Nudging Behaviors in a Dynamic Common Pool Renewable Resource Experiment

Murielle Djiguemde, Dègnon David Dadakpete, Dimitri Dubois, Mabel Tidball

Nudging Behaviors in a Dynamic Common Pool Renewable Resource Experiment

Murielle Djiguemde,
David Dadakpete,
Dimitri Dubois,
&
Mabel Tidball

CEE-M Working Paper 2024-07

Nudging Behaviors in a Dynamic Common Pool Renewable Resource Experiment

Djiguemde, M.[1], Dadakpete, D.[2], Dubois, D. *[1], and Tidball, M.[1]

[1] *CEE-M, Univ. Montpellier, CNRS, INRAe, Institut Agro, Montpellier, France.*
[2] *LEDi, Université de Bourgogne-Franche Comté, Dijon, France.*

January 7, 2024

Abstract

The efficient management of common pool resources has long been a subject of economic inquiry, with seminal works by Gordon (1954) and Hardin (1968) underscoring the importance of regulatory measures. In recent times, there has been a shift towards incorporating behavioral insights into policy design, with 'nudges' – subtle policy tools aimed at influencing decision-making – gaining increasing attention. This paper explores the effectiveness of nudges, particularly those rooted in descriptive and injunctive social norms, in the management of common pool resources within the framework of differential games. Using a series of economic experiments, we examine how these nudges influence individual and group behaviors in dynamic settings. Contrary to expectations, our results reveal that nudges, in this context, do not significantly impact the strategic decision-making processes in managing shared resources. This finding challenges the prevailing assumption about the universal applicability of nudges and suggests a need for a more nuanced understanding of their role in diverse economic scenarios.

*Corresponding author, dimitri.dubois@umontpellier.fr.

Keywords : Dynamic Optimization; Experimental Economics; Renewable Resources; Nudges;
JEL Codes : C91; C92; Q20; Q58

1 Introduction

The issue of environmental resource management has gained considerable scholarly and policy attention, especially since Hardin's landmark 1968 study, which posited that common pool resources (CPRs) are susceptible to overexploitation in the absence of effective regulation. This vulnerability is largely attributed to the inherent rivalrous and non-excludable nature of such resources. Notably, Elinor Ostrom's groundbreaking work has further nuanced our understanding of CPR management, demonstrating that local communities can self-organize to manage resources sustainably under certain conditions (Ostrom, 1990). A pivotal question that has occupied economists is the identification of mechanisms that can induce resource users to engage in sustainable exploitation. Historically, the primary approach has been the deployment of monetary instruments, such as taxation schemes. For instance, ambient tax/subsidy frameworks have been widely utilized in the regulation of nonpoint source pollution, combining reward mechanisms for exceeding water quality targets with penalties for non-compliance (Segerson, 1988; Xepapadeas, 1991; Cochard et al., 2005). However, it is increasingly recognized that monetary incentives can produce a crowding-out effect, diminishing individual intrinsic motivation to act in an environmentally responsible manner. Moreover, such monetary mechanisms often entail significant administrative and enforcement costs.

Among the array of non-monetary instruments, "nudges" stand out as a particularly noteworthy mechanism. Defined by Thaler & Sunstein (2009) as a form of choice architecture, nudges represent a specialized instance of libertarian paternalism. In this framework, a planner subtly guides individuals towards making choices that are deemed beneficial, all while preserving their freedom to choose otherwise. Lauded for their cost-effectiveness, non-coercive nature, and ease of implementation, nudges have garnered increasing attention in policy circles. In the United States, President Obama underscored the importance of behavioral sciences in policy formulation by signing a memorandum in 2009. Similarly, in the United Kingdom, Prime Minister David Cameron established the Behavioral Insights Team, colloquially known as the "nudge unit," to evaluate the efficacy of behavioral instruments like nudges (Croson & Treich, 2014). Singler

(2015), in his book "Green Nudges", advocates for the broader adoption of nudges as a potent tool for advancing sustainable development, noting their underutilization in France. Furthermore, international bodies such as the World Bank have also endorsed nudges as a novel means of fostering sustainable behavioral change, as articulated in their report "Mind, Society, and Behavior" (Bank, 2014).

The central question this study aims to address is how non-monetary instruments can be employed to enhance cooperation and foster pro-environmental behavior, particularly in the context of dynamically evolving resources. To tackle this issue, we adopt a dynamic framework that operates in continuous time, allowing the resource to evolve seamlessly over an infinite horizon. Our preference for a continuous-time framework is underpinned by several key factors. First, continuous time has been found to provide participants with greater flexibility, as substantiated by Djiguemde et al. (2022a), in comparison to discrete-time models. Importantly, continuous time serves as a catalyst for cooperation by enabling rapid adjustments in players' decisions and offering a more realistic simulation of the real-world dynamics of common pool resources. Second, a study by Djiguemde et al. (2022b) reveals that only 20% of experienced groups approximate the optimal theoretical path (45.71% if we consider the category called "convergent"), indicating significant room for improvement.[1] In our experiment, we model the renewable resource as a groundwater basin, although the framework is versatile enough to accommodate other types of resources. The laboratory implementation of continuous time is a recent and challenging advancement, as it permits subjects to make decisions at any moment during the experiment. To the best of our knowledge, the only experiments in continuous time applied to renewable common pool resources have been conducted by Tasneem et al. (2017, 2019) and Djiguemde et al. (2022a,b). Our continuous-time model is based on the framework proposed by Djiguemde et al. (2022a), where subjects engage in one trial round before playing the 2-player game once.

The primary aim of this study is to steer a majority of participants toward a tacit cooperation – specifically, the solution that maximizes the joint payoff

[1]The term 'experienced' is used here because in (Djiguemde et al., 2022b) players initially played alone before being introduced to strategic interactions in the game. Additionally, in both scenarios, participants engaged in two trial rounds before the actual gameplay that determined their payoffs.

– utilizing paternalistic mechanisms such as nudges. Within the diverse taxonomy of nudges, we focus on those that leverage social norms. Social norms serve as the ethical guidelines within a group and can be categorized into descriptive and injunctive norms. As delineated by Cialdini et al. (1991), descriptive norms encapsulate the perception of what the majority engages in, thereby informing behavior – essentially outlining "what is done". In contrast, injunctive norms convey societal approval or disapproval, thereby prescribing behavior – or specifying "what ought to be done". Our secondary objective is to discern which type of norm, descriptive or injunctive, is more efficacious in promoting cooperation and pro-environmental behavior. This study contributes to the existing literature by empirically evaluating the effectiveness of different types of nudges in a continuous-time framework, thereby offering new insights into the mechanisms that can foster sustainable behavior in the management of common pool resources.

Our study reveals that nudges do not significantly influence the dynamics of resource management by groups. Despite exploring various aspects such as efficiency and inequalities, we found no discernible differences between the two nudge treatments, nor in comparison to the control treatment. However, an interesting observation emerged: players with a higher degree of environmental sensitivity demonstrated a greater inclination towards resource conservation than their less environmentally sensitive counterparts.

The remainder of the paper is as follows: the second Section discusses the literature related to nudges. The third Section sets out the theory behind the common pool resource game used in the experiment. The fourth Section describes the experiment. The fifth Section gives the results and the last Section provides some concluding remarks.

2 The Literature

Our study contributes to the burgeoning literature on experimental research employing non-monetary instruments, such as nudges, to encourage pro-environmental behavior. Nudges, requiring fewer resources for implementation and enforcement, present a financially viable alternative for promoting sustainable behavior, especially in contexts with limited resources for monitoring and enforcement (Thaler & Sunstein, 2008; Capraro et al., 2019). These tools have found widespread application in diverse domains such as food (Hansen et al., 2016; Wansink et al., 2012), energy (Schultz et al., 2007; Allcott & Mullainathan, 2010; Caballero & Ploner, 2022), and transportation (Lieberoth et al., 2018; Whillans et al., 2021). Their utility has recently extended to public goods (Fosgaard & Piovesan, 2015; Barron & Nurminen, 2020) and renewable common pool resources (CPRs) (Eisenbarth et al., 2021; Buckley & Llerena, 2022).

Nudges are categorized based on their operational mechanisms (Lehner et al., 2016; Schubert, 2017). Some exploit default settings, leveraging human inertia, like default double-sided printing. Others alter the physical environment to influence behavior; for instance, Kallbekken & Sælen (2013) demonstrated that smaller plate sizes could reduce food waste. A further category includes nudges that leverage self-image, simplifying information or employing social identity framing to stimulate competition for social status. The most prevalent category, however, utilizes social norms, where individuals tend to mimic socially accepted behaviors. This includes descriptive nudges, illustrating common practices, and injunctive nudges, indicating socially prescribed behaviors.

Comparative studies have assessed the effectiveness of tax-based incentives versus nudge-based incentives in public goods and CPRs contexts. For example, Festré et al. (2019) contrasted the impact of advice (a blend of descriptive and injunctive social norms) with sanctions in a repeated public good game, finding that while advice initially boosts cooperation, its effect wanes over time, unlike sanctions. Furthermore, My & Ouvrard (2019) demonstrated that the effectiveness of nudges depends on individual environmental sensitivity and may diminish over time. Additional empirical research by Ferraro & Price (2013) provides evidence on the efficacy of non-monetary strategies, including nudges, in influencing environmentally responsible behavior.

Recent research has also revealed the nuanced effects of nudges. Le Coent et al. (2021) found that injunctive norms could enhance participation in Payments for Environmental Services (PES) schemes, but descriptive norms might counteract this under certain conditions. The efficacy of nudges in areas like water conservation and smart meter adoption has shown mixed results (Chabé-Ferret et al., 2019; Ouvrard et al., 2023).

Our study distinguishes itself by focusing on social norm-based nudges within a dynamic CPR model operating in continuous time and over an infinite horizon. Specifically, we compare the effectiveness of descriptive versus injunctive social norms, thereby contributing unique insights to the literature on sustainable resource management.

3 The Model

We consider a simple continuous time linear quadratic model in which two farmers harvest simultaneously a renewable groundwater basin. Each farmer i make their extraction decision at each instant of the real time and the resource evolves continuously over an infinite horizon. Water extraction provides each of them a revenue $B(w)$ depending only on the extraction rate w, but also involves costs $C(H, w)$ depending negatively on the level of the groundwater H. Figures 6 and 7 in Appendix A show a farmer's revenue function and the marginal cost function. Equation (1) denotes an agent's instantaneous payoff, which is given by the difference between revenue and costs (a, b, c_0 and c_1 are positive parameters):

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

where the marginal cost $c(H))$ is given by Equation (2):

$$c(H) = \begin{cases} (c_0 - c_1 H) & \text{if } 0 \leq H < \dfrac{c_0}{c_1} \\ 0 & \text{if } \quad H \geq \dfrac{c_0}{c_1} \end{cases} \tag{2}$$

The resource evolves continuously, and at each instant, each agent has to choose an extraction rate that maximizes their payoff. Behavior is explored under three benchmarks: social optimum, Nash feedback and myopic decision-making. In the social optimum equilibrium, the resource is maintained at an efficient level by maximizing the joint discounted net payoff of both farmers. Farmers behaving in a Nash feedback way maximise their individual discounted payoff. Myopic farmers ignore the dynamics of the groundwater in their maximization problem, maximizing their instantaneous payoff at each instant.

The social optimum equilibrium is found by solving the following maximization problem:

$$V(H_0) = \max_{w_1(t), w_2(t)} \int_0^{\infty} e^{-rt} \sum_{i=1}^{2} \left[a w_i(t) - \frac{b}{2} w_i(t)^2 - \max(0,\ c_0 - c_1 H(t)) w_i(t) \right] dt \tag{3}$$

s.t

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

where R is the constant rainfall recharge and 1 - α is the return flow coefficient.

The Nash feedback equilibrium is found when each player solves the previous maximization problem without the sum, while the myopic maximization equilibrium is found when each player solves only the equation in brackets. By considering the constraints, the myopic solutions provides a feedback representation.[2]

4 Experimental Design and Procedures

We conducted three distinct treatments at the Experimental Economics Laboratory of Montpellier (LEEM).[3] The baseline treatment, which served as a control, involved 98 participants and was carried out from November to December 2020. The data for this treatment were sourced from an experiment conducted for a

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

[3]The experimental design has been presented and discussed in the LEEM working group composed of behavioral and experimental economists at the CEE-M research unit who ensure that the design complies with the ethics of the community and the usual practices of the experimental methodology in economics. Data were collected anonymously and stored on a secure dedicated server in our research unit, as required by the data management plan.

previous article (Djiguemde et al., 2022a). Subsequent treatments focusing on the effectiveness of descriptive and injunctive social norms were conducted in two phases: first in July and September 2021 with 65 participants, and then in July and September 2023 with an additional 62 participants. Each session lasted between one and one-and-a-half hours. Demographic information for each treatment is provided in Table 1.

Employing a between-subjects design, each participant took part in only one treatment. After reading the instructions individually, an experimenter read them aloud for clarification. Participants then completed a computerized comprehension questionnaire to ensure their understanding of the resource dynamics and payoff calculations. Participants were free to ask questions at any time by raising their hands.

To familiarize themselves with the graphical interface and game dynamics, participants engaged in a ten-minute training phase before proceeding to the ten-minute paid phase.[4] Groups were randomly reformed for each phase. In each treatment and at the beginning of each phase, participants individually chose an initial extraction rate, ranging from 0 to 2.8 units, by adjusting a graduated slider that allowed values to two decimal places. Subsequent screens displayed the evolution of individual and group extraction rates, resource dynamics, and payoffs, as illustrated in Figure 8 in Appendix B. An additional text box presented the same information in textual form. Participants could review the instructions at any time by clicking the "Instructions" button located in the upper right corner of their screens. They also had the option to adjust their extraction rates at any point by moving the slider. All information was updated every second to simulate continuous time. The concept of an infinite horizon was simulated through the payoffs, which consisted of a cumulative payoff from the experiment's start to the present instant, augmented by a continuation payoff projected from the current instant to infinity. Table 2 enumerates the parameters employed in the experiment, while Figure 1 illustrates the corresponding theoretical paths.[5]

In all treatments except the baseline, participants completed a control task af-

[4]The application has been developed with the oTree platform (Chen et al., 2016).

[5]For more details on the model, the implementation of continuous time and the infinite horizon, as well as the choice of parameters, please refer to (Djiguemde et al., 2022a).

ter the game : the General Ecological Behavior (GEB) Scale questionnaire (Kaiser, 1998). This allowed us to measure their environmental sensitivity and to distinguish between groups with varying degrees of environmental awareness.[6] A demographic questionnaire concluded the experimental session.

Treatment	Participants	Age		Gender (male)	
		mean	*std*	*mean*	*std*
Baseline	98	28.474	8.542	0.464	0.501
Descriptive	92	26.522	7.891	0.478	0.502
Injunctive	100	25.930	7.637	0.440	0.499

Table 1: Summary Statistics of Sample Characteristics by Treatment

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 2: Parameters for the experiment

The Nudge treatments

In this study, we implement graphical nudges. The first nudge employs an injunctive social norm, presenting subjects with theoretical time paths for the

[6] The baseline did not include the GEB questionnaire as it was conducted prior to the nudge treatments and addressed a different research question (continuous vs. discrete time, Djiguemde et al. (2022a)).

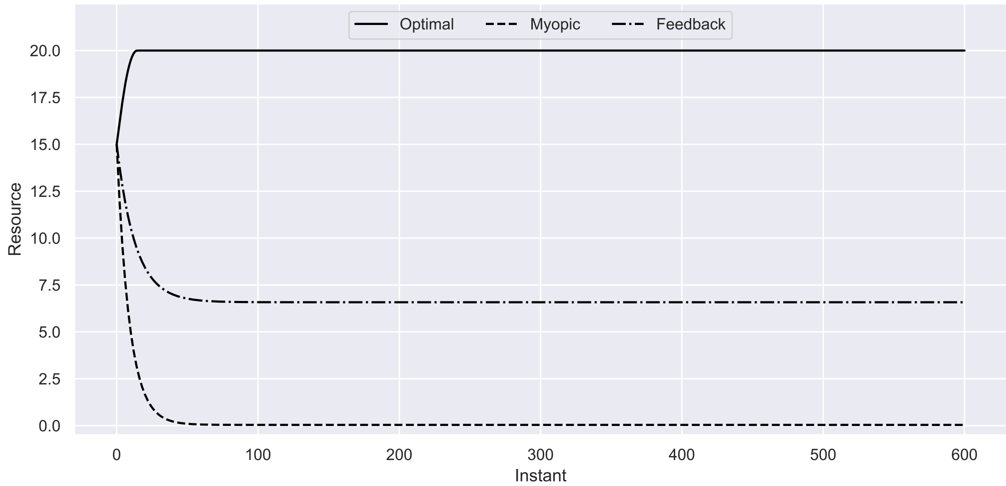


Figure 1: Optimal, Myopic and Feedback theoretical paths

resource based on three benchmarks, along with corresponding payoffs in experimental currencies. More details on this treatment are in Appendix B.2. The second nudge uses a descriptive social norm, showing subjects resource time paths observed in the baseline treatment, their frequency, and the average individual payoffs in experimental currencies. Further information on this treatment is available in Appendix B.3. This graphical information, displayed post-training, can be revisited by clicking the 'Information' button next to the instructions review button, as shown in Figure 11 in Appendix B. Subjects are informed that they may choose to either consider or ignore this information.

The two social norm treatments vary in several aspects. The injunctive norm's curves are derived from an infinite-horizon model, while the descriptive norm uses a scrap value to approximate the infinite horizon, as elaborated in the payoff description. The injunctive norm explicitly states its theoretical basis and assumes symmetrical players. In contrast, the descriptive norm presents results from the baseline, where player symmetry is not guaranteed. Additionally, the descriptive norm includes an extra curve, representing behaviors not covered by theory, and details the proportion of the population associated with each resource level. Considering these differences, we propose Conjecture 1:

Conjecture 1 *Nudge treatments will lead to greater resource preservation than the* *baseline.*

This conjecture is based on the premise that visual representations of resource management strategies have a significant impact on decision-making. Both treatments display a curve that highlights the dynamics leading to the highest payoff, whether theoretical or empirical. This visual aspect is crucial, as it illustrates that optimal resource management, especially in the game's early stages, involves allowing the resource to accumulate up to a certain threshold (here, 20 units). It also demonstrates that early resource depletion results in significantly lower average payoffs. We expect these visual cues to give players a clearer understanding of their initial decisions' consequences on resource sustainability. Thus, we hypothesize that exposure to these curves will heighten players' awareness of the impact of early resource management decisions. By visually emphasizing the benefits of initial resource growth and the drawbacks of early depletion, we anticipate that players will be more likely to adopt strategies that promote resource flourishing in the game's initial phase. This approach is expected to lead to more effective and sustainable management of the renewable resource, aligning player actions with the optimal strategy depicted by the curves.

Earlier in the paper, we discussed how injunctive social norms center on what others approve or disapprove of, in contrast to descriptive social norms that focus on what others do. As outlined by Cialdini et al. (1991), injunctive norms inform about socially sanctioned behaviors and expected actions within a culture or group. This emphasis on approval and disapproval fosters a stronger motivation for individuals to conform to the norm, driven by the desire for social rewards and the avoidance of social punishments. Conversely, descriptive norms merely inform about common practices without offering moral guidance. This absence of moral direction and social consequences might render descriptive norms less influential in shaping behavior. Based on Cialdini et al. (1991)'s reasoning, we expect the injunctive norm, rooted in theoretical optimization and the assumption of symmetrical players, to reduce free-riding and be more effective, as stated in Conjecture 2:

Conjecture 2 *The injunctive social norm will encourage greater cooperation than* *the descriptive social norm.*

In addition to the aforementioned conjectures, we propose a hypothesis regarding the behavior of environmentally sensitive groups. Building on findings from relevant literature, such as the studies by Buckley & Llerena (2018) and My & Ouvrard (2019), we posit that environmentally conscious individuals are more inclined towards resource preservation, irrespective of associated payoffs. These studies indicate that such individuals tend to consume fewer resources and contribute more significantly to public goods. This behavior aligns with an inherent motivation to protect and sustain the environment, transcending immediate economic incentives. Based on these insights, we articulate this hypothesis in Conjecture 3:

Conjecture 3 *Groups characterized by high environmental sensitivity will demonstrate lower resource consumption, thereby facilitating resource growth.*

This conjecture aims to examine the impact of environmental values and attitudes on resource management strategies within the game. It underscores the potential influence of intrinsic environmental concern on decision-making, independent of the external incentives or nudges provided.

5 Results

In this section, we present results from the experiment. We begin by providing descriptive statistics, then we describe the procedure used to rank subjects regarding the theoretical time paths. We conclude with the results of the GEB questionnaire.

5.1 Descriptive Statistics

Figure 2 illustrates the temporal evolution of the average resource level across the three treatments. The graph reveals a striking similarity among the three curves, thereby implying an absence of significant treatment effects. This observation is particularly salient during the initial phases of the game, a period during which the two nudge treatments offer explicit information about the potential advantages of allowing the resource to initially grow to a steady-state level of 20 units.

Table 3 corroborates these graphical insights by presenting the initial and final extraction rates, as well as the final resource levels for each treatment. The average initial extraction rates are remarkably consistent across the treatments, with values ranging from 1.179 to 1.230. A similar pattern is observed for the final extraction rates, which range from 0.532 to 0.601, and for the final resource levels, which vary between 11.220 and 11.250. Importantly, the p-values from the Student's t-tests, listed at the bottom of the table, exceed the conventional significance threshold of 0.05. This further substantiates the lack of statistically significant differences in either the initial or final extraction rates, or in the final resource levels, across the treatments.

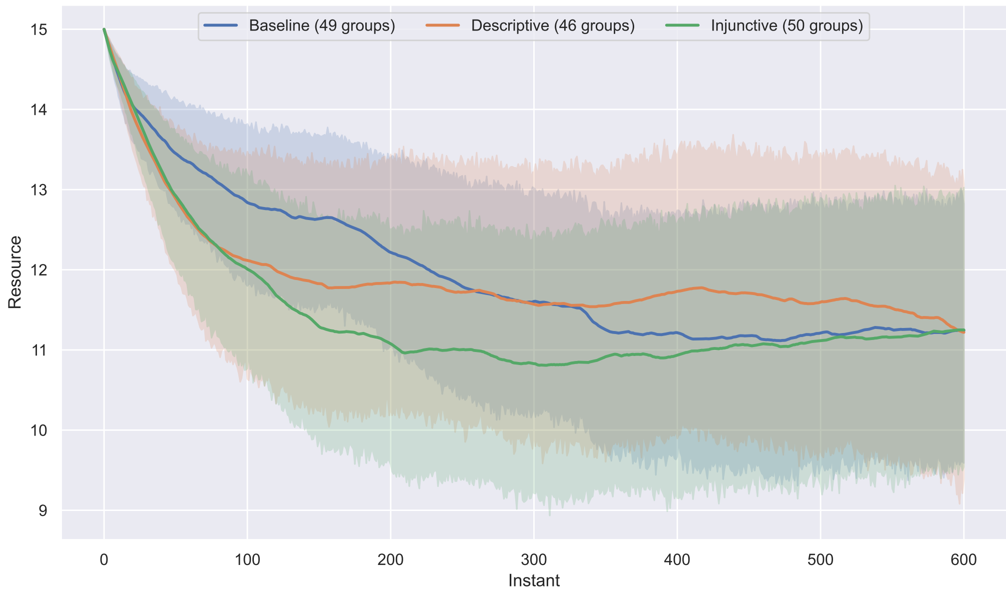


Figure 2: Evolution of the average resource by treatment

Treatment	Groups	Initial Extraction	Final Extraction	Final Resource
Baseline	49	1.179	0.597	11.242
		(0.912)	(0.392)	(6.051)
Descriptive	46	1.122	0.601	11.220
		(0.821)	(0.403)	(6.693)
Injunctive	50	1.123	0.532	11.250
		(0.935)	(0.181)	(6.225)
Student test (Between treatment p-values)				
Baseline vs. Descriptive		0.754	0.968	0.986
Baseline vs. Injunctive		0.783	0.291	0.995
Descriptive vs. Injunctive		0.553	0.281	0.982

Standard deviations in brackets

Table 3: Summary Statistics and Between-Treatment Comparisons for Initial and Final Extraction Rates, and Final Resource Levels

To scrutinize the influence of treatment on resource levels over time, we employed a linear mixed-effects model. This model incorporates both fixed effects, such as time and treatment, and random effects to account for inter-group variability. The results, presented in Table 4, reveal that the rate of resource depletion is significantly influenced by time, as indicated by a negative and highly significant coefficient for the 'Instant' variable (coefficient = -0.005, $p < 0.001$). Furthermore, interaction terms between time and treatment were included to examine how the rate of resource depletion varies across different treatments over time. Both interaction terms are significant, suggesting that the rate of resource depletion is slower in both Descriptive and Injunctive treatments compared to the Baseline, albeit the main effects of the treatments themselves are not statistically significant. Specifically, the interaction term for Descriptive treatment is positive and significant (coefficient = 0.002, $p < 0.001$), as is the interaction term for Injunctive treatment (coefficient = 0.002, $p < 0.001$).

Variable	Coefficient	Std. Err.	z	P>|z|
Intercept	13.399	0.707	18.954	0.000
Fixed Effects				
Instant	-0.005	0.000	-67.911	0.000
Descriptive	-0.690	1.016	-0.679	0.497
Injunctive	-0.996	0.995	-1.001	0.317
Interaction Terms				
Instant:Descriptive	0.002	0.000	21.162	0.000
Instant:Injunctive	0.002	0.000	15.729	0.000
Random Effects				
Group Var	24.459	1.376	–	–

Table 4: Mixed Linear Model Regression Results for Resource Levels Depending on Treatment

5.2 Group profiles

In order to determine which theoretical predictions the groups most closely align with, we computed the conditional mean squared deviation (MSD^c) for each treatment and theoretical prediction. Here, the term "conditional" refers to the fact that groups have the flexibility to continuously adjust their choices throughout the experiment. The conditional mean squared deviation is calculated between the observed extractions, denoted as $w_i(t)$, and the conditional theoretical extractions, denoted as $w(t)_i^c$.

$$MSD^c = \frac{\sum_{t=1}^{T} (w_i(t) - w_i(t)^c)^2}{T} \tag{4}$$

The behavior of each group (myopic, optimal, feedback) is determined by the lowest value of MSD^c. To ensure robust and significant results, we supplement this with the following regression model:

$$w_i(t) = \beta_0 + \beta_1 w_i(t)^c + \varepsilon_t \tag{5}$$

Here, $w(t)_i^c$ represents the conditional extraction rate associated with each behavior. A group will be categorized as either 'myopic,' 'feedback,' or 'optimal' if β_1 is positive and significantly different from zero.[7] Further details about the conditional MSD are provided in our previous work (Djiguemde et al., 2022a). Groups that cannot be classified are designated as "Undetermined".

The distribution of groups across different profiles, based on treatments, is presented in Table 5. Figure 3 displays the average resource evolution for these profiles. A Chi-square test reveals no significant difference in the distribution of profiles across treatments (p-value = 0.215). Regardless of the treatment, the "Undetermined" profile is the most common, indicating that most groups struggle to adhere to any of the theoretical paths. This observation calls for further research to better comprehend the behaviors exhibited by both individual players and groups.

Treatment	Optimal	Feedback	Myopic	Undetermined
Baseline	1	6	3	39
Descriptive	0	5	7	34
Injunctive	2	12	6	30

Table 5: Distribution of Group Classifications Across Treatments.

5.3 Efficiency

We supplement our analysis by examining group-level efficiency for each treatment. The maximum payoff a group could attain is 240 ECUs. To calculate the efficiency ratio, we divide the total payoff earned by the two members of the group by this maximum possible group payoff. The highest efficiency was observed in the injunctive nudge treatment, with a rate of 68.89%, followed by the descriptive treatment at 64.23%. The average efficiency ratio for the baseline treatment was 63.24%. However, as indicated by the Student's t-test p-values presented in Table

[7] We also conducted an augmented Dickey-Fuller test to check for the presence of unit roots. Serial correlation of the errors is addressed using Newey-West standard errors, and sensitivity tests were performed using one lag.

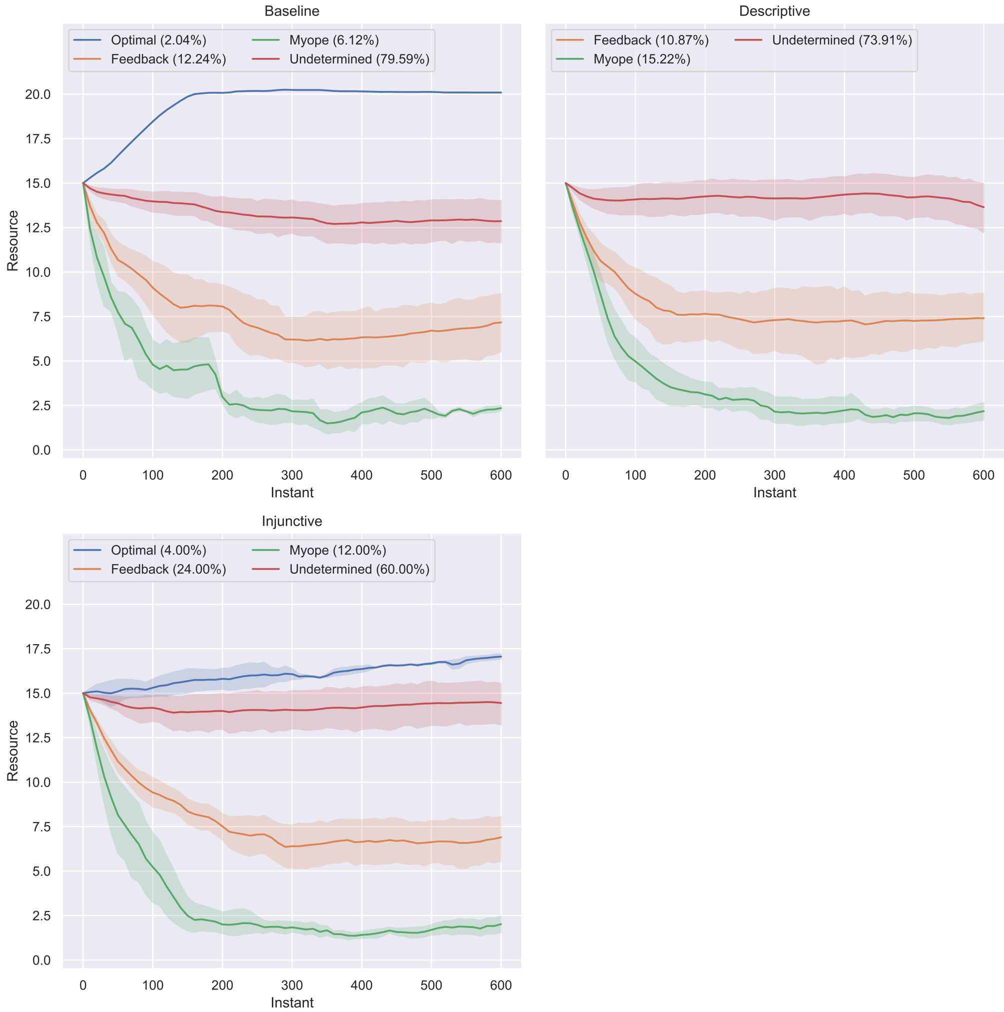


Figure 3: Average resource evolution according to profiles in the three treatments

6, these differences in average efficiency across treatments were not statistically significant.

Treatment	**Efficiency**
Baseline	63.24
	(30.19)
Descriptive	64.23
	(27.73)
Injunctive	68.89
	(25.20)
Student test (Between treatment p-values)	
Baseline vs Descriptive	0.868
Baseline vs Injunctive	0.315
Descriptive vs Injunctive	0.394

Standard deviations in brackets.

Table 6: Summary statistics for efficiency

5.4 Within groups inequalities

To investigate within-group inequalities, we computed the absolute difference between individual final payoffs within each group. The Lorenz curve, a graphical representation of this difference's distribution, is displayed in Figure 4. For context, the Lorenz curve plots the cumulative share of groups against the cumulative share of their payoff differences. A Lorenz curve coinciding with the line of equality would indicate identical within-group payoff differences for all groups.

To quantify the degree of inequality, we also calculated the Gini index, a scalar value ranging from 0 (perfect equality) to 1 (maximum inequality). This index serves as a numerical complement to the Lorenz curve, offering a more precise measure of inequality. For the Baseline treatment, the Gini index is 0.44, suggesting a moderate level of inequality. This index slightly increases to 0.47 in the Descriptive Norm treatment and further to 0.51 in the Injunctive Norm treatment.

To assess the statistical significance of the observed differences in the Gini indices across various treatments, we employed a bootstrap method. This non-parametric technique allowed us to generate 95% confidence intervals for each treatment based on 1000 bootstrap samples. The resulting intervals are as follows: for the Baseline treatment, the interval is [0.37, 0.49]; for the Descriptive Norm treatment, it is [0.38, 0.52]; and for the Injunctive Norm treatment, it is [0.41, 0.56]. The overlap of the confidence intervals among the three treatments suggests that there is no statistically significant difference in the levels of inequality as measured by the Gini index across these treatments.

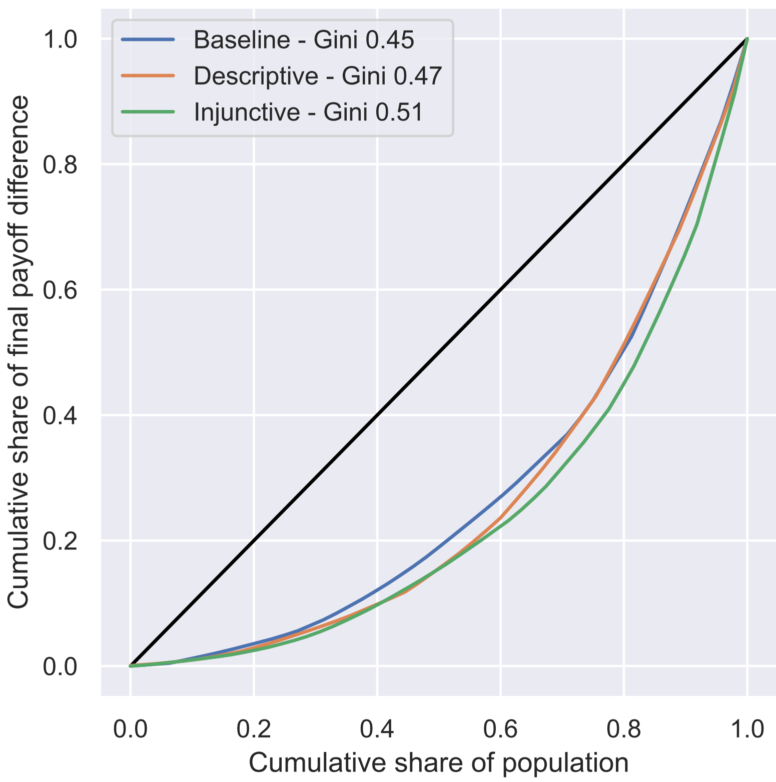


Figure 4: Lorenz curves - Within-group difference in final payoffs

5.5 The General Ecological Behavior Scale

The General Ecological Behavior (GEB) scale served as a control task, designed to measure subjects' environmental sensitivity. Indeed, studies by Schultz & Zelezny (2003) and Costa & Kahn (2010) show that certain personality traits such as altruism, political sensitivity, and environmental sensitivity are relevant indicators of good reactivity to nudges. Appendix D presents the GEB questionnaire used in the experiment. We implemented the short version with 28 items proposed by Davis et al. (2009, 2011).[8] This version encompasses ecological garbage removal, water and power conservation, ecologically aware consumer behavior, garbage inhibition, and ecological automobile use. Of the 28 items, 17 are formulated positively and the remaining 11 are formulated negatively. In line with My & Ouvrard (2019) and Buckley & Llerena (2018), we allow for a Likert scale response format with five possible answers: "never", "seldom", "sometimes", "often" or "always". Alternatively, a yes/no response format is also possible, as suggested by Kaiser (1998). The advantage of this response format is that it allows for more freedom of choice, in addition to being a less rigid rating scale.

Positively formulated items were recoded from 1 for "never" to 5 for "always", and negatively formulated items were recoded from 5 for "never" to 1 for "always". With a Cronbach's Alpha $\alpha = 0.78$, the GEB scale is acceptable and in line with findings in the literature.[9] The mean total score is $M = 103.37$.[10] Players whose score was below the mean were considered to have low environmental sensitivity, while those whose score was above the mean were considered to have high environmental sensitivity. This categorization enabled us to identify three distinct levels of environmental sensitivity at the group level, each determined by the individual sensitivities of group members. We thus identify "High-High" groups, where both members exhibit high environmental sensitivity; "Low-Low" groups, where both members have low environmental sensitivity; and "High-Low" groups, where one member has high environmental sensitivity while the

[8]One of the initial versions of the GEB questionnaire was proposed by Kaiser (1998), and consisted of 40 items grouped in 7 subscales respectively as follows: prosocial behavior, ecological garbage removal, water and power conservation, ecologically aware consumer behavior, garbage inhibition, volunteering in nature protection activities and ecological automobile use.

[9]The Cronbach's Alpha measures the internal consistency of the questionnaire. Davis et al. (2009) found $\alpha = 0.76$ and $\alpha = 0.75$ in Davis et al. (2011). My & Ouvrard (2019) found $\alpha = 0.74$ and Buckley & Llerena (2018) found $\alpha = 0.73$.

[10]My & Ouvrard (2019) found a mean total score $M = 104$.

other has low environmental sensitivity. Table 7 provides a summary of the effectives of group composition in the two nudge treatments. To examine whether the distribution of environmental sensitivity varies across the two nudge treatments, we conducted a Chi-square test, which revealed no significant difference (p-value=0.361).

Treatment	**High-High**	**High-Low**	**Low-Low**
Descriptive	15	22	9
Injunctive	11	24	15

Table 7: Distribution of Group Composition by General Ecological Behavior (GEB) Category

In Figure 5, the top panel illustrates the average resource levels over time for the three GEB categories: Low-Low, Low-High, and High-High. The curve corresponding to the High-High category consistently remains above the other two, indicating a slower rate of resource depletion. Conversely, the Low-High category shows a slightly faster rate of depletion compared to the Low-Low category, as evidenced by its curve lying below that of the Low-Low category. The bottom panels further disaggregate these trends by treatment – Descriptive and Injunctive. While the general patterns observed in the top panel persist across treatments, a noteworthy divergence is observed in the Injunctive treatment. Specifically, in the Injunctive treatment, the curve corresponding to the High-High GEB category not only remains elevated but also shows a slight upward trend over time, maintaining a resource level consistently greater than 14.

To investigate the influence of group composition based on General Ecological Behavior (GEB) categories and treatments on resource levels over time, we employed linear mixed-effects models. These models incorporate both fixed effects – such as time, GEB category, and treatment – and random effects to capture variability across different groups. The model also includes two-way interaction terms to explore how the rate of resource depletion varies across different GEB categories and treatment over time.[11] The results, presented in Table 8, reveal

[11]The general form of the linear mixed-effects model used in our analysis is as follows: $Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \ldots + \beta_k X_{kij} + u_j + \epsilon_{ij}$, Where: Y_{ij} represents the resource level

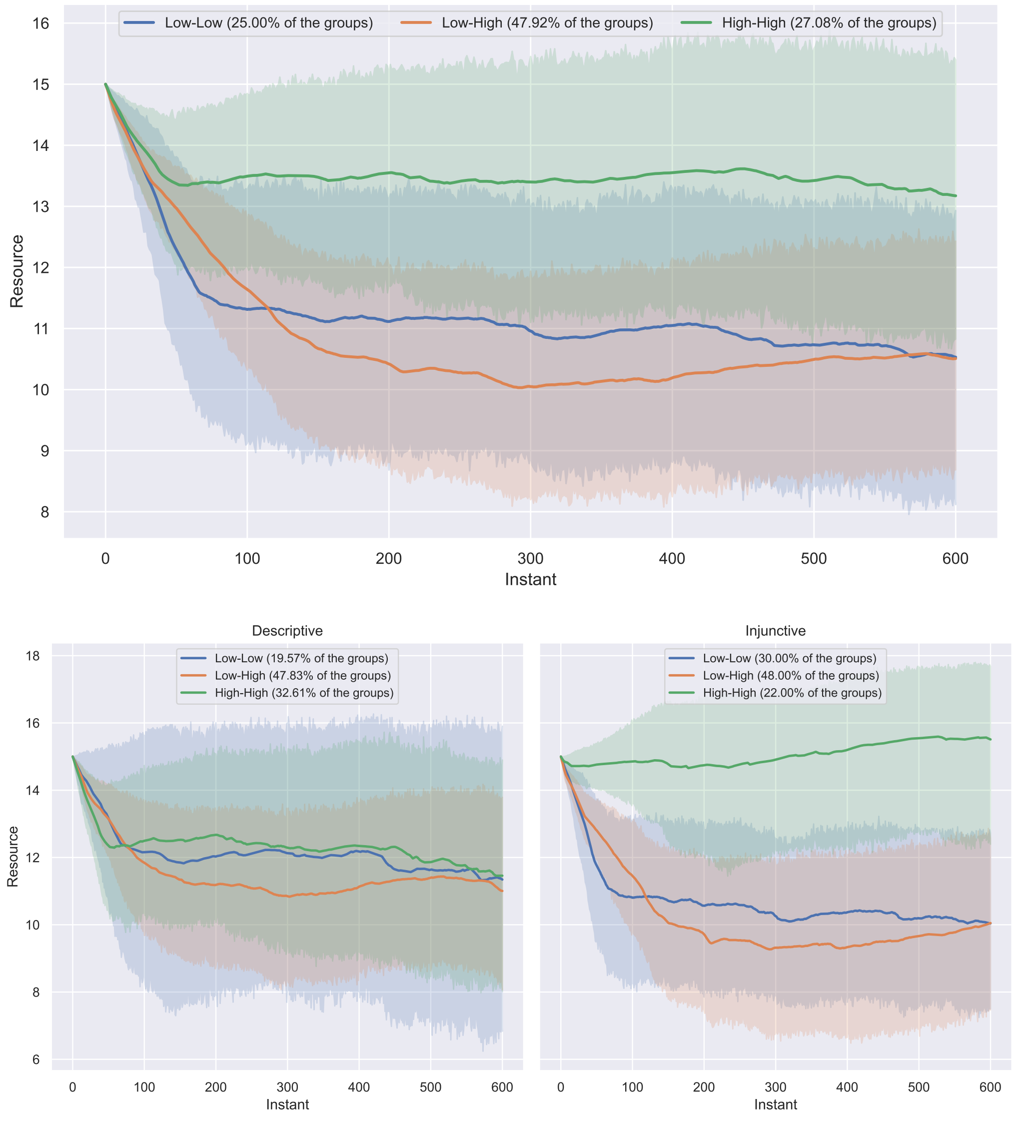


Figure 5: Evolution of Resource Levels Across Different General Ecological Behavior (GEB) Categories and Treatments

significant differences in depletion rates across GEB categories.

In the combined treatment model, the rate of resource depletion for the High-High category is notably slower than for the Low-Low category (coefficient = 0.003, $p < 0.001$). Conversely, for the Low-High category, the depletion rate is slightly but significantly faster than for the Low-Low category (coefficient = -0.001, $p < 0.001$). The treatment alone does not significantly influence resource levels ($p > 0.05$), and the interaction between treatment and GEB category, while showing interesting patterns, does not reach statistical significance at conventional levels.

When examining the treatments separately, the coefficients for GEB categories are not significantly different from zero. A notable distinction is observed between the treatments: in the Descriptive treatment, the resource depletion rate does not significantly differ between the Low-Low and Low-High categories (coefficient = -0.000, $p = 0.517$). However, in the Injunctive treatment, the asymmetry in environmental attitudes (Low-High category) seems to lead to stronger resource depletion over time (coefficient = -0.002, $p < 0.001$).

for group i at time j; $X_{1ij}, X_{2ij}, \ldots, X_{kij}$ are the fixed effects, including time, GEB category, and treatment; $\beta_0, \beta_1, \ldots, \beta_k$ are the coefficients for the fixed effects; u_j is the random effect for group j, capturing the unobserved heterogeneity across groups; and ϵ_{ij} is the error term.

	All (96 groups)			Descriptive (46 groups)			Injunctive (50 groups)		
Variable	**Coef.**	**Std.Err.**	**P>|z|**	**Coef.**	**Std.Err.**	**P>|z|**	**Coef.**	**Std.Err.**	**P>|z|**
Intercept	13.123	1.713	0.000	12.958	1.808	0.000	11.801	1.266	0.000
Fixed Effects									
Instant	-0.003	0.000	0.000	-0.003	0.000	0.000	-0.004	0.000	0.000
Low-High	-0.360	2.033	0.859	-0.562	2.146	0.793	-0.008	1.614	0.996
High-High	-0.599	2.167	0.782	0.063	2.287	0.978	2.755	1.947	0.157
Injunctive	-1.421	2.166	0.512	–	–	–	–	–	–
Interaction Terms									
Injunctive:Low-High	0.115	2.644	0.965	–	–	–	–	–	–
Injunctive:High-High	4.131	2.975	0.165	–	–	–	–	–	–
Instant:Low-High	-0.001	0.000	0.000	-0.000	0.000	0.517	-0.002	0.000	0.000
Instant:High-High	0.003	0.000	0.000	0.001	0.000	0.010	0.005	0.000	0.000
Random Effects									
Group Var	26.389	–	–	29.397	–	–	24.031	–	–

Table 8: Comparative Mixed Linear Model Regression Results for Resource Levels Depending on the GEB Category and Treatment

6 Discussion and conclusion

The aim of this study was to assess the effectiveness of nudge-based instruments in promoting resource-friendly behavior. We employed a dynamic model in continuous time over an infinite horizon to examine the extraction decisions of two-player groups. Three treatments were conducted using a between-subject design, with the first serving as a baseline. The other two treatments implemented nudges based on descriptive and injunctive social norms, respectively. In the descriptive norm treatment, participants received information about the observed resource paths, along with their frequency and average payoffs, from the baseline for comparison. The injunctive norm treatment provided subjects with theoretical resource time paths and corresponding payoffs.

Contrary to our initial hypothesis (Conjecture 1), our findings indicated no significant differences across treatments in terms of initial and final extraction rates and final resource levels. This outcome challenges the presumption that nudges effectively help to conserve resources compared to a baseline scenario.

Furthermore, our analysis across various dimensions – group profiles, efficiency, and inequality of final payoffs within group – did not reveal significant differences between both nudge treatments, thereby refuting our second conjecture (Conjecture 2). The only notable finding was the influence of environmental sensitivity on resource depletion when environmentally conscious players managed the resource together (Conjecture 3), aligning with findings by My & Ouvrard (2019) and extending them to a dynamic context.

Chabal (2021) critically assesses the application of nudges in public policy, emphasizing the need for context-specific implementations and questioning their long-term effectiveness. Our study's inconclusive results on the impact of nudges may reflect this need for contextualization. The neutral experimental setting potentially limited participants' ability to fully comprehend the implications of their decisions on resource sustainability. A potential solution is to provide more contextual information and target populations with inherent environmental sensitivities. Such an approach could leverage the influence of descriptive norms, encouraging environmentally conscious behavior through social mimicry.

Another factor possibly contributing to the lack of significant findings is the external sourcing of social-norm prescriptions, either from other participants or theoretical models proposed by researchers. Future research could explore the role of social acceptability in the effectiveness of nudges. Possible extensions include investigating communication mechanisms, such as 'cheap talk' periods, where players discuss strategies after the reading of the instruction, or the implementation of reward-based systems, like positive or negative stickers, contingent on resource levels over time.

References

Allcott, H., & Mullainathan, S. (2010). Behavior and energy policy. *Science*, *327*(5970), 1204–1205.

Bank, W. (2014). *World development report 2015: Mind, society, and behavior*. The World Bank.

Barron, K., & Nurminen, T. (2020). Nudging cooperation in public goods provision. *Journal of Behavioral and Experimental Economics*, *88*, 101542.

Buckley, P., & Llerena, D. (2018). Demand response as a common pool resource game: Nudges versus prices. *Working Paper GAEL*.

Buckley, P., & Llerena, D. (2022). Nudges and peak pricing: A common pool resource energy conservation experiment. *Journal of Behavioral and Experimental Economics*, *101*, 101928.

Caballero, N., & Ploner, M. (2022). Boosting or nudging energy consumption? the importance of cognitive aspects when adopting non-monetary interventions. *Energy Research & Social Science*, *91*, 102734.

Capraro, V., Jagfeld, G., Klein, R., Mul, M., & van de Pol, I. (2019). Increasing altruistic and cooperative behaviour with simple moral nudges. *Scientific reports*, *9*.

Chabal, A. (2021). *Souriez, vous êtes nudgé: comment le marketing infiltre l'état*. Éditions du Faubourg. Retrieved from https://books.google.fr/books?id=h3ddzgEACAAJ

Chabé-Ferret, S., Le Coent, P., Reynaud, A., Subervie, J., & Lepercq, D. (2019). Can we nudge farmers into saving water? evidence from a randomised experiment. *European Review of Agricultural Economics*, *46*(3), 393–416.

Chen, D. L., Schonger, M., & Wickens, C. (2016). otreeâĂŤan open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88–97.

Cialdini, R. B., Kallgren, C. A., & Reno, R. R. (1991). A focus theory of normative conduct: A theoretical refinement and reevaluation of the role of norms in human behavior. In *Advances in experimental social psychology* (Vol. 24, pp. 201–234). Elsevier.

Cochard, F., Willinger, M., & Xepapadeas, A. (2005). Efficiency of nonpoint source pollution instruments: an experimental study. *Environmental and Resource Economics*, *30*(4), 393–422.

Costa, D. L., & Kahn, M. E. (2010). Energy conservation" nudges" and environmentalist ideology: Evidence from a randomized residential electricity field experiment, nber working paper 15939.

Croson, R., & Treich, N. (2014). Behavioral environmental economics: promises and challenges. *Environmental and Resource Economics*, *58*(3), 335–351.

Davis, J. L., Green, J. D., & Reed, A. (2009). Interdependence with the environment: Commitment, interconnectedness, and environmental behavior. *Journal of environmental psychology*, *29*(2), 173–180.

Davis, J. L., Le, B., & Coy, A. E. (2011). Building a model of commitment to the natural environment to predict ecological behavior and willingness to sacrifice. *Journal of Environmental Psychology*, *31*(3), 257–265.

Djiguemde, M., Dubois, D., Sauquet, A., & Tidball, M. (2022a). Continuous versus discrete time in dynamic common pool resource game experiments. *Environmental & Resource Economics*, 985–1014.

Djiguemde, M., Dubois, D., Sauquet, A., & Tidball, M. (2022b). Individual and strategic behaviors in a dynamic extraction problem: results from a within-subject experiment in continuous time. *Applied Economics*, 1–24.

Eisenbarth, S., Graham, L., & Rigterink, A. S. (2021). Can reminders of rules induce compliance? experimental evidence from a common pool resource setting. *Environmental and Resource Economics*, *79*, 653–681.

Ferraro, P. J., & Price, M. K. (2013). Using nonpecuniary strategies to influence behavior: Evidence from a large-scale field experiment. *Review of Economics and Statistics*, *95*(1), 64–73.

Festré, A., Kirakozian, A., & Toumi, M. (2019). Menacer, sanctionner ou conseiller? prosociaux vs individualistes: quels leviers incitatifs pour quels individus? *Revue économique*, *70*(6), 1125–1138.

Fosgaard, T. R., & Piovesan, M. (2015). Nudge for (the public) good: How defaults can affect cooperation. *PloS one*, *10*(12), e0145488.

Gordon, H. S. (1954). The economic theory of a common-property resource: the fishery. In *Classic papers in natural resource economics* (pp. 178–203). Springer.

Hansen, P. G., Skov, L. R., Jespersen, A. M., Skov, K. L., & Schmidt, K. (2016). Apples versus brownies: a field experiment in rearranging conference snacking buffets to reduce short-term energy intake. *Journal of Foodservice Business Research*, *19*(1), 122–130.

Hardin, G. (1968). The tragedy of the commons'(1968) 162. *Science*, *1243*, 63.

Kaiser, F. G. (1998). A general measure of ecological behavior 1. *Journal of applied social psychology*, *28*(5), 395–422.

Kallbekken, S., & Sælen, H. (2013). "nudging" hotel guests to reduce food waste as a win–win environmental measure. *Economics Letters*, *119*(3), 325–327.

Le Coent, P., Préget, R., & Thoyer, S. (2021). Farmers follow the herd: a theoretical model on social norms and payments for environmental services. *Environmental and Resource Economics*, *78*(2), 287–306.

Lehner, M., Mont, O., & Heiskanen, E. (2016). Nudging–a promising tool for sustainable consumption behaviour? *Journal of Cleaner Production*, *134*, 166–177.

Lieberoth, A., Jensen, N. H., & Bredahl, T. (2018). Selective psychological effects of nudging, gamification and rational information in converting commuters from cars to buses: A controlled field experiment. *Transportation research part F: traffic psychology and behaviour*, *55*, 246–261.

My, K. B., & Ouvrard, B. (2019). Nudge and tax in an environmental public goods experiment: Does environmental sensitivity matter? *Resource and Energy Economics*, *55*, 24–48.

Ostrom, E. (1990). *Ostrom, e. 1990. governing the commons: The evolution of institutions for collective action.* Cambridge University Press.

Ouvrard, B., Préget, R., Reynaud, A., & Tuffery, L. (2023). Nudging and subsidising farmers to foster smart water meter adoption. *European Review of Agricultural Economics*, *50*(3), 1178–1226.

Schubert, C. (2017). Green nudges: Do they work? are they ethical? *Ecological Economics*, *132*, 329–342.

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. *Psychological science*, *18*(5), 429–434.

Schultz, P. W., & Zelezny, L. (2003). Reframing environmental messages to be congruent with american values. *Human ecology review*, 126–136.

Segerson, K. (1988). Uncertainty and incentives for nonpoint pollution control. *Journal of environmental economics and management*, *15*(1), 87–98.

Singler, E. (2015). *Green nudge: Changer les comportements pour sauver la planète.* Pearson.

Tasneem, D., Engle-Warnick, J., & Benchekroun, H. (2017). An experimental study of a common property renewable resource game in continuous time. *Journal of Economic Behavior & Organization*, *140*, 91–119.

Tasneem, D., Engle-Warnick, J., & Benchekroun, H. (2019). Sustainable management of renewable resources: an experimental investigation in continuous time. *Applied Economics*, *51*(35), 3804–3833.

Thaler, R. H., & Sunstein, C. R. (2008). Nudge: improving decisions about health. *Wealth, and Happiness*, *6*, 14–38.

Thaler, R. H., & Sunstein, C. R. (2009). *Nudge: Improving decisions about health, wealth, and happiness.* Penguin.

Wansink, B., Just, D. R., Payne, C. R., & Klinger, M. Z. (2012). *Retracted: Attractive names sustain increased vegetable intake in schools.* Elsevier.

Whillans, A., Sherlock, J., Roberts, J., O'Flaherty, S., Gavin, L., Dykstra, H., & Daly, M. (2021). Nudging the commute: Using behaviorally informed interventions to promote sustainable transportation. *Behavioral Science & Policy*, *7*(2), 27-49.

Xepapadeas, A. P. (1991). Environmental policy under imperfect information: incentives and moral hazard. *Journal of environmental economics and management*, *20*(2), 113–126.

Appendices

A Figures

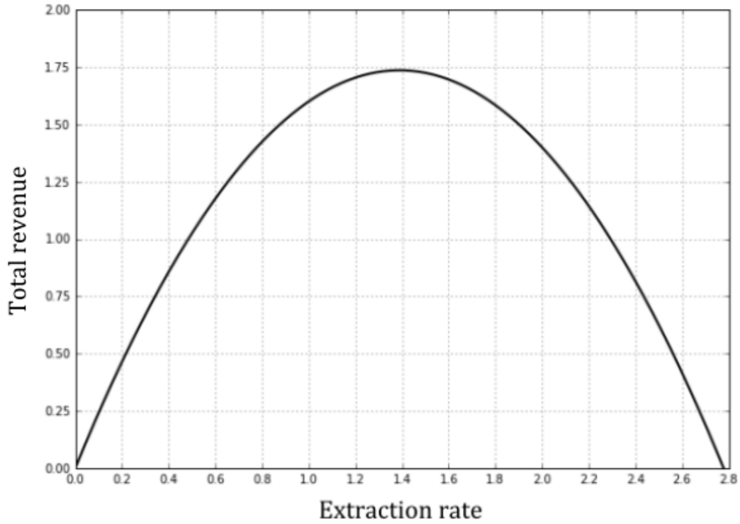


Figure 6: Total revenue from extraction

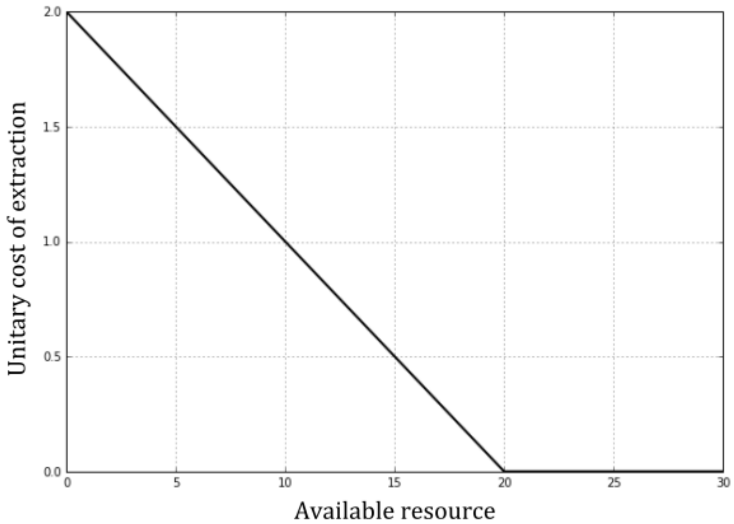


Figure 7: Unitary cost of extraction

B Instructions

Translated from French

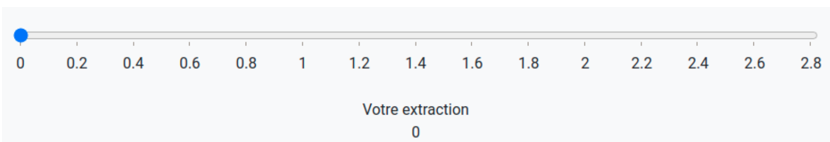
B.1 The Baseline

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 theses instructions out loud when all participants have finished. All your decisions will be anonymously treated. You will indicate your choice using the computer in front of which you are seated. From now on, we ask you to remain quiet. If you have any questions, just raise your hand and an experimenter will come and answer you privately.

Earnings are in experimental currency units (ECU). The exchange rate of ECU into euros is specified in the instructions. The experiment includes a 10-minute training phase and a 10-minute experimentation phase. The final payoff of the experimentation phase is the one taken into account for your remuneration.

General framework

At the beginning of the experiment, the central computer will randomly form pairs of 2 players. Each pair initially has 15 resource units, and at any time both players can extract between 0 and 2.8 resource units with up to two-decimal points of precision. You and the other player are free to choose the extraction rate you want, namely 0, 0.01, 0.02 . . . 2.79, 2.8. To make your choice, each player must move a slider similar to the one below.



Resource dynamics

The available resource continuously evolves. Its evolution depends on two elements:

(i) the total extraction rate of the two players at each instant t, that is: $(E_{1,t} + E_{2,t})$, where $E_{1,t}$ is the Player 1's extraction rate and $E_{2,t}$ is the Player 2's extraction rate, and

(ii) a fixed rate of 0.56 automatically added at each instant t.

Thus the resource evolves as follows:

- when the extraction rate of the two players is higher than the fixed rate, the resource decreases
- when the extraction rate of the two players is lower than the fixed rate, the resource grows
- when the extraction rate of the two players 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 the extraction rate of both players is higher than the available resource, both players' extraction rates are set to zero. You must choose another extraction rate compatible with the available resource.

Payoff

When you extract the resource, you get a total revenue but you also incur a cost. Your revenue only depends on your extraction rate, while the cost depends both on the available resource and indirectly on the extraction rate of both players.

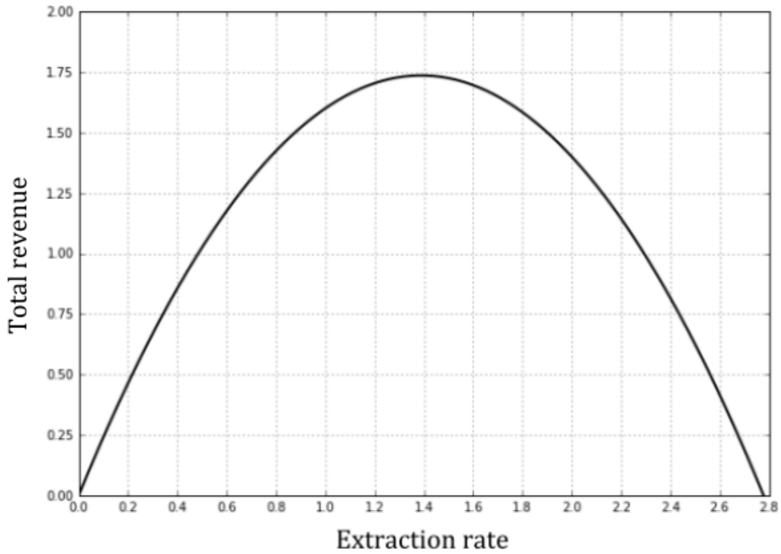
Total revenue from extraction

At the instant t, the total revenue denoted REC_t is equal to:

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

where E_t is your extraction rate. Thus, it does not depend on the extraction rate of the other player.

The figure below shows the total revenue according to the extraction rate.



Example

Let's assume that at a given instant t your extraction rate is 1.4, the total revenue will then be 1.736 units.

Cost of extraction

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

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

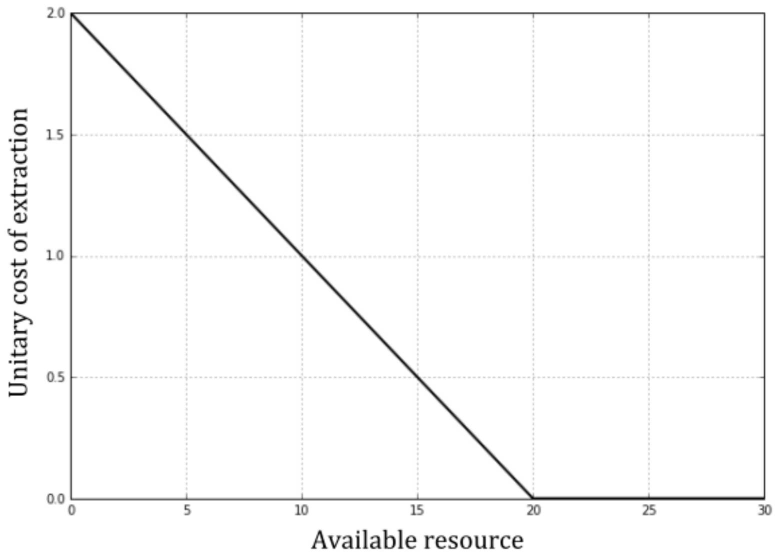
Thus,

✓ cost increases when the available resource decreases

✓ 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

✓ **cost depends indirectly on the total extraction rate of the two players through the available resource**

Figure below shows the unitary cost according to the available resource.



Total cost C_t is equal to the extraction rate times the unitary cost: $C_t = E_t \times c_t$

Discounted instantaneous payoff

Each instant, for each of the two players, the instantaneous payoff (G_t), which is equal to the difference between total revenue and total cost ($G_t = REC_t - C_t$), 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 in concrete terms 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's take a 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 $t = 10$ the discounted payoff equals $0.5 \times e^{-0.005 \times 10} = 0.4756$
At instant $t = 60$ the discounted payoff equals $0.5 \times e^{-0.005 \times 60} = 0.3704$

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

Payoff for the experiment

Your payoff for the experiment, as well as that of the other player, includes two elements: (i) your cumulated payoff from the discounted instantaneous payoffs from 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 and that of the other player** being fixed to the present instant $(t = p)$.

Your remuneration for this experiment is your payoff for the last instant of the game. This payoff corresponds to your cumulated payoff over all the instants of the game, plus the payoff computed as if the game continued indefinitely using your extraction rate and that of the other player's fixed at the rate of the last instant.

How the experiment works

Before the experiment starts, you and the other player should each decide upon an initial extraction rate. This rate will apply at the beginning of the experiment. As soon as the experiment has started, each of you can change this rate whenever you want by moving the slider in the window displayed on your screen. When you do not move the slider, the value that is considered at each instant is the last one that each of you set.

The computer performs the calculations every second, and the data displayed on your screens is updated every second as well. A second corresponds to 0.1 instant, as has been described previously. Thus, 10 minutes corresponds to 600 seconds and to 60 instants.

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. The Figure below gives you a shot of the decision screen. Description of areas is as follows :

- ✓ graphic at the top left: your extraction rate and the total extraction rate of both players
- ✓ graphic at the top right: the available resource
- ✓ graphic at the bottom left: your payoff of the experiment, which, as explained previously, is composed of your cumulative payoff up to the present instant, plus your payoff if your extraction and that of the other player were applied indefinitely
- ✓ text area at the bottom right: the same information as the curves but in text form, namely for each instant, your extraction rate, the total extraction rate of both players, the available resource, your discounted instantaneous payoff and your payoff of the experiment

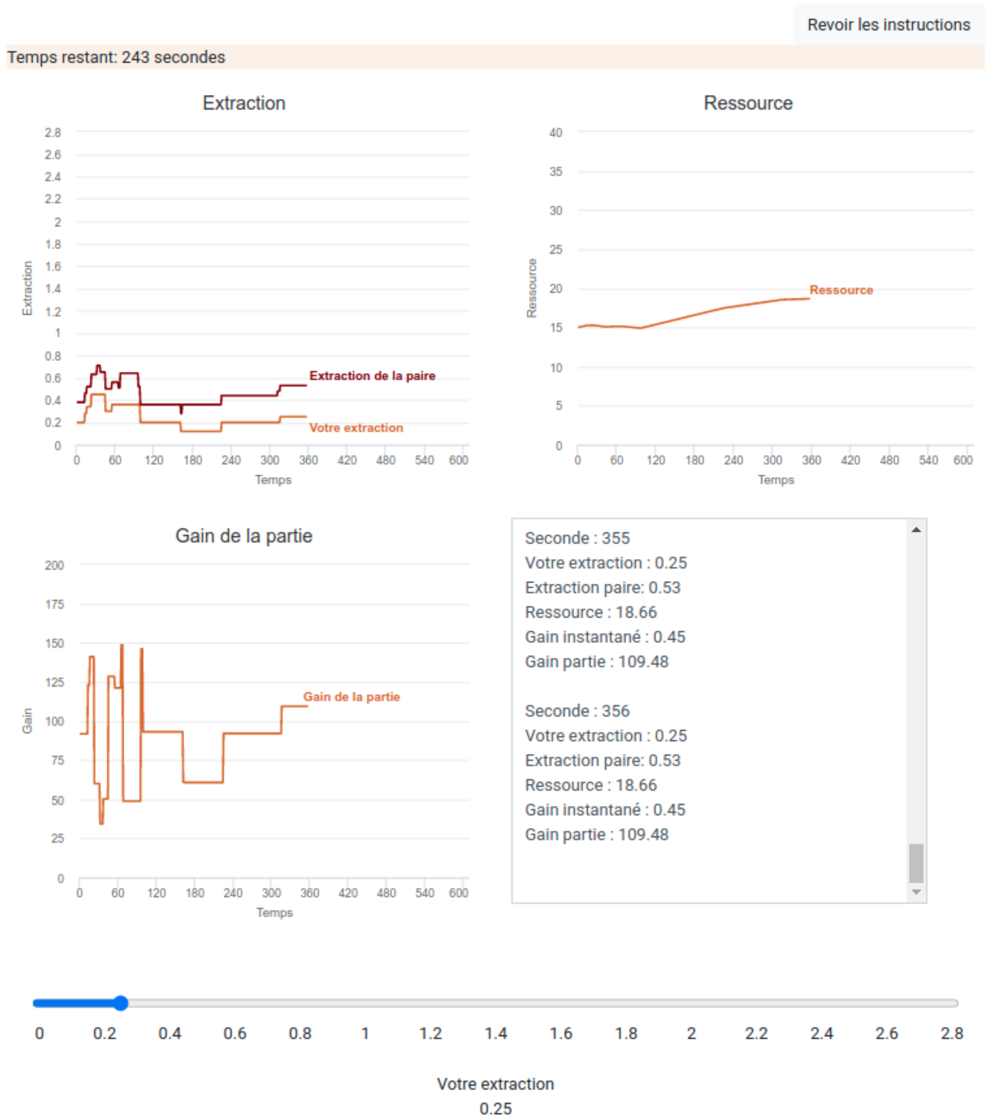


Figure 8: The game screen shot

Final details

This experiment includes a 10-minute training phase and a 10-minute experimentation phase. It's your payoff for the experiment that will be taken into account for your remuneration in euros. The exchange rate of ECUs to euros is as follows: 10 ECUs = 0.5€.

B.2 The Nudge: Injunctive Norm

Information:

In the theoretical analysis of this game without communication, three typical behaviors were identified. The resource evolution curves for these behaviors are shown in the figure below. For each curve, you also have information on the individual payoff, which is half of the group payoff.

- The dark pink curve results from the extraction choices of two perfectly symmetrical players who jointly maximize the group's payoff over the long term
- The blue curve results from the extraction choices of two perfectly symmetrical players who maximize their individual payoff over the long term
- The golden curve results from the extraction choices of two perfectly symmetrical players who maximize their individual payoff over the short term

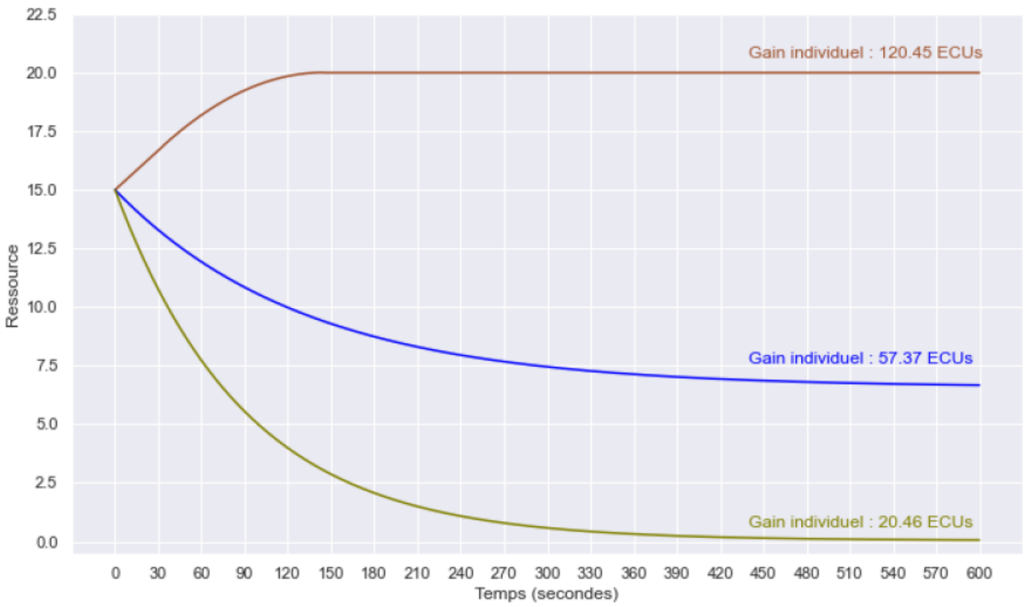


Figure 9: The injunctive norm

B.3 The Nudge: Descriptive Norm

Information:

In previous sessions of this game without communication, four typical behaviors were identified. The average resource evolution curves for these behaviors are shown in the figure below. For each curve, you also have information on the observed frequency and the average individual payoff.

- The dark pink curve results from the extraction choices of two players who, according to the interpretation suggested by the theory, corresponds to a joint maximization of the group's payoff over the long term
- The blue curve results from the extraction choices of two players who, according to the interpretation suggested by the theory, corresponds to a maximization of their individual payoff over the long term
- The golden curve results from the extraction choices of two players who, according to the interpretation suggested by the theory, corresponds to a maximization of their individual payoff over the short term
- The pink curve results from the extraction choices of two players with atypical behaviors whose interpretation escapes the theory

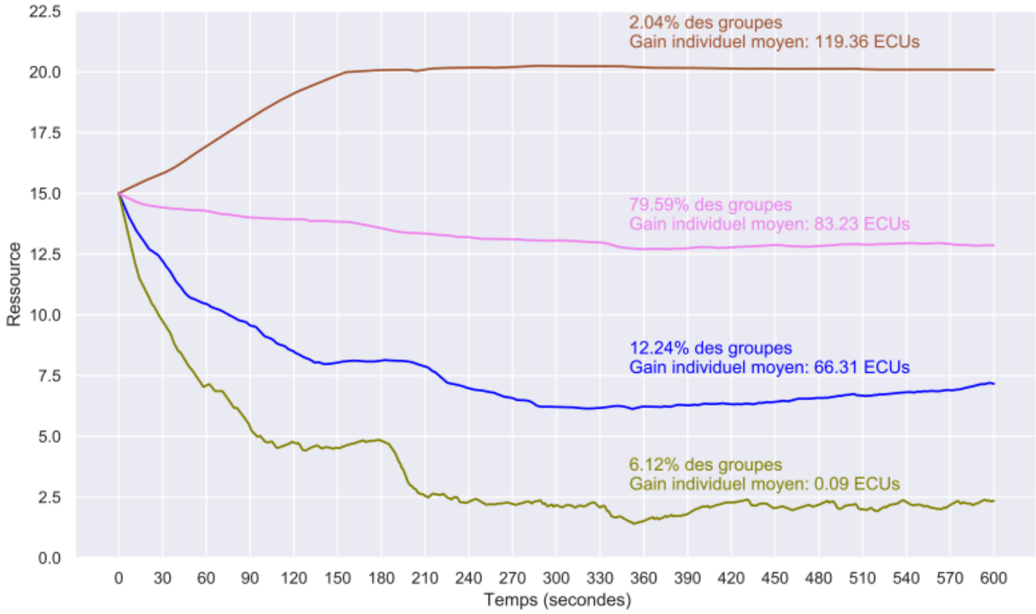


Figure 10: The descriptive norm

The Figure below shows the user's interface in the two nudge treatments. The information displayed on the upper right corner differs depending on whether the experiment relates to the injunctive social norm or the descriptive social norm.

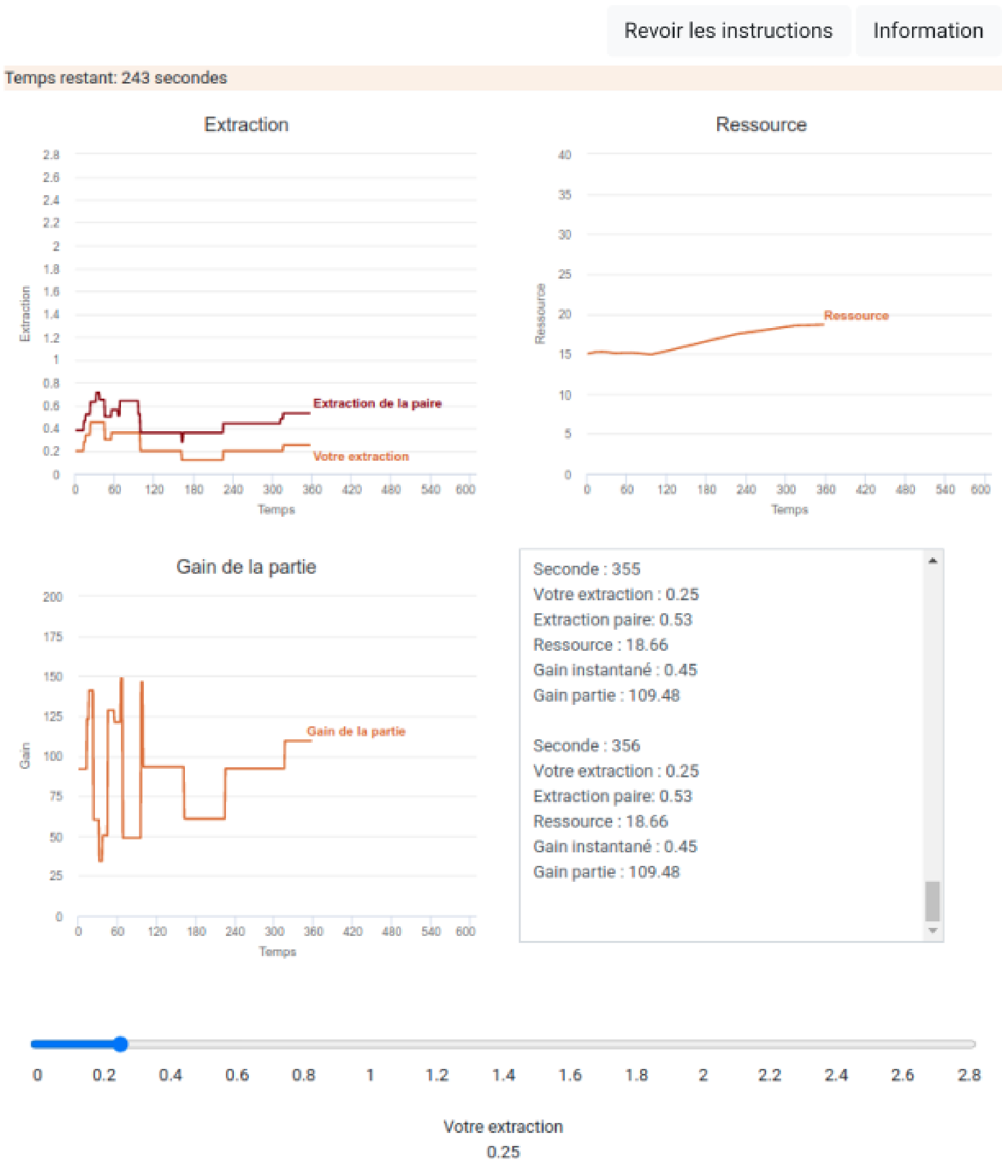


Figure 11: The game screen shot for nudge treatments

C Comprehension Questionnaire

Translated from French.

Question 1 – The amount of available resource evolves continuously and depends on two elements: the extraction rate of the two players and the fixed rate of 0.56 :

- ■ true
- ☐ false

Comment: The amount of the available resource evolves continuously, depending on the extraction rate of both players and the fixed rate of 0.56. Specifically, if the extraction rate of both players is greater than 0.56 the amount of the available resource decreases. If it is less than the fixed rate it increases, and if it is equal to the fixed rate, the amount of the available resource remains stable.

Question 2 – The instantaneous payoff depends on the amount of available resource :

- ■ true
- ☐ false

Comment: The instantaneous payoff is the difference between the total revenue and the cost at this instant. The total revenue only depends on the extracted rate, but the cost depends on the amount of the available resource. Whether the unitary cost or the total cost (unitary cost $\times$ extraction rate), the cost increases when the amount of the resource decreases but becomes null as soon as the amount of the available resource is greater than or equal to 20.

Question 3 – The discounted instantaneous payoff is the one taken into account in the calculation of the cumulated payoff :

- ■ true
- ☐ false

Comment: The instantaneous payoff (difference between the total revenue and the cost at this instant) is given as information, but it is the discounted instantaneous payoff that is taken into account in the calculation of the cumulated payoff (and that is therefore one of the two elements used to compute the payoff for the experiment).

Question 4 – The payoff for the experiment at time $t = x$ is composed of two elements: (i) the cumulated discounted payoff of each instant between $t = 0$ and $t = x$, and (ii) the calculated payoff from instant $t = x$ to infinity, assuming that your extraction rate and your partnerÂŠs rate are those of instant $t = x$:

■ true

☐ false

Comment: Each instant the computer gives you the payoff of the experiment as if the experiment was to immediately end with the two elements mentioned above: (i) the discounted cumulated payoff from the initial instant $(t = 0)$ to the present instant, and (ii) the payoff from the present instant to infinity assuming that the dynamics of the resource evolves according to the defined rule, but also that you and the other player of the pair no longer change your extraction rate. Your payoff in euros for the experiment is your payoff at the last instant of the game, namely at time $t = 600$ $(10$ minutes of play).

D General Ecological Behavior - GEB - Scale Questionnaire

1. I use energy-efficient bulbs.
2. If I am offered a plastic bag in a store, I take it.*
3. I kill insects with a chemical insecticide.*
4. I collect and recycle used paper.
5. When I do outdoor sports/activities, I stay within the allowed areas.
6. I wait until I have a full load before doing my laundry.
7. I use a cleaner made especially for bathrooms, rather than an all-purpose cleaner.*
8. I wash dirty clothes without prewashing.
9. I reuse my shopping bags.
10. I use rechargeable batteries.
11. In the winter, I keep the heat on so that I do not have to wear a sweater.*
12. I buy beverages in cans.*
13. I bring empty bottles to a recycling bin.
14. In the winter, I leave the windows open for long periods of time to let in fresh air.*
15. For longer journeys (more than 6h), I take an airplane.*
16. The heater in my house is shut off late at night.
17. I buy products in refillable packages.
18. In winter, I turn down the heat when I leave my house

19. In nearby areas, I use public transportation, ride a bike, or walk.
20. I buy clothing made from all-natural fabrics (e.g. silk, cotton, wool, or linen).
21. I prefer to shower rather than to take a bath.
22. I ride a bicycle, take public transportation, or walk to work or other.
23. I let water run until it is at the right temperature.*
24. I put dead batteries in the garbage.*
25. I turn the light off when I leave a room.
26. I leave the water on while brushing my teeth.*
27. I turn off my computer when I'm not using it.
28. I shower/bath more than once a day.*

* Negatively formulated items.

CEE-M Working Papers[1] - 2024

WP 2024-01 Ivric Valaire Yatat-Djeumen, **Luc Doyen**, Jean Jules Tewa & Bapan Ghosh
« Bioeconomic Sustainability and Resilience of Savanna »

WP 2024-02 **Mathieu Cuilleret**, **Luc Doyen** & Fabian Blanchard
« Reducing IUU for Bioeconomic Resilience of Fisheries: Necessary but Not Sufficient »

WP 2024-03 **Luc. Doyen**, M. D. Smith, U. R. Sumaila, G. Zaccour, I. Ekeland, P. Cury, C. Lett, O.Thebaud, J.-C. Poggiale, A. Moussaoui, J.-M. Fromentin, S. Gourguet, P. Guillotreau, H. Gomes, **Pierre. Courtois, Robert Schaap,** F. Blanchard, C. Rainer, **Mathieu Cuilleret,** T. Villain, F. Menard, & T. Sari.
« Mathematical Bio-Economics 2.0 for Sustainable Fisheries »

WP 2024-04 **François Bareille & Raphaël Soubeyran**
« Individual vs. collective agglomeration bonuses to conserve biodiversity »

WP 2024-05 Gabriela Demarchi, **Julie Subervie**, Cauê Carrilho, Thibault Catry, Antoine Pfefer & Philippe Delacote
« Greater Flexibility in Payments for Ecosystem Services: Evidence from an RCT in the Amazon »

WP 2024-06 **Marion Davin**, **Dimitri Dubois**, **Katrin Erdlenbruch** & **Marc Willinger**
« Discounting and extraction behavior in continuous time resource experiments»

WP 2024-07 **Djiguemde**, **M.**, **Dadakpete**, **D.**, **Dubois**, **D.** & **Tidball, M.**
« Nudging Behaviors in a Dynamic Common Pool Renewable Resource Experiment »

[1] **CEE-M Working Papers / Contact** : laurent.garnier@inrae.fr
- RePEc https://ideas.repec.org/s/hal/wpceem.html
- HAL https://halshs.archives-ouvertes.fr/CEE-M-WP/