? If you could only have one piece of information on the decision screen, which one would you choose?

Options: the extraction | the resource | the game's gain | the extraction and the resource | the extraction and the game's gain | the resource and the game's gain | all three

4. If you could only have one piece of information on the decision screen, which one would you choose?

Options: the extraction | the resource | the game gain

5. How do you plan to exploit the resource?

Options (the same for the three questions a, b, c below: in a practically constant manner from the beginning to the end | with strong extractions from time to time | with weak extractions from time to time | in a constant manner by levels, adjusting extractions from time to time | in a constant manner with occasional more significant extractions if opportune | in a constant manner with occasional weaker extractions if necessary | with strong extractions from the beginning to the end | with weak extractions from the beginning to the end | with strong extractions followed by weak extractions | with weak extractions followed by strong extractions | adaptively, according to my observations | none of the proposed methods

   a. Your first method of doing so (the most important)
   b. Your second method of doing so
   c. Your third method of doing so (the least important of the three)

6. If you wish to describe how you plan to exploit the resource

7. How often do you think you will need to change your extraction?

Options: at every moment | approximately every 10 seconds | approximately every 20 seconds | approximately every 30 seconds | approximately every minute | the initial extraction should be kept fixed unless it does not yield the desired result | the extraction should be changed when the information followed on the screen does not evolve as desired | none of these frequencies

8. If you wish to indicate the frequency at which you think you will need to change your extraction

9. Will you perform calculations to develop your extraction plan?

Options: Yes | No, I operate approximately | No, I operate intuitively | No, I will react as things progress | No, I don't have a plan

10. Please indicate the quantity of resource you aim to have at the end of the 300 instants. Leave blank if you do not know yet.

11. What do you think will be your total gain at the end of the 300 instants, in ECUs?

Post-game questionnaire

1. What is the information on the decision screen that you consulted most often?

Options: the extraction | the resource | the game gain

2. Did you mostly follow the extraction plan that you had initially envisioned?

Options: Yes, rather | No, not really | I didn't really have an extraction plan

3. If not, please explain why

C Additional tables

	Extraction (1)	Extraction (2)	Extraction (3)	Extraction (4)
(Intercept)	3.81***	3.90***	3.89***	4.56***
	(0.14)	(0.26)	(0.36)	(0.55)
p-discounting	0.32*	0.32*	0.34*	0.36*
	(0.15)	(0.16)	(0.16)	(0.16)
Questionnaire	0.06	0.05	0.05	0.04
	(0.15)	(0.15)	(0.16)	(0.16)
Patience (CTB)		−0.01	−0.00	−0.00
		(0.01)	(0.01)	(0.01)
Risk (BRET)		0.00	0.00	0.00
		(0.00)	(0.00)	(0.00)
Risk (declared)			0.02	0.03
			(0.04)	(0.04)
Patience declared			−0.02	−0.02
			(0.03)	(0.03)
Gender (Male)				−0.06
				(0.17)
Age				−0.04
				(0.02)
Study level				0.05
				(0.05)
AIC	257479.19	257499.96	257513.42	257528.58
BIC	257531.88	257570.22	257601.25	257642.75
Log Likelihood	−128733.59	−128741.98	−128746.71	−128751.29
Num. obs.	48160	48160	48160	48160
Num. groups: instant	301	301	301	301
Num. groups: participant	160	160	160	160
Var: instant (Intercept)	0.51	0.51	0.51	0.51
Var: participant (Intercept)	0.90	0.91	0.91	0.92
Var: Residual	12.00	12.00	12.00	12.00

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 11: Mixed linear models

The table 11 shows mixed linear model regressions of treatment on extraction, with additional control variables. The treatment effect is significant and positive meaning that extraction is overall greater under the p-discounting treatment than under the z-discounting treatment. The questionnaire effect remains absent.

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