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Anmina Dulcie Murielle Djiguemde

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THÈSE POUR OBTENIR LE GRADE DE DOCTEUR DE L'UNIVERSITÉ DE MONTPELLIER

En Sciences Économiques

École doctorale Économie et Gestion de Montpellier (EDEG)

Unité de recherche Center for Environmental Economics - Montpellier

DYNAMIC GAMES AND RENEWABLE COMMON POOL RESOURCES: MODELING AND EXPERIMENTS

Présentée par Anmina Dulcie Murielle DJIGUEMDE
Le 14 Décembre 2021

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The Faculty of Economics of the University of Montpellier does not intend to give any approval or disapproval to the opinions expressed in this thesis. These opinions should be considered specific to their authors.

"Did you ever stop to notice

This crying Earth, these weeping shores? [...]

What about crying whales? [...] We're ravaging the seas [...]

What about forest trails? [...] Burnt despite our pleas [...]

What about nature's worth? [...] It's our planet's womb [...]"

Michael JACKSON (1958 – 2009), *Earth* song

Foreword and Acknowledgment

Since I was a little girl, I have been fascinated by themes related to the preservation of the environment. This thesis is an ambitious project that was the subject of a call for applications for a doctoral contract and for which I had the opportunity to be selected. It discusses how dynamic games can be used to explore the behaviors of users of renewable common pool resources. Then proposes methods that could be used to guide and incentivize users to better preserve these resources, while maintaining significant welfare.

To carry out our investigations, we benefited from the funding of the ANR Green-Econ, in particular for the laboratory experiments. Thus, we initially wanted to test in the laboratory, continuous time experiments with both one and several players. Then, the same scenario in discrete time, before repeating the same investigations this time with several players directly. Finally, depending on the results found, we would determine the type of public policy (monetary and/or non-monetary) to be implemented. But time constraints have led us to revise the different themes retained for the thesis and the hierarchy of our different chapters (as presented in the introduction).

The research was very challenging and would not have been possible without the involvement of a dynamic team. This is why I would like to thank the Economy and Management Doctoral School of Montpellier - EDEG - for the opportunity it offered me to realize one of my dreams.

I would also like to thank my supervisor, Mabel TIDBALL and co-supervisor, Dim-

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I am grateful to the members of my individual monitoring committee (CSI), Stefano FAROLFI, Lisette IBANEZ, Alexandre SAUQUET and Marc WILLINGER, for their comments, advice, and encouragement to improve the work. Thank you also to the members of the jury, Hassan BENCHEKROUN, François COCHARD, Paolo CROSETTO and Katrin ERDLENBRUCH for agreeing to evaluate this thesis. It is an honor to have them in my jury.

In general, I would like to thank all those who, at some point in my university career or throughout, have shown kindness, understanding and supported me.

Last but not least, I would like to thank my family and friends for their unwavering support and encouragement whenever required.

Abstracts

Abstract: The optimal management of renewable common pool resources (groundwater, forests, fisheries, etc.) is a major concern for political and economic debates, and is a major issue for current and future decades. To take into account the perpetual evolution of renewable common pool resources, economists are increasingly relying on dynamic models. These models offer not only the possibility to analyze the behaviors of resource users, but also to propose suitable methods to efficiently manage renewable common pool resources. These models make it possible to define different trajectories according to the exploitation behavior of users. Thus, they offer a realistic and adequate framework for proposing suitable economic instruments, which aims at the efficient management of common pool renewable resources. Moreover, behavioral and experimental economics have shown that compliance to social norms and ethical considerations are an integral part of the individual's decision-making process, creating a trade-off between costs and benefits when their decisions are related to the environment.

The purpose of this thesis is first to analyze and test in a dynamic laboratory setting in continuous time, the exploitation decisions of common pool renewable resources users. Secondly, it aims to propose policy instruments to encourage the adoption of behavior more respectful of the resources used. Chapter 1 reviews the dynamic resource extraction models that have been tested in the laboratory. This review of the literature shows that the use of discrete time is predominant. Chapter 2 presents a continuous time experiment in which the resource is first exploited by a single agent, then by two agents simultaneously. This allows us to first identify the individual profiles of subjects when they are alone to exploit the resource, and then to see how these profiles evolve in the presence of strategic interaction. Chapter 3 compares the laboratory results of the continuous time model and its discrete approximation. It appears that continuous time induce more cooperation than discrete time when several users

simultaneously exploit the same resource. Finally, Chapter 4 studies in continuous time the impact of a non-monetary policy of the "nudge" type, which aims to help resource users adopt socially optimal behavior. To do this, we compared a descriptive social norm to an injunctive social norm and found greater efficiency in the injunctive nudge. However, the results remain quite mixed between the two types of nudges.

Keywords: Common Pool Resources; Dynamic Games; Experimental Economics; Behavioral Economics; Nudges

Codes JEL : C01; C73; C92; Q20; Q58

Résumé : La gestion optimale des ressources communes renouvelables (eaux souterraines, forêts, stocks de poissons, etc.) est au cœur des préoccupations politiques et économiques et constitue un enjeu majeur pour les décennies en cours et à venir. Pour tenir compte du caractère évolutif de ces ressources, les économistes s'appuient de plus en plus sur des modèles dynamiques. Ces modèles permettent de définir différentes trajectoires selon les comportements d'exploitation des utilisateurs. Ils offrent ainsi un cadre réaliste et adéquat pour proposer des instruments économiques adaptés, ayant pour finalité une gestion efficace des ressources communes renouvelables. Par ailleurs, l'économie comportementale et expérimentale ont montré que le conformisme aux normes sociales et les considérations éthiques font partie intégrante du processus de décision de l'individu, créant de ce fait un compromis entre coûts et bénéfices lorsque leurs décisions sont liées à l'environnement.

L'objectif de cette thèse est dans un premier temps d'analyser et de tester en laboratoire dans un cadre dynamique en temps continu, les décisions d'exploitation des utilisateurs de ressources communes renouvelables. Dans un second temps, elle vise à proposer des instruments de politiques, pour favoriser l'adoption de comportements plus respectueux des ressources utilisées. Le Chapitre 1 passe en revue les modèles dynamiques d'extraction de ressource qui ont été testés en laboratoire. Cette revue de la littérature fait ressortir que l'utilisation du temps discret est prédominante. Le Chapitre 2 présente une expérience en temps continu dans laquelle la ressource est d'abord exploitée par un seul agent, puis par deux agents simultanément. Cela permet d'identifier tout d'abord les profils individuels des sujets lorsqu'ils sont seuls à exploiter la ressource, puis de voir comment ces profils évoluent en présence d'interaction stratégique. Le Chapitre 3 compare les résultats testés en laboratoire, du modèle en temps

continu et son approximation discrète. Il ressort que le temps continu suscite davantage de coopération que le temps discret lorsque plusieurs utilisateurs exploitent simultanément la même ressource. Enfin le Chapitre 4 étudie en temps continu, l'impact d'une politique non-monnaire de type "nudge" dont l'objectif est d'aider les utilisateurs de ressources à adopter un comportement socialement optimal. Pour cela, nous avons comparé une norme sociale descriptive à une norme sociale injonctive et avons trouvé une efficacité plus grande dans le nudge injonctif. Toutefois, les résultats restent assez mitigés entre les deux types de nudges.

Mots-clés : Ressources Communes ; Jeux Dynamiques ; Économie Expérimentale ; Économie Comportementale ; Nudges

Codes JEL : C01 ; C73 ; C92 ; Q20 ; Q58

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General Introduction

Faced with the multiple environmental disturbances observed over the last few decades (extreme weather events, famine), we are witnessing an awareness for environmental preservation. Indeed, in their study of 2002, [Rose](#) stated that given the impact of human activity in all environmental dimensions, to reflect primarily on the question of human social organization as a whole, would allow to protect the environment. Environmental preservation is one of the three components of sustainable development and one of the eight goals set out in the United Nations Millennium Summit Declaration. In this sense and in order to encourage more environmentally friendly behaviors, the international community has formulated restrictive environmental policies through a number of conferences. An example is the Conference of the Parties (COP) on climate change, with the Cop 21 which allowed the signing of the Paris Agreement in 2015, the goal of which is to limit global warming to less than two degrees Celsius.

Renewable common pool resources (CPRs), such as forests, groundwater, fish stocks, etc., are among the environmental goods to be protected. Their specificity is that they are rivalrous and non-excludable, and thus subject to over-exploitation. In order to avoid what [Hardin \(1968\)](#) has called the "Tragedy of the Commons", it is therefore essential that these resources be managed efficiently. This thesis is part of that framework. More specifically, it aims to understand the decision-making processes of resource users, with the goal of learning lessons that will help preserve resources. Common pool resource management is a discipline of particular interest to economics. A number of scientific studies in this field were initially conducted within a static framework, which does not always take into account all the changes in the environment

in which people make their decisions. It is only in the 1970s that a transition towards more realistic dynamic models took place, with the use of dynamic programming, game theory and equilibrium analysis, to solve the problems of individual decision-making.

Moreover, experimental and behavioral economics allowed economics to progressively question a certain number of assumptions, notably on homo oeconomicus, who are considered to be perfectly rational, selfish individuals, placing their happiness above that of others and wanting to impose themselves on others. It has also enabled economics to revise the foundations of what motivates individuals to make decisions. This has led to the integration of new dimensions into economic models, such as aversion to inequality, emotions, ethics, social norms, etc., thus mobilizing multidisciplinary knowledge from psychology, sociology and even neuroscience. It is in this sense that this thesis will rely on modeling, experimentation and analysis of behaviors observed in the laboratory.

The purpose of this thesis is to start from a dynamic framework, more realistic than the static one, to analyze the decision-making of common pool resources users and to ultimately induce in them, more pro-environmental behaviors. The idea is therefore to test in the laboratory whether, in this dynamic framework in continuous time, individuals are able to identify the optimal theoretical trajectory, i.e. the one that preserves the resource over the long term. However, testing in the laboratory a dynamic model in continuous time over an infinite horizon, raises a number of methodological and practical questions, such as the choice between continuous and discrete time (for the laboratory representation of the continuous time model), between finite and infinite horizon, but also whether or not to take into account the strategic interactions between resource users.

In **Chapter 1**, we collect and structure scientific work that has focused on the management of dynamic renewable common pool resources in the laboratory. It appears from this review of the literature that very few studies are carried out in continuous time. Moreover, some studies use a theoretical model in continuous time, while the experiments are performed in discrete time. Finally, among the continuous time papers, many of them implement continuous time in the laboratory by means of extensive form models and are therefore qualified as "quasi-continuous" articles.

One of the conclusions of Chapter 1 is that very few studies have tested in the lab-

oratory a dynamic model in continuous time, allowing the collection of data to understand the decisions of individuals in this context, even though it is close to the reality of the evolution of a renewable resource. **Chapter 2** has thus a threefold objective: (i) develop a dynamic model in continuous time over an infinite horizon, which gives clear predictions and remains fairly simple to implement in the laboratory, (ii) design an experimental protocol which is as faithful as possible to the theoretical model, and (iii) develop an approach for the analysis of the collected data. The theoretical benchmarks used to rank the subjects in the experiment are social optimum, feedback and myopic. Indeed, myopic individuals maximize their individual payoffs over the short term, while those adopting a feedback behavior maximize their individual payoffs over the long term. Finally, the social optimum refers to a situation in which individuals jointly maximize their payoffs over the long term. Besides these rather methodological aspects, the research question addressed is: (i) how do individuals behave in a dynamic environment compared to theoretical benchmarks? (ii) what is the impact of strategic interaction in this context? The experiment was carried out using a "within-subject design". This means that the same players took part in the different treatments constituting the experiment. This allows us to first identify the individual profiles of the subjects when they are alone to exploit the resource, then to see how these profiles evolve in the presence of strategic interaction. In this chapter and all those that follow, we have chosen to carry out our investigations over a infinite horizon, because we believe that it could be a signal that guarantees the sustainability of the resource, while reminding its renewable nature. From a theoretical point of view, the infinite horizon was chosen to simplify the calculations. In addition to the standard behaviors predicted by the theory, such as the social optimum, feedback and myopic behavior, we have determined intermediate behaviors, qualified as convergent. These are individuals who start with myopic behavior, and who slowly converge towards the social optimum. We also found individuals who underexploit or overexploit the resource, but in general, the introduction of strategic interaction favors the overexploitation of the resource.

During the designing of the experimental protocol for Chapter 2, a methodological question arose: given the impossibility of implementing continuous time in the laboratory, what would be the difference between continuous time and its discrete ap-

proximation, and is it possible based on the model, to test the impact of the nature of time (continuous vs. discrete approximation) on the decisions and trajectories adopted by individuals? This inspired the realization of **Chapter 3**. Following an experimental protocol in between-subject design, i.e. with different individuals for each treatment, we performed four treatments that combine the nature of time (continuous vs. discrete) and the presence or the absence of strategic interaction (one player vs. two players). Our results show that without strategic interaction, the nature of time does not impact individuals' decision trajectories. With strategic interaction, however, continuous time leads to more cooperation between individuals within a group than discrete time.

Having answered the various methodological questions, proposed a classification of the behaviors observed in the laboratory and found relatively few optimal subjects in a strategic interaction situation, we were now able to vary the nature of the information provided to resource users for their decision-making (e.g., the evolution of costs). We could also look for the type of public policy that would guide more resource users towards a behavior that is more respectful of the resource used and that provides them with a greater payoff. This is the purpose of **Chapter 4**, in which we start with the continuous time model with several players developed in Chapter 3, while introducing non-monetary instruments of "nudges" type, which are known for their efficiency, but also for their very low implementation cost. According to [Thaler & Sunstein \(2009\)](#), "nudges" can be defined as "*... any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives.*" Among the different categories of "nudges" that exist, we focused on social norms and compared the effects of two types of social norms: descriptive (what is done) and injunctive (what should be done). We found mixed results between the two types of nudges. Indeed, the descriptive nudge seems to give better results in terms of classification of treatments according to the average level of resources. However, in terms of group classification according to the profiles observed in each treatment, the injunctive nudge allows for optimality and ensures the greatest efficiency. Moreover, this classification in the nudge treatments seems consistent with the nature of the information displayed to the experimental subjects. Thus, this thesis has established a theoretical and methodological framework to study individual and collective behaviors in a dynamic environment, on a common renew-

able resource management issue. This framework allows for multiple extensions and deepenings, notably on the question of public intervention to avoid overexploitation of the resource.

Introduction Générale

Face aux multiples bouleversements environnementaux observés au cours des dernières décennies (phénomènes météorologiques extrêmes, famine), nous assistons à une prise de conscience pour la préservation de l'environnement. En effet, dans ses travaux de 2002, [Rose](#) soutenait qu'étant donné l'impact de l'activité humaine dans toutes les dimensions environnementales, réfléchir prioritairement à la question de l'organisation sociale humaine dans sa globalité, permettrait de protéger l'environnement. La préservation de l'environnement est un des trois piliers du développement durable et un des huit objectifs énoncés dans la Déclaration du Sommet du Millénaire établie par l'ONU. Dans ce sens et afin de susciter chez les agents économiques des comportements plus respectueux de l'environnement, la communauté internationale a formulé à travers un certain nombre de conférences, des politiques environnementales restrictives. Un exemple est donné à travers la Conférence des Parties (COP) sur les changements climatiques, avec la Cop 21 qui a permis la signature de l'Accord de Paris en 2015, dont l'objectif est de limiter le réchauffement climatique à moins de deux degrés Celsius.

Les ressources communes renouvelables (CPRs), comme les forêts, les nappes phréatiques, les stocks de poisson, etc. font partie des biens environnementaux à protéger. Leur particularité est d'être rivales et non-excluables; ce qui les rend sujettes à la sur-exploitation. Afin d'éviter ce que [Hardin \(1968\)](#) a appelé la "Tragédie des Communs", il est indispensable que ces ressources soient gérées de manière efficace. Cette thèse s'inscrit dans ce cadre. Elle a pour objectif plus spécifique de comprendre les processus de décisions des utilisateurs de ressources, dans le but de tirer des leçons qui aideront à la préservation des ressources. La gestion des ressources communes est une dis-

cipline qui intéresse particulièrement la science économique. La majorité des études scientifiques dans ce domaine se sont inscrites dans un premier temps dans un cadre statique, qui ne prend pas toujours en compte toutes les évolutions de l'environnement dans lequel les individus prennent leurs décisions. Ce n'est que dans les années 1970 qu'une transition vers l'utilisation de modèles dynamiques plus réalistes s'est opérée, avec l'utilisation de la programmation dynamique, la théorie des jeux et l'analyse de l'équilibre, pour résoudre les problèmes de prises de décisions des individus.

Parallèlement, l'économie expérimentale et comportementale a permis à la science économique de progressivement remettre en cause un certain nombre de postulats, notamment celui de l'homo œconomicus, un individu parfaitement rationnel, égoïste, plaçant son bonheur au dessus de celui des autres et voulant s'imposer face à eux. Elle a aussi permis à la science économique de réviser les fondements de ce qui motive les individus à prendre leurs décisions. Cela a conduit à l'intégration de nouvelles dimensions dans les modèles économiques, telles que l'aversion aux inégalités, les émotions, l'éthique, les normes sociales, etc., mobilisant ainsi des connaissances pluridisciplinaires venant de la psychologie, de la sociologie et même des neurosciences. C'est dans ce sens que cette thèse va s'appuyer sur la modélisation, l'expérimentation et l'analyse des comportements observés en laboratoire.

L'objectif de cette thèse est de partir d'un cadre dynamique, plus réaliste que le cadre statique, afin d'analyser les prises de décisions des utilisateurs de ressources communes et susciter in fine chez eux, des comportements plus respectueux des ressources utilisées. L'idée est donc de tester en laboratoire, si dans ce cadre dynamique en temps continu, les individus sont en mesure d'identifier la trajectoire théorique optimale, c'est-à-dire qui préserve la ressource sur le long terme. Cependant, tester en laboratoire un modèle dynamique en temps continu sur un horizon infini pose un certain nombre de questions méthodologiques et pratiques telles que le choix entre temps continu et temps discret (pour la représentation en laboratoire du modèle en temps continu), entre horizon fini et horizon infini, mais aussi la prise en compte ou pas des interactions stratégiques entre utilisateurs de ressources.

Dans le **Chapitre 1**, nous rassemblons et structurons les travaux scientifiques qui se sont intéressés à la gestion dynamique des ressources communes renouvelables en laboratoire. Il ressort de cette revue de la littérature que très peu d'études sont réalisées en temps continu. De plus, certaines études utilisent un modèle théorique en temps

continu, alors que les expériences sont réalisées en temps discret. Enfin, parmi les articles en temps continu, grand nombre d'entre eux implémentent le temps continu en laboratoire par le biais des modèles sous forme extensive et sont de ce fait qualifiés d'articles "quasi-continus".

L'une des conclusions du Chapitre 1 est que très peu d'études ont testé en laboratoire un modèle dynamique en temps continu, permettant de collecter des données pour comprendre les décisions des individus dans ce contexte pourtant proche de la réalité de l'évolution d'une ressource renouvelable. Le **Chapitre 2** a donc un triple objectif : (i) développer un modèle dynamique en temps continu sur un horizon infini, qui donne des prédictions claires et reste suffisamment simple à implémenter en laboratoire, (ii) élaborer un protocole expérimental qui soit le plus fidèle possible au modèle théorique et (iii) développer une démarche d'analyse des données collectées. Les benchmarks théoriques retenus pour classer les sujets dans l'expérience sont l'optimum social, le feedback et le myope. En effet, les individus myopes maximisent leurs gains individuels sur le court terme, tandis que ceux qui adoptent un comportement feedback maximisent leurs gains individuels sur le long terme. Enfin, l'optimum social fait référence à une situation dans laquelle les individus maximisent conjointement leurs gains sur le long terme. En parallèle à ces aspects plutôt méthodologiques, la question de recherche posée est celle de savoir : (i) comment se comportent les individus dans un environnement dynamique par rapport aux benchmarks théoriques ? (ii) quel est l'impact de l'interaction stratégique dans ce contexte ? L'expérience a été réalisée en "within-subject design". C'est-à-dire que les mêmes joueurs ont pris part aux différents traitements constituant l'expérience. Cela permet d'identifier tout d'abord les profils individuels des sujets lorsqu'ils sont seuls à exploiter la ressource, puis de voir comment ces profils évoluent en présence d'interaction stratégique. Dans ce chapitre et tous ceux qui suivront, le choix a été fait de réaliser nos investigations sur un horizon infini, car nous estimons qu'il pourrait être un signal qui garantit la soutenabilité de la ressource, tout en rappelant son caractère renouvelable. Du point de vue de la modélisation, l'horizon infini a été retenu à des fins de simplification de calculs. En plus des comportements standards prédits par la théorie, tels que l'optimum social, le comportement feedback et myope, nous avons déterminé des comportements intermédiaires, qualifiés de convergent. Il s'agit d'individus qui commencent avec un

comportement myope, et qui lentement convergent vers l'optimum social. Nous avons aussi trouvé des individus qui sous-exploitent ou sur-exploitent la ressource, mais de façon générale, l'ajout de l'interaction stratégique favorise la sur-exploitation de la ressource.

Lors de l'élaboration du protocole expérimental du Chapitre 2, une question méthodologique s'est posée : étant donné l'impossibilité d'implémenter le temps continu en laboratoire, quelle serait alors expérimentalement la différence entre le temps continu et son approximation discrète, et est-il possible à partir du modèle construit, de tester l'impact de la nature du temps (continu vs. approximation discrète) sur les décisions et les trajectoires adoptées par les individus ? C'est ce qui a inspiré la réalisation du **Chapitre 3**. Suivant un protocole expérimental en "between-subject design", c'est-à-dire avec différents individus pour chaque traitement, nous avons réalisé quatre traitements qui combinent la nature du temps (continu vs. discret) et la présence ou l'absence d'interaction stratégique (un joueur vs. deux joueurs). Nos résultats indiquent qu'en l'absence d'interaction stratégique, la nature du temps n'impacte pas les trajectoires de décision des individus. Avec l'interaction stratégique par contre, le temps continu conduit à davantage de coopération entre les individus au sein d'un groupe que le temps discret.

Après avoir répondu aux différentes questions méthodologiques, proposé une classification des comportements observés en laboratoires et trouvé assez peu d'optimaux en situation d'interaction stratégique, nous étions maintenant en mesure de faire varier la nature des informations fournies aux utilisateurs de ressources pour leurs prises de décisions (par exemple l'évolution des coûts). Nous pouvions aussi rechercher le type de politique publique qui permettrait de guider davantage d'utilisateurs de ressources vers un comportement plus respectueux de la ressource utilisée et qui leur procure un gain plus important. C'est l'objet du **Chapitre 4**, dans lequel nous partons du modèle en temps continu avec plusieurs joueurs développé dans le Chapitre 3, tout en introduisant des instruments non monétaires de type "nudges", réputés pour leur efficacité, mais aussi leur faible coût d'implémentation. Les "nudges" se définissent selon [Thaler & Sunstein \(2009\)](#) comme "*...tout aspect de l'architecture de choix qui modifie le comportement des gens de manière prévisible sans interdire aucune option ou changer de manière*

significative leurs incitations économiques." Parmi les différentes catégories de "nudges" existantes, nous avons choisi de nous concentrer sur les normes sociales et de comparer les effets de deux types de normes sociales : descriptives (ce qui est fait) et injonctives (ce qui devrait être fait). Nous avons trouvé des résultats assez mitigés entre les deux types de nudges. En effet, le nudge descriptif semble donner de meilleurs résultats en terme de classification des traitements selon le niveau moyen de ressource. Cependant en terme de classification des groupes selon les profils observés dans chaque traitement, le nudge injonctif permet d'avoir des optimaux et assure l'efficacité la plus grande. De plus, cette classification dans les traitements nudges semble consistante avec la nature de l'information présentée aux sujets expérimentaux. Ainsi, cette thèse a posé un cadre théorique et méthodologique pour étudier les comportements individuels et collectifs dans un environnement dynamique, sur une problématique de gestion de ressource commune renouvelable. Ce cadre permet de multiples extensions et approfondissements, notamment sur la question de l'intervention publique pour éviter la sur-exploitation de la ressource.

Chapter 1

A Survey on Dynamic Common Pool Resources: Theory and Experiment

Abstract:

Keywords: Common Pool Resources; Dynamic games; Experimental Economics

Codes JEL :

This paper provides a survey on the literature using dynamic games to analyse the decision-making processes of common pool resource (CPR) users. The purpose of this paper is to emphasize the implementation of dynamic games in laboratory experiments. In this way, we focus on articles presenting both a theoretical model with experiments, by making a distinction between continuous time and discrete time. We also examined the econometric tools used to analyse experimental data.

Résumé :

Mots-clés : Ressources Communes ; Jeux Dynamiques ; Économie Expérimentale

Codes JEL :

Cet article présente un aperçu de la littérature utilisant les jeux dynamiques pour analyser les processus de prises de décisions des utilisateurs de ressources communes (CPR). L'objectif est de mettre en évidence l'implémentation des jeux dynamiques dans les expériences de laboratoire. Ainsi, nous mettons l'accent sur les articles présentant à la fois un modèle théorique avec des expériences, en faisant la distinction entre temps continu et temps discret. Nous avons également examiné les outils économétriques utilisés pour analyser les données expérimentales.

1.1 Introduction

The issue of common pool resource (water, fisheries, forestry, pastures, etc) management remains a practical concern, since without regulation, they are the locus of the "Tragedy of the Commons" (Hardin, 1968). In other words, common pool resource users are faced with dilemmas which can lead to a severe overexploitation when they are not solved, and even to the destruction of the resource. Without rules, resource users will engage in a race for its use (Janssen & Ostrom, 2006). Thus, in 1970's, a transition from a static framework to a more realistic dynamic framework took place in studies dealing with the management of common pool resources (CPRs), with authors like Dasgupta & Heal (1979); Gisser & Sanchez (1980); Clark (1990); Basar & Olsder (1999); Dockner et al. (2000); Haurie & Zaccour (2005); Engwerda (2005); Van Long (2010). Moreover, experimental economics is a powerful tool used to test theoretical models, and have with cognitive and social psychology challenged the rationality of individuals, leading to consider the influence of social interactions and the role of emotions in people's rational decision-making (Carlsson & Johansson-Stenman, 2012; Croson & Treich, 2014). While there is an extensive theoretical literature on dynamic common pool resource management, the literature combining theory and experiments on dynamic CPRs is very scarce, with some of the studies using continuous time, others using discrete time and others again making a mix of both continuous and discrete time. Notice however that a continuous time model has different predictions from a discrete time model, except if the latter is a discretization of the continuous time model.

This review aims to shed some light on how dynamic games are implemented in laboratory, especially continuous time, since implementing continuous time is very recent and challenging. Hence, we are particularly interested in how experimental instructions were presented to subjects, the different time horizons (finite vs. infinite), as well as the methods used to analyze experimental data. The behavioral benchmarks to which subjects are frequently compared in this survey are the social optimum equilibrium, the Nash feedback equilibrium and the myopic equilibrium. The social optimum equilibrium is equivalent to a joint maximization problem. In the Nash feedback equilibrium, each subject takes into account the dynamics of the resource in his decision process, but maximises his/her individual payoff. When behaving myopically, a subject ignores the dynamics of the resource in his decision process. The difference with

[Tasneem & Benchekroun \(2020\)](#) is that we propose a synthesis of the selected articles, taking care to present models, experiments and results. Moreover, we classify the different articles according to whether they are in continuous time, discrete time or a mixture of both. Among the continuous time papers, we distinguish those classified as "quasi-continuous" time papers from those that are "pure" continuous time. The idea is to allow the reader to have a digest of information that one seeks to identify very quickly, namely : the research question, the type of model used (continuous or discrete), the time horizon (finite or infinite), the number of participants in the experiment, the presence or the absence of a framing, the types of analysis, the main results. We have also taken care to harmonize the notations to facilitate reading between the different articles and thus simplify comparison between them.¹ Of course, this review is not exhaustive, as we are particularly interested in articles that combine theory and experimentation, but it is complementary to that of [Tasneem & Benchekroun \(2020\)](#), and therefore constitutes a base that can be completed as we go along.

The rest of the paper is organized as follows : Section 2 reviews discrete time articles, Section 3 is devoted to continuous time articles, Section 4 presents articles having combined continuous and discrete time. Section 5 is devoted to a discussion of the analysis methods used in the reviewed articles, and the last Section provides some concluding remarks.

1.2 Discrete Time Models of CPRs

The vast literature combining theory with experimentation in the management of common pool resources (CPRs) is in discrete time and over a finite horizon, since laboratory experiments have been successful in this framework. Discrete time offers the opportunity to experimental agents to make their decisions at the same time. It can also be assimilate to a repeated game in which a variable evolves over periods, which makes it easy to implement in the lab. However, repeated games are widely implemented in lab experimentation. They can be defined as static games which are repeated over a given number of periods without changing the conditions of the game. Repeated games differ from dynamic discrete time games, in which a state variable evolves over time and

¹See Appendices [A.1](#) of Chapter 1 for a summary of notations.

affects subjects' decision processes. Hence, the change in the conditions of the game is specific to discrete time, which is also called "supergame" (Pénard, 1998).

1.2.1 Externalities from the Use of CPRs

In the last five decades, a growing number of scholars have started to use the theory of dynamic games to model the dynamic interactions involving in the use of common pool resources. These interactions create externalities having mostly a time dependence structure. Herr et al. (1997) and Mason & Phillips (1997) discuss dynamic and static externalities related to costs in the use of CPRs, while Gardner et al. (1997) distinguish three kinds of dynamic externalities occurring in the use of groundwater : a strategic externality, that appears because the use of groundwater via ownership creates depletion; a congestion externality, that is due to the short distance between the wells allowing to pump groundwater, and creates a loss in efficiency. The last externality is a stock externality, occurring because the use of water by an individual reduces the available amount for others, thus increasing their pumping costs.

Herr et al. (1997) investigate the effects on agents behaviors, of two types of externalities (static and dynamic) resulting from the use of a common non-renewable resource assimilated to a groundwater bassin. Time independent or static externalities are situations in which the current extraction of an agent leads only to an increase of the current extraction costs of other agents, whereas time dependent or dynamic externalities involve both an increase in current and future extraction costs of others. Supposing no discount rate, they used a linear quadratic finite horizon model where n agents share an access to a groundwater bassin. Each agent i has to maximize his net benefit function, which is the difference between the benefit function (B_{it}) and the cost function (C_{it}), under the dynamics of the marginal cost (c_t). The net benefit depends on the agent's extraction, x_{it} , at period t and the total group extraction X_t . The authors have defined three benchmark solutions that are the social optimum, the Nash feedback equilibrium and the myopic solution.

For time independent externalities, the marginal cost as well as the depth to water are reset to their initial values at each period, so that $c_t = c$. It is a static game repeated over T periods where in each period, the Nash equilibrium for multiple players is

obtained by maximizing equation (1.1). For time dependent externalities however, the marginal cost is linearly increasing by k as the depth to water becomes high, so that the Nash feedback equilibrium for multiple players is given by maximizing equation (1.1) in each period, subject to equation (1.2) :

$$\max \sum_{t=0}^T \underbrace{ax_{it} - bx_{it}^2}_{Benefit} - \underbrace{x_{it}(c_t + kX_t/2)}_{Cost}, \quad (1.1)$$

$$s.t \ c_{t+1} = c_t + kX_t. \quad (1.2)$$

The authors ran eight experimental sessions of a non contextualized experiment. These sessions involved five treatments : three time independent and two time dependent, and lasted about an hour and a half each. In each experimental session, the authors ran two training phases followed by two experiment phases called "series". When the treatment involved a time independent setting, an experiment phase consisted of 10 repetitions of a one-shot game where the marginal cost is reset to its original value each period. However, when the treatment involved a time dependent setting, an experiment phase consisted of a single 10 periods game where the marginal cost is linearly increasing over periods. In this case, it was possible that the phase stopped before the 10th period, when the cost of the base token became so higher that positive profits disappeared. In each experimental session, groups of two and five subjects had to individually and simultaneously with the other members of the group order entire values of tokens between a lower bound of zero and an upper bound according to the parameterization chosen by the authors. The cost incurred by an individual for a given period depends on both the number of tokens he has ordered and the total number of tokens ordered by the group. Subjects were given a benefits table showing them the total benefits they can individually earn. At each experiment phase, they were also informed of the total number of tokens ordered by the group, the average cost of a token and their individual profits. They had the ability to see at any time the results of previous periods.

The different size of the groups allowed the authors to measure the level of depletion of the resource. They found high depletion rates in the initial periods, with a large number of subjects. This initial depletion was higher in dynamic designs. They also

found by applying a Mean Squared Deviation (MSD) to token orders, that individual token orders are more closed to the Nash equilibrium than to the social optimum when considering time independent externalities. However, they found in time dependent externalities a higher number of myopic subjects, which exacerbates the tragedy of the commons. The authors finally found significantly higher payoffs in time independent externalities compared to those in time dependent externalities.

In line with [Herr et al. \(1997\)](#), [Mason & Phillips \(1997\)](#) were also interested in the study of static and dynamic externalities from the use of common pool resources. In their infinite horizon model, n agents assimilated to firms share an access to a renewable fishery, so that the authors tried to investigate the effect of industry size in the emergence of cooperation. Static and dynamic externalities are introduced through costs that are assumed to be additively separable. Each firm has to maximize his profit π_{it} , which is the difference between the benefit function and the cost function, under the dynamics of the stock, which evolves according to a logistic growth function. The profit depends on the firm i 's harvest level, x_{it} , and the industry total harvest level, X_t . In both the static and the dynamic externalities, the authors computed the Nash and the social optimum predictions.

For their static cost externalities, the maximization problem is determined by equation (1.3), where c_1 is the static cost externality and c_2 is equal to zero. For their dynamic cost externalities, using the assumption of symmetry in which each firm i uses the same harvest strategy $x^e(S)$, the maximization problem described by equation (1.3) takes into account the dynamics of the stock (1.4), which evolves according to a logistic growth function, where c_2 reflects the dynamic cost externality and c_1 is equal to zero :

$$\max_{x_{it}} \sum_{t=0}^{\infty} \rho^t \left[\overbrace{P(X_t)x_{it}}^{\text{Benefit}} - \underbrace{[c_f + c_1(X_t) + c_2(S_t)]x_{it}}_{\text{Costs}} \right], \quad (1.3)$$

$$s.t \ S_{t+1} = S_t + RS_t \left[1 - \frac{S_t}{K} \right] - \sum_{i=1}^n x_{it}, \text{ with } x_t = x^e(S). \quad (1.4)$$

The discount factor is denoted by ρ , c_f is fixed costs, R is the intrinsic growth rate

and K denotes the carrying capacity. The authors assumed that fish stock is perishable, so that all the stock (S_t) of a given period is sold in that period. They also assumed that firms' harvests are strategic substitutes and that the market price $P(X_t)$ in each period t is an inverse demand function of the harvests. In both the static and the dynamic externalities, the authors wanted to test the hypothesis that subjects will cooperate more than in the one-shot Nash prediction.

The authors ran eight experimental sessions involving four treatments of static externalities and four treatments of dynamic externalities. The treatments consisted with industry sizes of two, three, four and five firms, and each treatment lasted from about an hour and a half to two hours. In each experimental session, the authors ran a training phase to make sure that subjects well understood the experimental conditions. However, in sessions involving dynamic externalities, subjects also had to complete a question, allowing them to understand how their current harvest decisions affect future costs. In each period, subjects had to make a harvest decision individually and simultaneously with the other members of their firm. The authors described a payoff table depending on the number of firms in the industry, so that it allowed subjects to know the calculated profit for each possible combination of harvest they might collectively make with their rivals. Each subject was informed of the choices and payoffs of the other members of his group.

The infinite horizon was simulated by applying a random termination rule. In this case, the discount factor can be interpreted as a continuation probability, allowing the authors to deduce the termination probability which is equal to 0.2. In other words, after 35 periods of play, the experiment stopped at the end of each period with a probability of 0.2. While static stock externalities were included in the payoff table given to subjects, dynamic cost externalities were implemented by giving to subjects a penalty table. This table provides them information about the adjustment of their payoffs, resulting from each of their choices. They were also given a detailed description of the link between costs and stock, as well as the current harvest and future stocks. Finally, to analyze potential extinction in the dynamic cost externality design with large industry size, the authors ran four supplementary sessions with industry of size five.

Using a learning or a partial adjustment model to analyze current harvest decisions, the authors found that subjects learn to adjust their actions over time in both

the static and dynamic cost externalities.² Despite a faster convergence to the steady state in the dynamic framework than in the static framework, their results suggest highest cooperation in static cost externalities than in dynamic cost externalities, where they found more aggressive behavior. Moreover, they found an optimal industry size of four in the static treatment (which is larger than the optimal number of firms in the Nash prediction), while this number is three in the dynamic treatment (which is equal to the Nash prediction). They also found little evidence of extinction in the dynamic cost externalities.

Considering externalities resulting from the use of a non-renewable groundwater, Gardner et al. (1997) investigate the relationship between groundwater property rights doctrines and extraction behaviors of the users from 17 states in the American West.³ They distinguished four property rights doctrines. The absolute ownership doctrine, in which the owner of the land overlying an aquifer can extract the aquifer without limitation. The reasonable use doctrine, based on the same principle as the previous doctrine, except that it takes into account the fact that water can originate from the property of the neighbors. The correlative rights doctrine, in which landowners overlying the aquifer must use it reasonably, as the doctrine imposes an individual quota on the resource stock. Strategic externalities are suppressed under this doctrine but stock externalities persist. The last doctrine is the prior appropriation doctrine, which restricts the entrance to new pumpers by protecting reasonable pumping levels of senior appropriators.

Supposing no discount rate and using a linear quadratic finite horizon model in which n users share an access to a groundwater aquifer, each agent i has to maximize his net benefit function under the dynamics of the depth to water (d_t). Water is used as an input in agricultural production. The net benefit function is the difference between the benefit function (B_{it}) and the cost function (C_{it}) and depends on the agent's extraction x_{it} , as well as the total group extraction X_t . The authors consider for their study three property rights that are the absolute ownership doctrine, the prior

²See section 1.5 for a detailed explanation of the partial adjustment model.

³The 17 states are Arizona, California, Colorado, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oklahoma, Oregon, South Dakota, Texas, Utah, Washington, Wyoming.

appropriation doctrine and the correlative rights doctrine. Under each doctrine, they compute the social optimum and the Nash equilibrium. For example in the absolute ownership doctrine, the social optimum maximization problem is given by equation (1.5) :

$$\max \sum_{i=1}^n \sum_{t=0}^T \overbrace{ax_{it} - bx_{it}^2}^{\text{Benefit}} - \underbrace{[(d_t + AX_t + B) x_{it}]}_{\text{Cost}}, \quad (1.5)$$

$$\text{s.t } d_{t+1} = d_t - R + s \sum_{i=1}^n x_{it},$$

where a , b , A and B are positives parameters, s is a parameter depending on the size and the configuration of the aquifer and R denotes the constant recharge rate, which is equal to zero. The finite horizon, the no discount and the no resource recharge are the restrictive assumptions that the authors have made to simplify the model and the experiment, and focus subjects' attention on strategic and stock externalities.

Subjects participated in a non contextualized experiment involving three treatments. Each treatment include a set of three experiment phases. In the first two experiment phases, subjects were inexperienced in the decision environment, while the last experiment phase involved experienced subjects, randomly selected from the group of inexperienced. The baseline treatment, in which groups of 10 subjects played over 10 periods, illustrates the absolute ownership doctrine where no restriction is made on pumping levels. The second treatment illustrates the prior appropriation doctrine in which there is an entry restriction, limiting the number of subjects to groups of five. However, subjects played over 20 periods instead of 10 periods, in order to keep constant the maximal resource value. The last treatment, in which groups of 10 subjects played over 10 periods, illustrates the correlative rights doctrine where an individual stock quota of 25 is imposed. In each period, subjects had to individually and simultaneously with the other members of their groups, order entire values of tokens between a lower bound of zero and an upper bound according to the parameterization chosen by the authors in each treatment.

They were given the cost of a base token at the first period and were informed that this cost will increase by a given amount for each token ordered by the group, with the possibility that the experiment stops before the last period, when the token cost is so high that it no longer allows positive profits. In the baseline treatment, the experiment stopped after three, two and four periods respectively in the two inexperienced groups

and the experienced subjects. The experiment stopped after six, five and eight periods in the entry restriction treatment ; and after seven, four and three periods in the stock quota treatment. After each period, subjects were informed of the total number of tokens ordered by the group, the token cost for this period, the new cost of base token for the next period and profits for the current period.⁴

In their analyzes, the authors compared the tokens ordered by subjects in the experiment to the theoretical social optimum and Nash feedback token orders. Considering the first decision periods in each treatment, they found under the absolute ownership doctrine (no restriction treatment), higher average token orders than the Nash feedback prediction. The average token orders under the prior appropriation doctrine (entry restriction treatment) was also higher than the Nash feedback prediction. However, this number was close to the Nash feedback prediction under the correlative rights doctrine (stock quota treatment). Analysing efficiency, the authors also found that restricting entry and applying a stock quota improve performance.

1.2.2 The Role of Information

From what we saw above, the use of common pool resources generates some externalities among the users, leading to a race for the resource which is intensified by myopic behavior. However, [Gardner et al. \(1997\)](#) have shown that imposing a quota could mitigate this situation. This time, [Hey et al. \(2009\)](#) tried to know how would resource users behave in the absence of strategic interaction, when they are given different types of information.

In a single agent finite horizon model, they investigate the role that information about the stock and the growth function of a renewable resource can have on agents' harvesting decisions. Assimilating the resource to a fishery, the authors assume zero costs with prices normalized to one. Each fisherman has to maximize his extraction x_t , which is the difference between the stock before and the stock after extraction, under the dynamics of the stock, which evolves according to a logistic growth function :

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- ⁴ • The token cost for an individual is equal to the average cost of the token for this period \times the total number of tokens ordered for this period.
 - The new cost of base token is equal to : $(1 + \text{the total number of tokens ordered in previous periods}) \times \text{the amount of the increase}$.

$$\max \sum_{t=0}^T \rho^t x_t = \max \sum_{t=0}^T x_t, \quad (1.6)$$

$$\text{s.t } S_{t+1} = S_t - x_{it} + RS_t \left[1 - \frac{S_t}{K} \right], \text{ with } S_0 = K.$$

The discount factor is denoted by ρ , which is equal to unity. R is the intrinsic growth factor and K is the carrying capacity. Thus, the optimal solution is the most rapid approach to the Maximum Sustainable Yield (MSY), with an extinction at the last period.⁵

A total number of 121 subjects participated in two experimental sessions of a non contextualized experiment.⁶ These sessions involved four treatments and lasted about an hour. A first treatment with a stock information and an accurate signal about the number of existing resource units. A second treatment with information on the growth function and a noisy signal on the number of existing resource units. In other words, the noisy signal means that the stock was multiplied by a random number pulled from a uniform distribution. The third treatment is a full information treatment in which information on both the stock and the growth function were given to subjects. They received in addition an accurate signal on the existing number of resource units. The last treatment was a zero information treatment, with a noisy signal on the existing number of resource units. Unlike other subjects, subjects in the second and the third treatments were given an on-screen facility, allowing them to anticipate the consequences of their extraction choices before confirming their decisions.

In each treatment, the authors tried to determine the optimal theoretical strategy. In all the treatments but the full information treatment, they were not able to derive optimal strategies. That's why they numerically defined for these treatments, reasonable theoretical strategies which are "prudent"; i.e. extraction strategies leading to a pre-mature extinction of the resource are excluded.⁷ In each treatment, subjects had

⁵the Maximum Sustainable Yield (MSY), is the largest extraction an agent can achieve from a given stock.

⁶The non contextualization was to avoid an emotional bias related to the pity subjects will feel when confronted with the slaughter of fish.

⁷To provide these prudent benchmarks, the authors used for the first treatment, a "hill-climbing algorithm" to identify the stock level inducing the maximum growth. For the second treatment, they applied a "Monte-Carlo simulation" on extraction excluding a pre-mature extinction of the resource. In the zero information treatment, they applied a combination of the two previous methods.

to decide one hundred times the number of units they wanted to transfer from a fictitious resource to their savings account, so that a logistic growth function was applied to the remaining units. The dynamics of the resource was then determined by the remaining stock and the initial stock was equal to the carrying capacity K . Subjects had to exhaust the resource at the last period, but in case of pre-mature exhaustion the experiment ends instantaneously. However in each treatment, subjects were warned when they choose an extraction of zero units or when the number of units extracted exceeds the stock signal.

From the experiment the authors found by applying a binomial test on the distribution of over-harvesters and under-harvesters, that a higher percentage of subjects under-harvest the resource when they do not receive any information.⁸ In terms of behavioral patterns, the authors found that subjects tried to control the dynamic system by holding constant the stock or their extraction level when they received accurate information on stocks. Furthermore, subjects who received a noisy stock information had a misperception of feedback, leading them to adopt a pulse extraction by alternating periods of extraction and periods of non-extraction. This allowed the resource to build up. Finally with no information, subjects tend to under-exploit the resource because they misperceive the non-linearity of the growth function. In other words, as subjects have in mind a linear relationship between the stock and the growth, they believe it would make sense to let the stock grow and harvest at the end the profit maximizing the stock size (as they think that growth increases with the stock size). For a deeper understanding of this misperception, see [Sterman \(1994\)](#) and [Moxnes \(1998\)](#).

1.2.3 Taking Into Account Spatial Characteristics

Problems of groundwater allocation have mostly been studied by using relatively simple models, sometimes to make it easy to understand and sometimes because of the difficulties to obtain actual data on pumping decisions. These models may mischaracterize the nature of the predicted resource use by ignoring the possibility for users behaviors to diverge from social optimum and myopic predictions. However, there is another part of the literature that in order to overcome the shortcomings of the traditional model,

⁸In case of only two categories (here, over-harvesters and under-harvesters), the binomial test allows the comparison between the observed distribution and the theoretical distribution.

takes into account the spatial effects of groundwater pumping (Gisser & Sanchez, 1980; Feinerman & Knapp, 1983; Rubio & Casino, 2003). Moreover, even if these studies take into account the spatial characteristics of groundwater, they find a rather paradoxical result known as the Gisser-Sanchez's effect (GSE). The GSE, discovered by Gisser & Sanchez (1980), suggests that the social benefits of optimal groundwater management are insignificant, because as the storage capacity of the groundwater increases, the difference between optimal management and private exploitation becomes negligible. This is even more when we consider that the optimal management is not costless.

Suter et al. (2012) analyze the impact of hydrogeologic characteristics of the aquifer on user's behavior and pumping rates by using an infinite time horizon model. They defined and compared two theoretical models that are a traditional bathtub model and a spatially explicit model, in which the spatial characteristics of the aquifer are taken into account. n users share a common groundwater and must choose individually at each period, a pumping rate that maximizes their profit, which is the difference between benefit and costs, taking into account the dynamics of the depth to water d_t .

In the bathtub model, the authors assumed that pumping made by a user increases equally in the next period the depth to water for all the users, while in the spatially explicit model it is the specific hydrogeologic characteristics of the aquifer (transmissivity, storativity, the distance between wells, and time) that determine how the depth to water is influenced by pumping in future periods.⁹ In each model they defined three benchmarks that are the social optimum, the Nash feedback and the myopic solution. The corresponding social optimum problem for the bathtub model is given by equation (1.7) and by equation (1.8) for the spatially explicit model :

$$\max \sum_{i=1}^n \left(\sum_{t=0}^{\infty} \rho^t \left(\underbrace{ax_{it} - \frac{b}{2}x_{it}^2}_{Benefit} - \underbrace{c_0 d_t x_{it}}_{Costs} \right) \right), \quad (1.7)$$

⁹The main difference between the spatially explicit model and the bathtub model is that in the spatially explicit model, the depth to water variable is specific to the location and depends on both the distance of the sequence of pumping occurred in all previous periods. Another difference between the two models lies in the memory of the system, meaning that the impact on well j of pumping in well i in period t is very small in period $t + 1$, but larger in later periods.

$$\begin{aligned}
& \text{s.t } d_{t+1} = d_t + \frac{\sum_{i=1}^n x_{it} - R}{AS}. \\
& \max \sum_{i=1}^n \left(\sum_{t=0}^{\infty} \rho^t \left(\underbrace{ax_{it} - \frac{b}{2}x_{it}^2}_{\text{Benefit}} - \underbrace{c_0 d_t x_{it}}_{\text{Costs}} \right) \right), \quad (1.8) \\
& \text{s.t } d_{it+1} = \sum_{k=1}^t \sum_{j=1}^n \frac{x_{ik} - x_{jk-1}}{4\pi T_r} \times w(t - k + 1, v(i, j)) - \frac{(t+1)R}{AS}.
\end{aligned}$$

R is the recharge rate and AS denotes the area time the storativity of the aquifer, ρ is the discount factor, b is the slope of the demande curve, a is the intercept of the demande curve, x is the quantity of groundwater pumped, c_0 is a cost parameter and r is the discount rate. $v(i, j)$ is the radial distance between well i and well j , T_r is the transmissivity and $w(t, v)$ is the well function. Solving the problem by means of the Hamiltonian and using the approximation of [Feinerman & Knapp \(1983\)](#) the authors are able to determine the optimal and the Nash feedback quantity of pumping in both the bathtub and the spatially explicit model.¹⁰ They found similar myopic pumping levels for the spatially explicit model and the bathtub model. The authors also found that both in the bathtub and the spatially explicit model, a higher storativity value leads to the reduction of the overall effect of pumping on the future depth to water.¹¹ In addition, the ratio of private to external costs increases with higher storativity values when transmissivity is low, and vice-versa.

A total number of 96 subjects participated in eight experimental sessions involving four treatments. The first treatment denoted Bathtub, illustrates a common bathub model. The second treatment denoted Spatial 1, illustrates a spatially explicit model with a low storativity. The third treatment denoted Spatial 2, illustrates a spatially explicit model with a high storativity. The last treatment denoted Individual Bathtub, illustrates an optimal control treatment in which a single user exploits the groundwater and where future costs of pumping are entirely private. There is no interaction between

¹⁰This approximation assumes that the costate variable λ is stationary, implying that future pumping is equal to current pumping. Thus, with $\lambda_t = \lambda_{t+1} = \lambda$, the first order condition gives $\lambda = nc_0x_t/(\rho - 1)$. Substituting it and solving for x_t gives the optimal quantity of pumping.

¹¹The storativity estimates the relation between pumping and its effect on the future depth to water, while transmissivity estimates the distance between wells. A low transmissivity value indicates that wells are more evenly spaced. When the transmissivity tends to infinity, the spatially explicit model converges to the bathtub model.

subjects in this treatment. The experiment was contextualized to an aquifer commonly shared by groups of six subjects. The aquifer was divided into six plots in which each subject has to operate one of the wells located in the middle of a plot, in order to make an individual and anonymous pumping decision in each period. The authors have intentionally made instructions vague to reflect the real-life groundwater dynamics which is not exactly known. Thus, they chose a discount factor and a transmissivity value that represent real-world cases.

Before the beginning of each session, subjects had to answer several comprehension questions. An experimental session was divided into a training phase followed by four experiment phases. After each phase, the groups of six subjects were randomly matched. The infinite horizon was simulated by applying a stochastic termination rule. The discount factor is then interpreted as a continuation probability (85%), allowing the authors to deduce the termination probability which is equal to 15%. This allowed the authors to find an expectation of 6.67 periods per experiment phase. Thus, the four experiment phases were respectively of six, ten, five and seven periods. The authors derived three predictions including subpredictions for each. The first prediction suggests that "differences in the hydrogeologic model across treatments lead to differences in pumping" levels. In other words, depending on the treatment, pumping levels are higher or lower.¹² The second prediction suggests that "differences in the hydrogeologic model across treatments lead to differences in the pumping strategy types used by participants". This prediction explains that the frequency with which subjects adopt a behavior (myopic, Nash feedback or optimal) depends on the treatment. The final prediction suggests that "differences in the hydrogeologic model across treatments lead to differences in the observed social efficiency". In other words, depending on the treatment, observed social efficiency is higher or lower.

The authors found support for all their predictions. Regressing pumping levels on myopic pumping in each treatment to analyse myopic behavior, they found on average more myopic in the Bathtub than in the Individual Bathtub treatment (single agent). Even if subjects pump less in the Individual Bathtub treatment on average, they pump more than the level that maximizes the discounted net benefits. The authors also found

¹²Here, authors made numerical predictions by regressing in each period the predicted pumping rates on treatment-specific indicator variables and also on the treatment indicators interacted with the period number.

on average that subjects' behavior in the two Spatial treatments are between optimal and Nash feedback predictions. Furthermore, analysing individual myopic behavior in each treatment, they found the fewest number of myopic subjects in the Individual Bathtub treatment. They also found few myopic subjects in the two Spatial treatments, with a high number of myopic subjects in the Bathtub treatment.¹³

With a social efficiency of 80%, and the resulting efficiency if all the subjects were myopic lying in the range of [50% – 80%], results suggest that efficiency gains from the management of pumping levels are less sufficient to offset the cost of implementing such a policy. This seems to be in line with the Gisser-Sanchez's effect (GSE). While the authors did not find robust results on learning effects (resulting from the stochastic termination rule), they observed a reduction of pumping levels in the third experiment phase compared to the previous two phases.¹⁴

1.3 Continuous Time Challenges

Another possible way to analyze subjects decisions in the use of common pool resources is to use continuous time, which emphasizes the non stop evolution of CPRs. Although there is a growing literature on the implementation of continuous time models in experiments, it is still quite recent. Few examples of continuous time situations in real life, with quick interactions can be electricity markets with high-frequency bidding, financial markets with high-frequency computerized trading (Bigoni et al., 2015).

We can find in the literature two ways of implementing continuous time in lab experiments : by using extensive form games and by using differential games. The first way is in line with Simon & Stinchcombe (1989) who suggested a general model of games played in continuous time. They considered discrete grids in the time interval $[0, 1)$ for games with finite numbers of players and actions. Thus, they obtained under some technical conditions (for example, keeping uniformly bounded for each player, the number of strategy switches) in the limit as the grid interval approaches zero, well-

¹³While a higher number of myopic subjects was found in the Bathtub treatment, the authors found on average that subjects in that treatment adopt a Nash feedback behavior. This difference in results can be explained by the fact that the fewest subjects exploiting less than the myopic prediction, allow the groundwater to grow, leading on average to a Nash feedback behavior.

¹⁴All along their analyses, the authors have clustered standard errors either at participant level or at group level.

defined games in continuous time. Therefore, articles using this method are qualified as quasi-continuous time articles ([Friedman & Oprea, 2012](#); [Oprea et al., 2014](#); [Bigoni et al., 2015](#); [Leng et al., 2018](#)). The second way is in line with [Tasneem et al. \(2017, 2019\)](#) who used dynamic models.

1.3.1 "Quasi-continuous" Time Experiments

In this subsection, we provide a short review of quasi-continuous time articles. For instance, [Friedman & Oprea \(2012\)](#) study a prisoner's dilemma in a finite horizon to measure the tension between efficient cooperation and inefficient defection. In addition to their continuous time treatment, they implemented a one-shot treatment and a discrete time treatment. They found, using a pairwise Mann-Whitney test on subject's median cooperation rates, that continuous time gives the highest level of cooperation. Cooperation was never appears in the one-shot treatment and was heterogeneous in the discrete time treatment. [Bigoni et al. \(2015\)](#) also study cooperation in a repeated prisoner's dilemma, with different termination rules (deterministic and stochastic time horizons) and different durations (long and short). They ran two deterministic treatments (long and short durations), two stochastic treatments (long and short durations) and one deterministic treatment with variable durations across supergames. By analysing median and mean cooperation rates, they found significantly high cooperation rates with short duration deterministic time horizon.¹⁵ However, they found similar cooperation rates with long duration, both for deterministic and stochastic time horizons.

[Oprea et al. \(2014\)](#), in a finite horizon framework, crossed time protocol (continuous vs. discrete time) and communication protocol (no communication vs. unrestricted communication) to get four treatments through which they study subject's contributions in a public good game. By analysing median and mean cooperation, they found higher contributions in continuous than in discrete time. However, the results suggested that without communication continuous time does not perform better than discrete time. Similar results have been found by [Leng et al. \(2018\)](#) who studied a minimum effort game by crossing time protocol (continuous vs. discrete time) and information

¹⁵In long duration treatments, subjects played supergames lasting 60 seconds each; whereas in short duration treatments, the supergame lasted 20 seconds.

feedback (group minimum effort level vs. each member of the group effort level) to measure cooperation in a minimum effort game, also called a weak-link game.¹⁶ Analysing the minimum and the average effort levels to measure cooperation, the authors used a two-sided Mann Whitney rank sum test and found contrary to their expectations that when the number of subjects become larger, continuous time without communication or an additional feedback information have no significant impact, because subjects hardly coordinate to increase the group minimum effort within a period. They also found no significant difference in the minimum effort level between continuous time and discrete time.

1.3.2 Real Time : A Feature of Continuous Time

In continuous time, interactions among agents are made in real time and imply an uninterrupted update of information in the lab. Thus, some recent experimental studies have tried to introduce more realism (mimic field settings) by taking into account spatial and temporal dimensions in the study of renewable social ecological systems. For example, [Janssen et al. \(2010\)](#) study the impact of communication and costly punishment in the governance of a renewable resource assimilate to a 29-by-29 grid of cells from which subjects have to harvest tokens. The resource dynamics is represented by the renewal rate, which depends on the density. They mainly found that communication allows the regeneration of the resource by reducing its exploitation. However, without communication, costly punishment does not allow the increase of the group payoff.¹⁷ Moreover, [Cerutti \(2017\)](#) revisited the experiment proposed by [Janssen et al. \(2010\)](#) to study the effects on subjects' behavior, of introducing a spatial representation of the resource. The author compared the baseline version of the experiment to a blind version. In the baseline version, the resource is assimilated to a grid of 18×18 cells from which subjects have to harvest tokens. Contrary to [Janssen et al. \(2010\)](#) there was neither communication nor costly punishment, but a bar representing the current amount of tokens. In the blind version, only the bar representing the current amount

¹⁶The minimum effort game is a coordination game having multiple Pareto-ranked Nash equilibria and where players coordinate on the less efficient equilibrium by choosing low effort, because of the high strategic uncertainty associated with the choice of a high effort which leads to the more efficient equilibrium. For more detailed information about the minimum effort game, see [Cartwright \(2018\)](#).

¹⁷The social optimum equilibrium is consistent with maintaining for most of the decision process a 50% density of token and harvesting at the end of the decision process the remaining tokens.

of tokens could be seen by subjects. The resource dynamics, represented by the renewal rate, depends only on the total amount of tokens in the grid. The main result was that, contrary to the baseline version, the blind version gives results close to the social optimum. The authors derive the social optimum equilibrium by simulating the behavior of ten thousand groups behaving cooperatively. Their finding was that in the social optimum, subjects allowed the resource to cover up to 50% before harvesting above this threshold.

1.3.3 Taking Into Account Strategies in CPRs

This subsection reviews continuous time article using differential games. To our knowledge, [Tasneem et al. \(2017\)](#) was the first article that has tried to implement differential games in the lab. The peculiarity of the articles reviewed here and in the following subsection is that the authors analyse agents' behavior according to Markovian strategies (state dependent strategies). [Tasneem et al. \(2017\)](#) investigates the choice of extraction strategies between linear and non linear, resulting from the use of a common renewable resource assimilated to a fishery. Using a linear quadratic infinite horizon model, they consider groups of two identical agents, who individually and simultaneously exploit the fishery. Assuming zero costs, each agent i has to maximize the present value of his discounted payoff, which depends only on his extraction rate $x_i(t)$, under the dynamics of the stock, which evolves according to a logistic growth function $F(S(t))$. The maximization problem is given by equation (1.9) :

$$\begin{aligned} & \max \int_0^{\infty} \exp^{-rt} \left(x_i(t) - \frac{x_i(t)^2}{2} \right) dt, & (1.9) \\ & \text{s.t } \begin{cases} S'(t) = F(S(t)) - x_i(t) - x_j(t), \\ S(0) = S_0, \\ x_i(t) \geq 0, \end{cases} \\ & \text{with } F(S) = \begin{cases} RS & \text{for } S \leq S_{th}, \\ RS_{th} \left(\frac{K - S}{K - S_{th}} \right) & \text{for } S > S_{th}. \end{cases} \end{aligned}$$

where r is the discount rate, R is the replenishing rate, RS_{th} denotes the maximum sustainable yield and K is the carrying capacity. This problem admits a piecewise linear Markov-perfect equilibrium and also a continuum of nonlinear local Markov-perfect equilibria which differs in terms of the aggressiveness of the resource exploitation.

A total number of 134 subjects participated in nineteen experimental sessions of a contextualized experiment. Each session lasted about two hours, with groups of two subjects randomly formed at the beginning of each session and remaining the same during the session. To make sure that subjects well understand the Markovian environment, they had to succeeded to a test before the beginning of a session, in which they learned how to manage their extraction rate. The test consisted in choosing an extraction rate to increase and keep the stock constant at this new level, then in decreasing and holding the stock constant to another level. This was called "constant rate".¹⁸ Subjects were given fifteen tries. They were dismissed in case of failure and received ten dollars show up fees. A total of 25 subjects failed this test.

In each experimental session, each subject, assimilated to a fisherman, had to decide in real time and simultaneously with the other member of his group, the speed at which he wants to harvest a fishery. The authors chose the replenishing rate R , the discount rate r and the initial stock, so that the time required to reach the steady state does not exceed four minutes. An experimental session consisted in four training phases followed by six phases for pay. A phase stops after four minutes, or with a stock level of zero or after 30 seconds of inactivity because a steady state is supposed to be reached. Continuous time has been implemented by updating all information every second and allowing subjects to take their decision at any time by using a graduated slider from zero to an upper bound, according to the parameterization chosen. Moreover, the infinite horizon has been simulated by discounting payoffs over a fixed period and computing a continuation payoff as if the phase went forever, assuming that the last extraction rate of the group remains constant. This computation also takes into account the probability the stock level could drop to zero. After making a decision, subjects could see the dynamics of the stock in real time, as well as other information (their extraction rate, the group extraction rate, the time elapsed). At each phase, the

¹⁸Knowing the replenishment rate and using the constant rate, subjects learned how to keep the stock at a constant level.

authors set both the starting stock level and the initial extraction rate. They varied the design according to two dimensions. First, by varying the initial extraction, with constant initial stock. This allowed them to analyse whether initial conditions affect subjects' extraction behavior. Second, by keeping constant the strategies resulting from initial extractions, they ran two treatments with a low initial stock and a high initial stock.

Analysing their experimental data, the authors found that when focusing on linear strategies, subjects' extraction rates reach the best possible steady state. However, taking into account non linear strategies allow them to find other possible steady states including those leading to the exhaustion of the stock. To analyse if a pair reached a steady state, they used a steady state detection algorithm called MSER-5.¹⁹ By investigating the effects of initial conditions, they found that different initial extraction rates did not affect subjects' behavior. Furthermore, grouping in each treatment all the phases for pay and applying a two-sample Kolmogorov-Smirnov test, the authors found that the steady state total extraction distribution in the second treatment (high initial stock) contains larger values than that of the first treatment (low initial stock).

Finally, to investigate whether subjects' decision-making are susceptible to be affected by other variables, the authors ran for each phase for pay a subject-by-subject individual Tobit regression on the general model shown by equation (1.10) :

$$x_t = \beta_0 + \beta_1 S_t + \beta_2 (S_t)^2 + \beta_3 x_{t-1} + \beta_4 x_{other, t-1} + \beta_5 t + e_t. \quad (1.10)$$

where x_t denotes the current extraction rate of a subject, x_{t-1} is his lagged extraction rate, the time in seconds for a decision is denoted by t , $x_{other, t-1}$ is the lagged extraction rate of the other subject of the group, e_t denotes the error term, and S_t is the current stock level.²⁰ They found that half of the strategies condition on time and that about half of the extraction strategies condition on the extraction rate of the other player of the group. Their results also shown that a high percentage of the models selected were non-linear strategies, and that a less but not negligible percentage were "rule-of-thumb" strategies, which do not depend on the stock level. The rule-of-thumb strategy

¹⁹For more details about the the MSER-5 (Mean Squared Error Reduction ou Marginal Standard Error Rule) algorithm, see their "Appendix C : Steady state analysis".

²⁰Authors used the "general-to-specific" modeling approach, consisting in detecting the best model. See their "Appendix D : General-to-specific algorithm" for more details.

is close to the social optimum equilibrium in the sense that it consists of choosing a zero or a very low extraction rate, in order to quickly increase the stock to the level allowing the highest extraction rate.

1.3.4 Sustainability in CPRs

Following [Tasneem et al. \(2017\)](#), [Tasneem et al. \(2019\)](#) investigate a private management of a renewable resource. More precisely, they want to know to what extent a single agent can manage a private fishery in a sustainable and efficient way. Assuming zero costs, each agent has to maximize the discounted sum of his instantaneous payoffs, which depends on his extraction rate $x(t)$, taking into account the dynamics of the stock $S(t)$. Using a linear quadratic infinite horizon model, the maximization problem is given by (1.11) :

$$\begin{aligned} \max_{x(t)} \int_0^{\infty} \exp^{-rt} \left(x(t) - \frac{x(t)^2}{2} \right) dt, \quad (1.11) \\ \text{s.t.} \begin{cases} \dot{S}(t) = RS(t) - x(t), \\ S(0) = S_0, \\ x(t) \geq 0. \end{cases} \end{aligned}$$

where r is the discount rate and R is the replenishing rate. The optimal solution is a piecewise extraction rate function composed of three regimes. The first regime consists in a null extraction regime allowing the stock to grow. In the second regime, the extraction rate is a linear function of the stock and the last regime is a steady state regime with the maximum extraction rate.

A total number of 31 subjects participated in three experimental sessions of a contextualized experiment. Each session lasted about two hours, where each subject had to decide in real time the speed at which he wants to harvest exclusively a fishery. The authors chose the discount rate r , the replenishing rate R and the initial stock, so that the time required to reach the steady state does not exceed two minutes. An experimental session consisted in ten training phases with the same initial stock, followed

by twenty phases for pay with different randomly increasing initial stocks within the range of the optimal solution. During a phase, the computer checked whether the stock would drop to zero or not and computed the discounted sum of future payoffs till infinity. In case of 30 seconds of inactivity, the computer assumes a steady state is reached and the phase stops. The phase also stops after two minutes, or with a lower stock level of zero or when the stock reaches its maximum level. The infinite horizon and continuous time were also implemented as in [Tasneem et al. \(2017\)](#), with the difference that all the information were updated every half second, which is faster enough to simulate continuous time. After making a decision, subjects could see the dynamics of the stock in real time, as well as other information (their extraction rate, the constant rate, their instantaneous and cumulative payoffs).²¹ The payoff in the experiment depends on both the quantity of fish extracted by a subject and the time of the extraction.

Adopting the same procedure as [Tasneem et al. \(2017\)](#) to analyse their experimental data, the authors, by using the steady state detection algorithm called MSER-5, checked whether an extraction behavior results in a steady state.²² To analyse the relationship between stock and extraction, the authors compared subjects' extraction behaviors to the optimal extraction policy. They did it because their design admits a cross-sectional analysis of initial extraction rates, as they chose their parameters in the range of the optimal extraction policy. Thus, in their phases for pay, and for nine different half seconds in time, the authors regressed subjects' extraction rates on the stock level according to equation (1.12).

$$x_{ij} = \alpha_0 + \alpha_1 S_{ij} + e_{ij}. \quad (1.12)$$

where i denotes the order of a phase for pay and j denotes the order of a subject (one up to thirty one). Comparing the regression to the optimal policy, they found that even below a certain stock level, subjects still tend to extract the resource when they should not. Investigating whether there was an improvement in subjects extraction behavior,

²¹The constant rate is the extraction rate allowing the stock level to be constant. The instantaneous payoff is a quadratic function of the extraction rate, where the maximum is reached for an extraction rate of one. The cumulative payoff is the sum of the discounted instantaneous payoffs, obtained by multiplying instantaneous payoffs by \exp^{-rt} .

²²To compute the MSER-5, the authors do not take into consideration situations involving a minimum stock of zero or a maximum stock of twenty five. For more details about this algorithm, refer to their Appendix 5 : Identifying Steady States in the Choice Data.

the authors found that the tradeoff between instantaneous payoff and the future sum of payoffs created by the discount factor, leads to initial overextraction of the resource which persists over sessions.²³ They also checked for the model that best describes the behavior of subjects in the different phases for pay, by estimating a more general model (1.13) with three subspecifications.²⁴

$$x_t = \beta_0 + \beta_1 S_t + \beta_2 (S_t^2) + \beta_3 x_{t-1} + \beta_4 t + e_t. \quad (1.13)$$

The first subspecification includes the current stock (S_t) and the lagged extraction rate (x_{t-1}). The second subspecification includes the time (t) in half seconds in the first subspecification, while the last subspecification includes the square root of the current stock (S_t^2) in the first subspecification. The results suggested that linear model better explains extraction rate than non linear model, and that the second subspecification was the most selected by subjects.

1.4 Mixed Time CPRs Models

As it is obvious from sections 2 and 3, the literature emphasizes the management of common pool resources either in discrete time or in continuous time. However, a small but significant part of the literature has studied CPRs by combining continuous and discrete time for various reasons (Noussair et al., 2015).²⁵ Most of the time in these articles, continuous time is used for the theoretical model, while discrete time is used for the experiment. One of these reasons could be the fact that the implementation of continuous time in the lab is relatively recent and a bit difficult, while discrete time is

²³To find this result, the authors regressed the difference between the initial extraction rate and the optimal extraction rate, on the order of the phases for pay, by controlling for the stock level and clustering standard errors by subjects. Given the panel structure of the data, there is a correlation between some observations, hence the necessity to adjust standard errors before any analysis in order to get a good specification.

²⁴In each phase for pay, the authors applied a multi-path search general to specific model selection approach to estimate the best-fitting extraction policy. See Their Appendix C : General-to-Specific Algorithm, for more details about this approach. Then, they estimated a two limit Tobit panel model with an upper bound of two and a lower bound of zero, where each subject is a panel unit, to find the three subspecifications.

²⁵For those interested, you can also refer to the paper of Muller & Whillans (2008), dealing with static vs. dynamic stock externality. We did not mention this study, as the methods used seem ambiguous to us.

quite simple and more rational. This property of discrete time makes it easy to implement in the lab. Another reason could be that using a very small discretization in time, continuous time can be approximated by discrete time, which avoids the difficulty of implementing continuous time in the lab.

1.4.1 An Example of Field Experiment

Laboratory experiments (in vitro), despite their relative simplicity and the reliability of the data obtained thanks to the control exercised by the experimenter, have been widely criticized for their lack of external validity (Loewenstein, 1999). Field experiments (in vivo) could be an alternative in providing external validity and can be divided into three main groups. Artefactual field experiments, which are identical to laboratory experiments, but are carried out with subjects representative of the active population. Framed field experiments, which are artefactual field experiments with realistic environment and information. Natural field experiments, also identical to framed field experiments except that the studied environment is the one in which subjects perform their tasks and they ignore that they are participating in an experiment. For precise details about experimental economics, see Serra (2012).

Framed field experiments have the advantage of testing the influence of context elements on agents' behavior. Based on this framework, Noussair et al. (2015) try to investigate cooperation among the users of a common renewable resource. Departing from the canonical model of Schaefer (1957), the authors defined a continuous time finite horizon model in which n agents share a fishery. Assuming zero costs, each agent i has to maximize his catch $x_i(t)$ under the dynamics of the stock $S(t)$, which is renewed according to a logistic growth function $F(S(t))$. Then, the authors derived two benchmarks that are the Nash and the social optimum outcomes. The corresponding social optimum problem is given by equation (1.14) :

$$\begin{aligned} \max_{x_i(t)} \int_{t=0}^T \sum_{i=1}^n \exp^{-rt} \bar{p} \underbrace{\alpha E_i(t) S(t)}_{x_i(t)} dt, & \quad (1.14) \\ \text{s.t } \dot{S}(t) = \overbrace{RS(t)}^{F(S(t))} \left(1 - \frac{S(t)}{K}\right) - \sum_{i=1}^n \underbrace{\alpha E_i(t) S(t)}_{x_i(t)}, & \text{ with } S_0 = K. \end{aligned}$$

where $E_i(t)$ denotes the harvesting effort and \bar{E} is the maximum amount of effort an agent can provide. R is the intrinsic growth, K is the carrying capacity and \bar{p} is the marginal value of an extracted resource unit.

Eight fixed groups of four subjects participated in two experimental sessions of a recreational fishing. To make sure that all the subjects well understand the game, they had to answer test questions before the start of a session. Each session consisted in four periods of one hour each and each member of a same group wore a colored ribbon to indicate to which group he belongs. The authors implemented their experiment by making a discrete approximation of the dynamics of the stock as shown by equation (1.15) :

$$S_{t+1} = S_t - X_t + F(S_t - X_t). \quad (1.15)$$

where $X_t = \sum_{i=1}^n x_{it}$ denotes the total catch. In the experiment, the stock size is also called the "allowable catch remaining" (ACR) at the beginning of period t . At the beginning of the first period, experimenters released into a pond 38 rainbow trout including a supplementary six trout, so that each subject can catch 2 trout. Then, as long as the total catch did not exceed the available amount for the group, each participant could harvest as many fish as he liked. Regeneration was simulated by adding at the end of each period and for groups that have not exhausted their stock, an amount of fish equals to the amount harvested in the previous period. This aimed to have the same amount of fish at the beginning of each period. At the end of each period, subjects were given all information to begin a new period, but in case of resource exhaustion before the last period, they had to leave the pond. To avoid the problem of negative marginal utility, subjects were allowed to take home all the fish they caught and received in addition five euros for each fish caught. The authors derived two main predictions to distinguish cooperation from non-cooperation. The first prediction is that the social optimum equilibrium is reached when the logistic growth function equals the discount rate. Given their parameterization, subjects should quickly harvest the stock until it remain four fish, stop catching for the stock to regenerate up to eight fish, and quickly catch again four fish. Thus, the fishing effort will depend on the remaining group stock under cooperation. The second prediction is that, contrary to the first prediction, subjects' will not modify their harvest over the four periods under the Nash equilibrium, which involves the depletion of the stock within the first period.

Although they found a lack of cooperation, consistent with the standard economic theory, the authors emphasize the importance of contextualization when testing the canonical renewable resource model. A Wilcoxon test on the distribution of the average group effort between the first and the fourth period, allowed them to find support to their second prediction. And applying a fixed effects regression confirmed that harvesting effort does not differ statistically regardless of the stock size.²⁶

1.5 Empirical Methods in the Reviewed Studies

A crucial step in the study of the behavior of CPR users is data analysis, as it is based on these results that policy implications can emerge to ensure the effective management of these resources. Experimental data collected in the studies we reviewed are generally panel data. That is, they contain several observations for the same individual over a period of time, and therefore have two dimensions : an individual dimension (cross-sectional) and a temporal dimension (time series). However, one of the key elements for the analysis of experimental data lies in the choice between parametric and non-parametric methods. Parametric methods are based on distributional assumptions (most commonly, the normality of the outcome variable) which holds if the analyzed variables are cardinal. Nevertheless, experimental data do not always satisfy normality condition, so that non-parametric methods seem to provide a compelling alternative to parametric methods.²⁷ Most of the articles studied in this survey adopted non-parametric methods, some used parametric methods and others made a combination of both. In this section, we will review the main methods frequently used by the authors to analyze their data.

Given their simplicity, statistical indicators are frequently used to get an initial overview of the data, before moving to complex analyses. Positional measures like the mean or the median are sometimes compared. For instance, [Oprea et al. \(2014\)](#) compared mean contribution levels to median contribution levels in their public good game experiment. This was also the case for [Bigoni et al. \(2015\)](#), for the determination of cooperation levels in their repeated prisoner's dilemma game. The research question

²⁶While theoretical predictions and the experimental earnings are mainly based on the number of fish caught, the harvesting effort is measured through the amount of times a fisherman casts his rod.

²⁷See [Moffatt \(2015\)](#) for a clear overview of econometric methods in experimental economics.

most frequently addressed in this review was the determination of the theoretical behavior to which experimental subjects are closest. To do this, the simplest parametric method was to compute the Mean Squared Deviation (MSD). It is a dispersion statistical indicator, used to accurately estimate the difference between the optimal and the observed behavior (Herr et al., 1997).²⁸ However, using only this statistical indicator could give misleading results, as it allows for a global classification of behaviors, without taking into account the fact that subjects may deviate from the theoretical solution. It is therefore necessary to combine it with regression methods for an accurate classification. Another statistical indicator frequently used, was to compute the ratio of the total observed payoffs to the optimal payoff (Herr et al., 1997; Suter et al., 2012; Tasneem et al., 2017, 2019). This indicator is called efficiency. Other definitions of efficiency are provided by Gardner et al. (1997) and Hey et al. (2009). While Gardner et al. (1997) defined it as the coefficient of resource utilization, for Hey et al. (2009), it is the ratio of observed extraction to optimal extraction. Unlike the other authors, Hey et al. (2009) used efficiency for the computation of payoffs, which they defined as the product between efficiency and a premium specific to each of their four treatments.

The most commonly non-parametric test used by authors is the Mann Whitney test.²⁹ It is the non-parametric alternative to the Student t-test, used to compare two paired groups, by computing and analyzing the difference between each set of pairs (Herr et al., 1997; Oprea et al., 2014; Noussair et al., 2015; Leng et al., 2018). The two-sample Kolmogorov-Smirnov test is similar to this test, as it allows to investigate whether two samples come from the same distribution (Tasneem et al., 2017). However, in case of more than two independent samples, the Kruskal-Wallis test is used as an extension of the Wilcoxon Rank-Sum test, but is replaced by the Jonckheere-Terpstra test of ordered alternatives when there is an expected order to the group medians (Hey et al., 2009).

²⁸Let n be the size of the sample, x_{it}^{obs} the observed behavior and x_{it}^{pred} the predicted or the theoretical behavior. The Mean Squared Deviation (MSD) is obtained through this formula :

$$MSD = \frac{\sum_i \sum_t (x_{it}^{obs} - x_{it}^{pred})^2}{n}.$$

²⁹The Mann Whitney test is also known under various names such as : the Mann Whitney U test, the two-sided Mann Whitney rank sum test, the pairwise Mann Whitney test, the Mann-Whitney-Wilcoxon test, the Wilcoxon-Mann-Whitney test, the Wilcoxon rank-sum test and the Wilcoxon signed rank test.

The authors also used different estimation methods, among which we can cite the Maximum Likelihood (ML) method. It allows to find the parameter that maximizes the probability of observing the sample actually observed, by assuming a conditional distribution of the explained variable with respect to the explanatory variables (Mason & Phillips, 1997). The Tobit model is intermediate between linear and dichotomous models. It is a censored regression model, describing the relationship between a limited dependent variable (which is continuous but can only be observed over a certain interval) and one or more independent variables.³⁰ When the dependent variable is limited by two bounds, the model used is a two-limit Tobit (Tasneem et al., 2017, 2019). Moreover, we noticed the use of dynamic regression models such as partial adjustment models, by authors like Mason & Phillips (1997) to study the decision-making of experimental subjects. They are used to justify taking into account one or more lags of the dependent variable in a regression function, and its use dates back to Nerlove (1958) for the investigation of the lags in farmers' response to price changes. The drawback of the partial adjustment model is that the Ordinary Least Squares (OLS) estimator, although convergent, is biased. Hence the use of alternative methods such as the Feasible Generalized Least Squares (FGLS), which is an implementable version of the Generalized Least Squares (GLS), used when the covariance of the errors is unknown. Feasible Generalized Least Squares were also used by Suter et al. (2012), but with the Prais-Winsten procedure, to analyse individual myopic behavior in each of their four treatments.

Ultimately, it is not always easy to deduce in advance in a study, the different tests that will be performed, simply based on the research question. In reality, it is the data that dictates which tests must be implemented. However, a common point in the articles that have been reviewed is that they give an important place to the analysis of efficiency. One might therefore think that this indicator serves as a measure to check the internal validity of the results.

³⁰In censored models, the entire sample contains observations of the explanatory variables.

TABLE 1.1 – A summary of articles combining theory with experiment

Paper	Research question	Nature of the resource	Theoretical model	Experiment	Main analyses	Main results
Herr et al. (1997)	Behavior in time dependent vs. time independent cost externalities	Non-renewable groundwater	Discrete time Finite horizon NF ²¹ , myopic, SO	No contextualization Static : token cost reset Dynamic : linear increasing token cost	Mean Squared Deviation (MSD)	More myopic in time dependent externality
Mason & Phillips (1997)	Effect of industry size in static vs. dynamic cost externalities	Renewable fishery	Discrete time Infinite horizon Comparison to NF outcome	No contextualization Random termination Industry size : two three, four & five firms	Maximum likelihood, Feasible Generalized Least Squares	High cooperation : static externality with industry size of four
Gardner et al. (1997)	Property rights & behavior	Non-renewable groundwater	Discrete time Finite horizon NF & SO	No contextualization No restriction, quota & entry restriction	Average token ordered, Efficiency	Efficiency improvement : quota & entry restriction
Hey et al. (2009)	Behavior & information structure	Renewable fishery	Discrete time Finite horizon Sole agent	No contextualization Information structure : full, stock no & growth	Two-tailed Wilcoxon signed ranks test, Efficiency	No information : 90% under harvest the resource
Suter et al. (2012)	Effect of hydrologic properties on behavior	Renewable groundwater	Discrete time Bathub vs. spatial models Infinite horizon NF, myopic & SO	Contextualization Stochastic termination Bathub : sole agent + n-agents	Feasible Generalized Least Squares, Efficiency	Few myopic : spatial & sole agent treatments
Tasneem et al. (2017)	Choice of strategies : linear vs. non linear	Renewable fishery	Continuous time Markovian strategies Infinite horizon	Contextualization Information update every second Continuation payoff	Two-sample Kolmogorov-Smirnov test, Tobit regression, Efficiency	Steady state : 41.5% non linear vs. 19% linear
Tasneem et al. (2019)	Efficient & sustainable management	Renewable fishery	Continuous time Markovian strategies Infinite horizon Sole agent	Contextualization Information update every half second Continuation payoff	Tobit regression, Efficiency	Suboptimal behavior : initial overextraction
Noussair et al. (2015)	Cooperation among subjects	Renewable fishery	Continuous time Finite horizon Nash, SO	Framed field Discrete time	Wilcoxon test, Fixed effects estimation	Lack of cooperation

1.6 Conclusion

In this survey, we attempted to bring an overview of the recent literature using dynamic games to examine the issues of common pool resources throughout experiments. The research questions, although different from one article to another, all refer to almost the same goal, namely the optimal management of CPRs, when considering a dynamic setting. We found that most of the articles were in discrete time and over a finite horizon, due to their relative simplicity of implementation in the lab compared to continuous time. For [Hey et al. \(2009\)](#) for instance, «infinite horizon cannot be implemented in laboratory». Moreover, implementing finite horizon instead of infinite horizon seems logical for them, since «... the earth does not exist indefinitely... ».

Therefore, we paid a particular attention to continuous time and infinite horizon, because their implementation in the lab is in its infancy, as they are very challenging. Indeed, continuous time makes it possible to mimic the non stop evolution of common pool resources, and we distinguished two ways of implementing it in lab experiments : continuous time using dynamic games ([Tasneem et al., 2017, 2019](#)) and quasi-continuous time using extensive form games ([Friedman & Oprea, 2012](#); [Oprea et al., 2014](#); [Bigoni et al., 2015](#); [Leng et al., 2018](#)).³²

From a theoretical point of view, the infinite horizon is simple to implement and allows for predictions over a very large time interval. From an experimental point of view, the infinite horizon ensures the sustainability of the resource, by giving to experimental subjects the ability to see how their decisions affect the resource up to infinity. This could motivate them to adopt less suboptimal behaviors. Moreover, although people don't live forever, they may care about their children by taking care of the resource. We thus found two ways of implementing infinite horizon in the lab : either by imposing a random termination rule ([Mason & Phillips, 1997](#); [Suter et al., 2012](#)), or by discounting payoffs over a fixed period while adding a continuation payoff, which computes the payoff that subjects would have obtained if the experimentation pursue indefinitely with the last conditions remaining constant ([Tasneem et al., 2017, 2019](#)). We suggest the use of the second alternative, because unlike the random termination

³¹NF : Nash Feedback equilibrium. SO : social optimum equilibrium.

³²An innovative aspect in the implementation of (quasi) continuous time in the lab by [Bigoni et al. \(2015\)](#), was the use of touch screens instead of a computer mouse in subjects' decision-making processes. This allowed the switch of decisions, not to be heard by the other members of the group.

rule, it allows to get rid of the use of a continuation probability. It also ensures the same end of the experiment for all the players. However, we found that the ability of continuous time to foster cooperation seems mixed, so that some authors suggest supplementary mechanisms like punishment, communication, regulation, voting processes to improve cooperation ([Gardner et al., 1997](#); [Noussair et al., 2015](#); [Leng et al., 2018](#)). We also found that in addition to commonly used statistical indicators like the mean or the median, efficiency was computed by almost all the reviewed papers. Moreover, the Mann Whitney test was the most frequent non-parametric test used.

What we can learn from this survey is that dynamic environments are very complex to set up in the laboratory, especially continuous time. They are also difficult to understand by the experimental subjects and lead most of the time to more myopic behaviors than static environments ([Herr et al., 1997](#); [Mason & Phillips, 1997](#); [Tasneem et al., 2019](#)) (especially when the number of players increases). However, these models thanks to their state variable, allow fairly well to simulate the evolving nature of common pool resources. Several improvements are therefore necessary and are in progress to set up robust experimental protocols, because it should not be forgotten that the application of dynamic games (and more precisely of continuous time models) to the study of CPRs remains very recent, but is also promising.³³

In the following chapter, we present the results of a continuous time experiment over an infinite horizon, aiming to analyze the extraction behaviors of groundwater users. We distinguish the situation without strategic interaction from the one involving strategic interaction.

³³For a supplementary review on groundwater management, see [Koundouri \(2004\)](#) and [Foley et al. \(2012\)](#) for habitat-fisheries.

Chapitre 2

Individual and Strategic Behaviors in a Dynamic Extraction Problem : Results from a Within-Subject Experiment in Continuous Time

Abstract:

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

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

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

Résumé :

Nous avons mené une expérience en laboratoire pour tester un modèle en temps continu, représentant un problème dynamique d'extraction d'eau souterraine sur un horizon infini. Nous avons ensuite comparé les observations à celles du sentier d'équilibre pour les comportements habituels, dans le cas où le joueur est seul à extraire la ressource (contrôle optimal) et lorsque deux joueurs extraient la même ressource simultanément (jeu différentiel), par le biais d'un within-sujet design. Cela nous a permis d'identifier les profils individuels des joueurs lorsqu'ils exploitent la ressource seuls, puis de caractériser les groupes en fonction de leur composition par rapport à ces comportements individuels. Nos résultats montrent qu'environ un quart des joueurs et des groupes réussissent à jouer (significativement) de manière optimale, et qu'aucun ne se comporte de façon myope. Nous avons aussi identifié d'autres catégories de joueurs et de groupes qui représentent près de 50% des observations et qui nécessitent une attention particulière.

Mots-clés : Jeux Différentiels ; Optimisation Dynamique ; Économie Expérimentale ; Ressources Renouvelables ; Économétrie Appliquée

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

2.1 Introduction

Although [Ostrom \(1990\)](#) shows that in numerous cases, institutional arrangements emerge without government intervention, the "tragedy of the commons", first mentioned by [Hardin in 1968](#), is still relevant today for many common resources, like forests or groundwater, that continue to be overexploited ([Boyd et al., 2018](#); [Frischmann et al., 2019](#)). Consequently, this market failure has attracted the attention of many natural resource economists over the past several decades. Until the 1970s, common-pool resources (CPRs) were conceptualized using static models. However, to keep up with the reality, it is necessary to account for the evolution of these resources over time and to study the behavior of agents in a dynamic context. Dynamic models are generally distinguished according to whether they are based on discrete or continuous time. Models based on the latter, called differential games, are widely used to model economic problems ([Dockner et al., 2000](#)), but very few are tested in the laboratory, especially on the issue of CPR. One of the reasons for this is that these games are quite

complicated to implement with experimental economics methods. To our knowledge, only [Tasneem et al. \(2017\)](#) test a differential game in the lab. They focus on the feedback pattern to determine whether subjects adopt a linear or nonlinear strategy. We contribute to the literature by proposing a differential CPR game model and testing various types of behaviors in a continuous-time experiment.

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

In the optimal control scenario, we find that slightly more than one-quarter of the players behave as predicted by the optimal theoretical pattern. A further 50% percent fall into two distinct categories based on similarities in the observed trajectories of their behavior – we named these player profiles of players respectively the *Convergent* and the *Under-Exploiter*. In the two-players game, we find 20% of groups that exhibit a trajectory significantly close to the socially optimal one (the cooperative solution). Most of these groups include at least one player who had already behaved optimally when extracting the resource alone. We also identify groups of *Convergent* and *Under-*

Exploiter groups in the game and a new category that brings together groups that overexploited the resource (the *Over-Exploiter*). Overall, we show that the behaviors predicted by the theoretical models represent only one-fourth of the experimental observations in the optimal control scenario and in the game. This indicates further investigation is needed, as well as models that better fit actual behaviors. We hope that this article offers a basis for future research on this fruitful topic.

The remainder of the article is organized as follows. In Section 2.2, we review the literature on dynamic CPR, focusing on studies that test their model in the laboratory. In Section 2.3, we describe our theoretical setup. In Section 2.4, we explain the experimental design and how we implement the continuous-time and infinite-horizon models. In Section 2.5, we present the results. We conclude this article in Section 2.6.

2.2 Related Literature

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

In this article we test a CPR game in continuous time with an infinite horizon. The aim of this section is to present a selection of studies that constitute important steps in the implementation in the laboratory of dynamic games in continuous time with an infinite horizon. We start by presenting two papers studying dynamic CPR models in discrete time with a finite horizon (Herr et al., 1997; Hey et al., 2009). Then we present two papers studying dynamic CPR models in discrete time with an infinite horizon

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

(Suter et al., 2012; Vespa, 2020). Finally, we present pioneering papers on the implementation of continuous time in the laboratory (Oprea et al., 2014; Bigoni et al., 2015), before describing the paper closest to ours (Tasneem et al., 2017). For a more detailed review of this literature see Tasneem & Benchekroun (2020) and Djiguemde (2020).

One of the first studies to experiment with a dynamic CPR model in the laboratory is Herr et al. (1997). In their groundwater model with n players, the authors compare static and discrete-time dynamic frameworks with a finite horizon. In the former, extraction by a player in a given period produces a negative externality (through the cost of extraction) for the other players in that period only. In the latter, the externality is present in both the current and following periods. More precisely, the marginal cost from one period to the next is equal to the cost of the last extraction unit ordered, plus a constant. As a result, costs increase monotonically with each repetition. Observations from the experiment show that as compared to the case for the static framework, the tragedy of the commons is exacerbated in the dynamic framework due to the higher number of myopic behaviors.²

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

In a discrete-time dynamic model, but this time over an infinite horizon, Suter et al. (2012) investigate how the introduction of the spatial characteristics of an aquifer influence the pumping decisions of individuals. In their experiment, the authors ran four treatments in a between-subject design. In the first three treatments, players played in

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

groups of six, while in the last treatment, they played without interaction. In one of the treatments, the cost function was the same for all players, while in the other two treatments, the cost function was asymmetric, depending on the location on the 2x3 lattice. The main result of the study is that in the 6-player game with symmetric costs, the proportion of observed behavior that is myopic is higher than in the other cases (optimal control and games with asymmetric costs).

Another paper that uses a discrete-time framework with an infinite horizon is that of [Vespa \(2020\)](#). The author conduct an experimental study of the trade-off between opportunistic behavior and efficiency within a dynamic common-pool game. Using a simplified version of [Levhari & Mirman \(1980\)](#), they study the extent to which subjects in the laboratory can reach efficient outcomes in a dynamic common-pool game. In their experiment, two agents share access to a savings account and must simultaneously and independently decide how much to withdraw in each period. The total amount available in the next period is determined in-between periods by the unused funds, which grow at an exogenous rate of interest. The infinite horizon was implemented as an uncertain horizon. The main finding was that, unlike an infinitely repeated prisoner's dilemma, a dynamic common-pool game involves greater strategic uncertainty. Thus, as the stock of funds increases, achieving cooperation in a dynamic common-pool game becomes more difficult even when the incentives to cooperate are relatively large.

Some authors have shown interest in the implementation of continuous-time models in the laboratory. [Oprea et al. \(2014\)](#) are among the first to perform continuous experiments in the laboratory.³ They compare continuous and discrete-time decisions in a public goods game. In the continuous-time treatment, players could change their decision at any time during the game's 10 minutes duration, with an immediate information available about the updated payoffs and the choices made by the others in the group. In the discrete-time treatment, players played ten one-minute periods during which they could change their decision without information about the choices of the other members of their group. At the end of the one-minute period, the last decision

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

made applied for the period. The authors find that in continuous-time, players contribute slightly more to the public good than they do in discrete-time and that this observation is stronger when communication between players is allowed. For the authors this is because the players' decision adjustments are faster and thus make it possible for cooperation to emerge in the group.

[Bigoni et al. \(2015\)](#) investigate the impact on the extent of cooperation of the time horizon in a prisoner's dilemma game played in continuous time. The authors' experiment is composed of four treatments that differ along two dimensions, the period duration – short (20 seconds) vs. long (60 seconds) – and whether this duration is deterministic or stochastic (with an average realized duration close to that of the deterministic duration). In treatments where the duration is deterministic, players knew they had 20 seconds (or 60) to make decisions. They could change their decision and observe the consequence of that (individual payoff) as often as they wanted during the time of play. The highest level of cooperation is observed when the period duration is long and deterministic. The main explanation is that this combination of conditions favors the prevalence of the cut-off strategy, which involves cooperating until a certain point in time and then, toward the end of the period, defecting forever. Conversely, the short stochastic duration favors the use of the "tit-for-tat" strategy, which, on average, leads to weaker cooperation than the "cut-off" strategy.

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

To our knowledge, only two papers have laboratory-tested dynamic models in

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

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

continuous time over an infinite horizon; these are [Tasneem et al. \(2017\)](#) for differential games and [Tasneem et al. \(2019\)](#) for optimal control. These papers are the closest to what we propose in this study. However, while they focus on Markovian strategies, we are also interested in other types of behaviors such as feedback, myopic, and socially optimal behaviors. Furthermore, we study the manifestation of these behaviors both with and without strategic interactions. [Tasneem et al. \(2017\)](#) consider simultaneous exploitation of a common renewable fishery by two identical players, in a linear-quadratic game, to determine whether subjects in the laboratory will choose between linear or nonlinear strategies. To that end, they build an experiment designed to ensure subjects have a good understanding of the idea of feedback strategies. The results suggest that most players employ nonlinear reasoning. Based on a similar experimental design, [Tasneem et al. \(2019\)](#) explore whether a single player can manage a renewable fishery in a sustainable and efficient manner. Their results suggest suboptimal behavior due to the initial over-extraction of the resource because of the trade-off between instantaneous payoff and the future sum of payoffs.

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

2.3 The Model

We consider a continuous-time linear-quadratic model in which farmers harvest a renewable resource that can be assimilated to groundwater. Water is the only input in the production process, and for purposes of simplification, the aquifer is assumed to have parallel sides and a flat bottom.⁶ At a given time t , extraction done by farmers gives them a revenue $B(w)$ depending only on the extraction rate w . They also incur a cost $C(H, w)$, which is positively dependent on the extraction rate w and negatively dependent on the level of the groundwater H . a, b, c_0 and c_1 are positive parameters. The farmers' instantaneous payoff is given by the difference between revenue and cost, as shown by Equation (2.1):⁷

$$aw - \frac{b}{2}w^2 - \underbrace{\max(0, c_0 - c_1H)}_{C(H,w)} w. \tag{2.1}$$

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

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

⁶ We use a simple "bathtub" model to describe the groundwater extraction.

⁷ We omit the subindex t when it is unnecessary.

feedback behavior, in addition to the behaviors mentioned above.

In an optimal control problem, the social optimum can be defined as a behavior in which a farmer's extraction decision allows them to maximize their discounted net payoffs to maintain the resource at an efficient level. The difference in the game, as compared to the optimal control problem, is that in the game, the resource is maintained at an efficient level by maximizing the joint discounted net payoff to all farmers. In this case, the social optimum is also called the cooperative solution. In both the optimal control problem and the game, the myopic solution is given by a situation in which the farmer is only interested in the maximization of their current payoff. Finally, the feedback equilibrium can be seen as a scenario in which farmers adopt non-cooperative behavior, maximizing their own discounted net payoffs and taking into account the evolution of the groundwater. Additional details for the different behaviors are provided in Appendices [B.1](#) and [B.2](#).

2.4 Experimental Design

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

2.4.1 Continuous Time and Infinite Horizon

The implementation of continuous time in the laboratory is challenging because, by definition, continuous time means that time does not stop. This is incompatible with the time that necessarily elapses between an individual's decision and its visible consequences on the resource and payoff. This time includes the sending of the information to the server, the calculations made by the server, the return of the information after these calculations, and their display on the screen of the player. In practice, the time that elapses between two instants must be short enough that the subject in the experiment feels like it is continuous. We chose to set one second as the time interval

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

between two instants. To our mind, the second, even if not the shortest possible interval we could have implemented in the laboratory (Oprea et al., 2014; Tasneem et al., 2017, 2019), is nevertheless pertinent for our experiment; it is understood by everyone, and enough time elapses between two seconds for computers to perform calculations and exchange information across the network. Moreover, the fact that one instant in the model corresponds to one second in the real time of the experiment facilitates the explanations in the instructions, and without doubt the understanding by the subjects.

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

The standard way to implement the infinite horizon in experimental economics

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

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

is to set a probability that the current period is the final one (e.g., [Suter et al., 2012](#); [Vespa, 2020](#)). On this approach, the subject does not know exactly when the repetitions will end. However, this method has two drawbacks. First, if the probability is defined individually or even per experimental session, it implies different endings to the game, which means a different number of decisions and a different history. This complicates analysis and comparison. Second, it may be interpreted by the subject as an unknown end rather than an infinite horizon.

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

This "scrap value" mechanism is also the one adopted by [Tasneem et al. \(2017, 2019\)](#). However, in their protocol, the game stops if the player holds their decision unchanged for thirty seconds or if the resource is exhausted. We proceeded differently. First, even if the subject left their decision unchanged, the game continued until the end. In this way, all subjects played for the same amount of time and could modify their decision even after 30 seconds without any change. In addition, rather than stopping the play, we defined a rule for when the available resource became scarce : if the extraction was greater than the available resource, the server automatically set the extraction to zero. This rule also applied in the game ; if the total extraction exceeded the resource stock, the extraction of both players was set to zero. The rule was explained in the instructions and was commonly understood. If implemented, the players could see when their extraction was set to zero by the computer. This information was obvious, on the graph that displayed their extraction and on the slider since the cursor moved automatically to the corresponding zero mark. The player had to move the cursor if they wanted to then extract a positive quantity. Other rules would have been possible, such

as providing the remaining available resource or, in the two-players game, dividing the remainder equally or proportionally to the quantity requested. We thought it easier for subjects' comprehension to keep the same rule whether they played alone or shared the resource. Moreover, setting an allocation rule for the extraction in proportion to the available resource would have led to a multiplicity of equilibria. This would have greatly complicated the empirical strategy needed to compare laboratory results to equilibrium paths without revealing any (particularly) interesting information on the behavior of agents.

2.4.2 Experiment

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

As a first step, subjects had to choose an initial level of extraction (corresponding to instant $t = 0$) between 0 and 2.8, by moving a cursor on a graduated slider, which allowed values with two decimals. We chose these values to ensure a positive benefit, given the quadratic nature of our benefit function. Figure B.4 in the Appendix of Chapter 2 shows the concave revenue curve, where the maximum benefit is reached for an extraction rate of 1.4. Figure B.5 shows the unitary cost function, which decreases as the level of groundwater increases and becomes equal to zero as soon as the level of the groundwater reaches the steady-state level of 20. Once the initial extraction rate was

selected, a new screen appeared, and the countdown began. Subjects could change their extraction rate at any moment by simply moving the cursor. Every second the graphic and textual information on the screen was updated. More precisely, the screen was composed of three graphs and a textual area : the graph at the top left showed the subject's extraction rate; the graph at the bottom left displayed the evolution of the resource and the graph at the top right showed the subject's payoff for the part, which corresponded to the sum of the cumulative and continuation payoff. At the bottom right of the screen, the same information was displayed in text form. All the subjects in the room started and finished at the same time. A screenshot of the user interface is given in Figure B.6 in the Appendix of Chapter 2.

Once Part 1 was completed, the subjects were given new instructions, specifying that the environment remained the same except that instead of extracting the resource individually, players would now be doing so in pairs. Part 2 also included two identical and successive training phases, followed by the third phase for pay. It was also understood that the pairs were randomly re-formed after each phase. The screen, given by Figure B.7 in the Appendix of Chapter 2 was identical to that in Part 1, except that in the top-left graph, two additional curves showed the extraction of the other player and the total extraction of the pair.

2.4.3 Parameters

Table 2.1 reports the parameters used in both the theoretical model and the experiment, which were determined by taking into account theoretical and experimental constraints. First, the speed of convergence to the steady state had to be reasonable, neither too short – a few seconds – nor too long – several minutes. In fact, the steady state can be interpreted as a static framework, which simplifies the experiment and allows subjects to stabilize their extraction rate and pay attention to the sustainability of the resource. Given the infinite horizon, this required setting a small discount rate r .

Second, as the steady-state extraction rate is the same for all types of behavior, we wanted a clear difference in the paths leading to the steady-state groundwater level for the socially optimal, feedback, and constrained myopic behaviors. More precisely, we chose these parameters to obtain a steady state for the social optimum, leading

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
$c_0 - c_1H$	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 2.1 – Parameters for the experiment

to a high level of groundwater while lowering the level of groundwater for the Nash feedback and constrained myopic paths. Third, for simplification, we set α , the return flow coefficient, equal to 1, and the natural recharge R somewhat smaller to avoid floods and highlight the renewable nature of the resource.¹¹ Figures 2.1 and 2.2 report the theoretical trajectories for the different types of behavior, for both the optimal control problem and for the game, according to the chosen parameters.

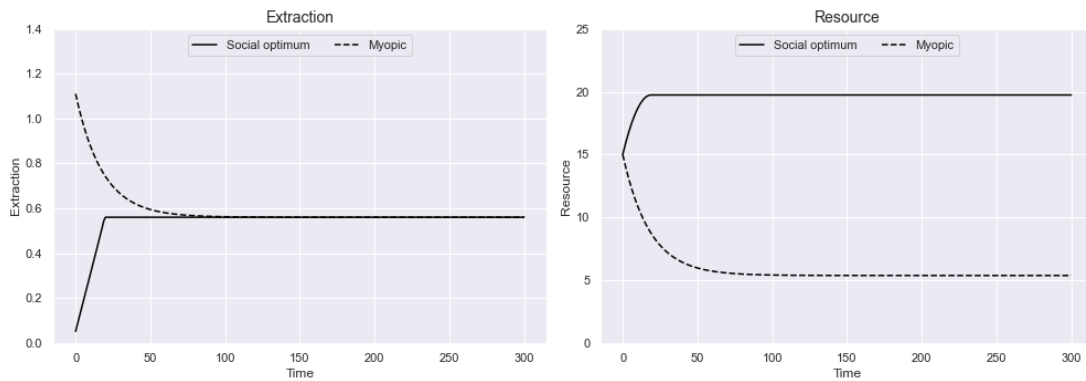


FIGURE 2.1 – Extraction rates and groundwater levels for the optimal and myopic behaviors in the optimal control problem

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

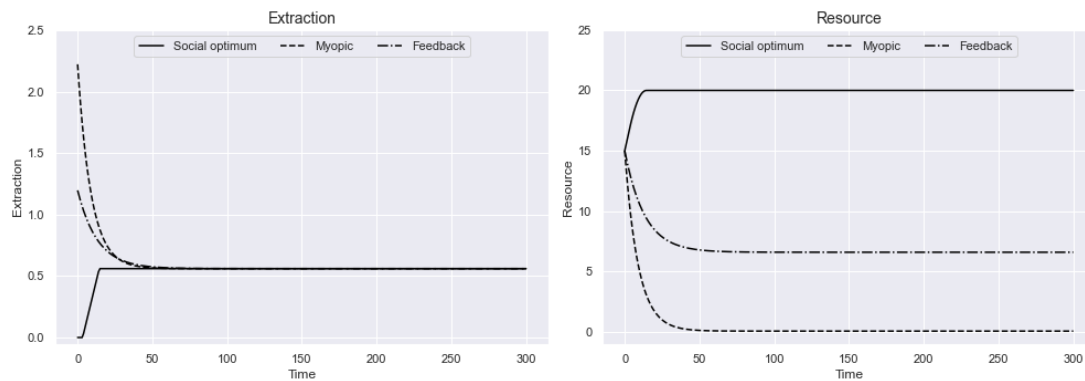


FIGURE 2.2 – Extraction rates and groundwater levels for the optimal, feedback and myopic behaviors in the game

2.5 Results

2.5.1 Descriptive Statistics

Figure 2.3 reports the evolution over time of the average extraction and the average resource in the optimal control problem and in the game. Visual inspection of the graphs led us to notice three main points. First, whatever the context (with or without interaction), on average, players started with a high extraction level, as myopic or feedback players would do. However, after a few instants (10 seconds in the optimal control and 15 in the game), the players adjusted their extraction level to a rate lower than 0.56 (the natural recharge) and therefore let the resource increase. Consequently, the curves that depict the evolution of the resource seem to be more consistent with the optimal than the myopic path (and feedback in the game). Second, there is more dispersion in the game than in the optimal control problem (the colored areas represent the 95% confidence interval around the mean). As will be shown with a more detailed analysis in the next subsections, this dispersion explains why, on average, the resource is close to 20 in the second half of play. Third, in the optimal control, the average stock exceeds 20 after 1'40" (100 seconds) and stays above that level until the end, meaning that some players under-exploit the resource, as also observed by [Hey et al. \(2009\)](#) and [Tasneem et al. \(2019\)](#).

Table 2.2 reports the averages and standard deviations based on individual and

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

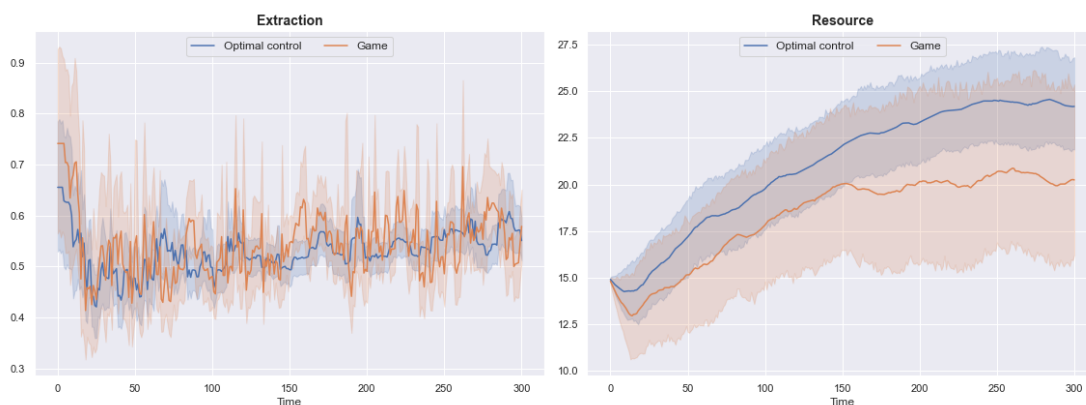


FIGURE 2.3 – Evolution of extraction and resource in the optimal control problem and the game. For the game the extraction curve represents the average group extraction. The area around the curves represents the 95% confidence interval.

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

TABLE 2.2 – Summary statistics of the optimal control problem and the game.

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

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

in the long run. Specifically, if the extraction at $t = 300$ exceeds the natural recharge (0.56), the resource will be depleted in the future. Figure 2.4 shows the distribution of extraction rates and resource stocks at the end of the 5 minutes of play in the optimal control problem and in the game. In the game 14 groups out of 35 (40%) set the last extraction to a level strictly greater than 0.56, and 17 players out of 70 (24.29%) in the optimal control did the same; this difference is, however, not statistically significant based on a Fisher Exact Test (p-value=0.115). More than 50% of the players in the optimal control problem ended with a resource stock between 20 and 30, compared to less than 40% in the game. A similar proportion of groups ended with a resource stock between 10 and 20, which explains why, in Figure 2.3, the curve representing the game is close to 20 at the end of play. As a result, the two distributions are significantly different according to a Kolmogorov-Smirnov test (p-value=0.005).

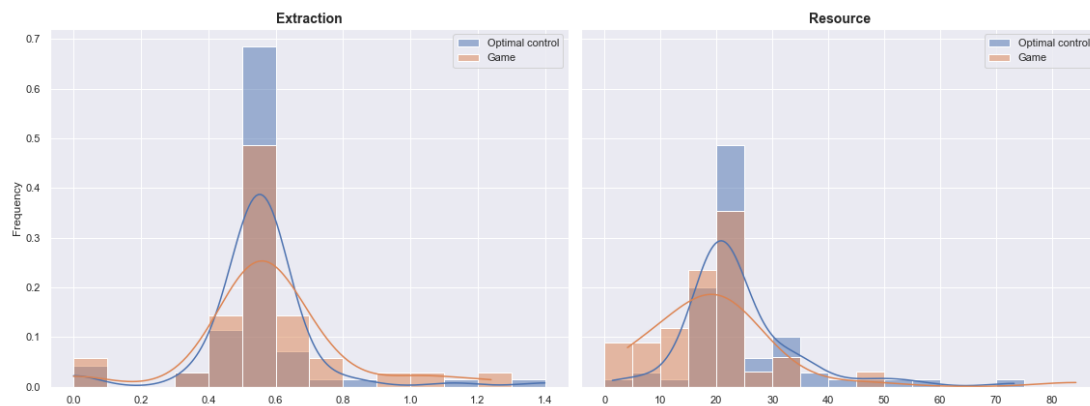


FIGURE 2.4 – Distribution of the extraction rate and the resource stock in the last instant of play ($t=300$)

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

2.5.2 Profiles

Empirical Strategy

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

$$\begin{aligned} MSD_{my}^{th} &= \frac{\sum_{t=1}^T (w(t) - w(t)_{my}^{th})^2}{T}, \\ MSD_{op}^{th} &= \frac{\sum_{t=1}^T (w(t) - w(t)_{op}^{th})^2}{T}, \end{aligned} \tag{2.2}$$

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

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

the observed $t - 1$ groundwater level, the natural recharge, and the conditional extraction. Thus, the MSDs we will consider are given by the following formula :

$$\begin{aligned} MSD_{my}^c &= \frac{\sum_{t=1}^T (w(t) - w(t)_{my}^c)^2}{T}, \\ MSD_{op}^c &= \frac{\sum_{t=1}^T (w(t) - w(t)_{op}^c)^2}{T}, \end{aligned} \quad (2.3)$$

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

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

$$\begin{aligned} w(t)_{my}^c &< w(t)_{op}^c, \quad or \\ w(t)_{my}^c &> w(t)_{op}^c, \end{aligned} \quad (2.4)$$

then we will perform the following regression :

$$\begin{aligned} w(t) &= \beta_0 + \beta_1 w(t)_{my}^c + \varepsilon_t, \quad or \\ w(t) &= \beta_0 + \beta_1 w(t)_{op}^c + \varepsilon_t. \end{aligned} \quad (2.5)$$

Therefore, we will consider a player to be significantly myopic (or optimal) if β_1 is positive and significantly different from 0. Consequently, players will be classified either as *Myopic*, *Optimal*, or *Undetermined*.¹⁴ Regarding the econometric time series treatments, we implement an augmented Dickey-Fuller test to detect the presence of unit

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

¹⁴ An alternative is proposed by [Suter et al. \(2012\)](#), who run a similar regression (without the constant term) and consider that a player follows a given behavior if the coefficient is not significantly different from 1. A natural way to do this is to implement a Wald test with :

roots in the series. In the case of the non-stationarity of the variables, we run our regressions on differentiated series. Serial correlation of the error terms is dealt with using Newey-West standard errors and sensitivity tests using 1, 5, and 10 lags are implemented.¹⁵ A player is classified as *Undetermined* if the trajectory of their decisions is neither significantly *Optimal* nor *Myopic*. We follow the same method to analyze the game data, but these are analyzed at the group level and for the three rather than the two theoretical behaviors, namely myopic, optimal, and feedback. An example of the application of the methodology is given in Appendix B.3 of Chapter 2.

Optimal Control

With the MSD classification method, we find 65 optimal players (92.86%) and 5 myopic players (7.14%), as shown in Figure 2.5. This figure presents the location of players with respect to the conditional optimal $MSD (MSD_{op}^c)$ on the y-axis and the conditional constrained myopic $MSD (MSD_{my}^c)$ on the x-axis. Players located above the bisector are considered as myopic ($MSD_{op}^c > MSD_{my}^c$) and those located below the bisector as optimal ($MSD_{my}^c > MSD_{op}^c$).

However, as explained in the previous subsection, the sole criterion of the MSD is not fully satisfactory and may lead to misinterpretations. Therefore, we applied our proposed regression filter, which drastically changed the picture. Specifically, we now find only 19 players (27.14%) that can be classified as significantly *Optimal* (olive markers in Figure 2.5), instead of 65, while the remainder (51, 72.86%, brown markers in Figure 2.5) is classified as *Undetermined*, since they cannot be classified either as significantly *Optimal* or *Myopic*.

Since actual observations do not always match theoretical behaviors, it is usual to visually inspect individual curves to complete the analysis and gain more insight into behaviors (see Hey et al., 2009, for example). We followed this method and looked at the evolution of the extraction and resource stock for the 51 players that we classified

$$\begin{cases} H_0 : \beta_1 = 1, \\ H_A : \beta_1 \neq 1, \end{cases} \quad \text{and} \quad W = \frac{(\hat{\beta}_1 - 1)^2}{var(\hat{\beta}_1)} \rightarrow F_{(1,300)}.$$

In this case, a very imprecisely estimated coefficient β_1 (very large $var(\hat{\beta}_1)$) will lead us to reject H_A and classify the player as myopic or optimal, while they follow neither an optimal nor myopic path. This is the reason we propose the alternative classification rule.

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

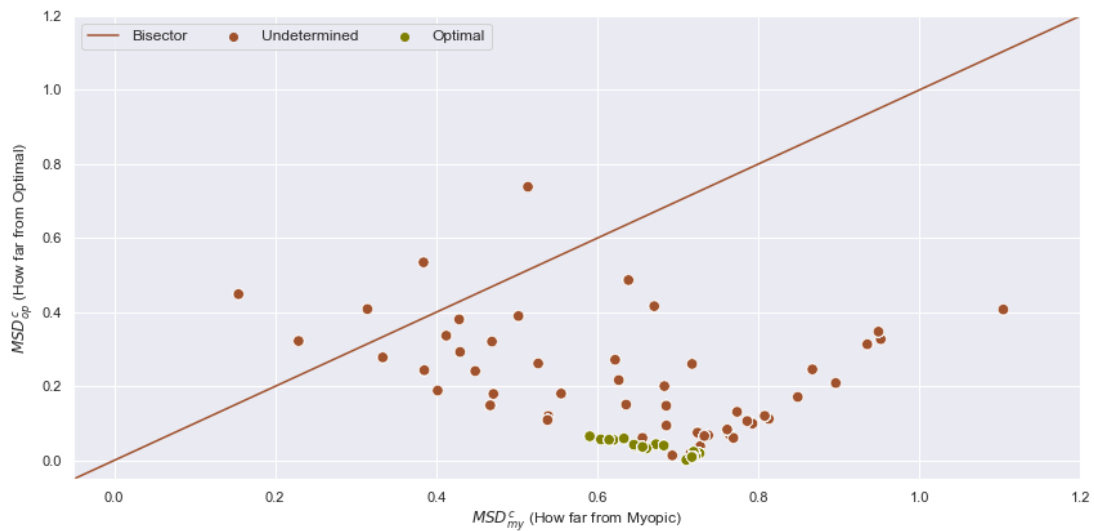


FIGURE 2.5 – MSD position of players in the optimal control. Colors represent the identified profiles after the regression filter.

as *Undetermined*.¹⁶ This led us to identify two distinct patterns. In the first, players who started by decreasing the stock of the resource, with a pattern close to the myopic behavior, and after a short time let it increase slowly and regularly toward the optimal steady state. Since the evolution of the resource stock for these players converges toward the optimal solution, we name this category *Convergent*. We identified 15 players who could be placed in this category. Second, we found 17 players who mostly extracted less than the rate of natural recharge, and thus let the resource increase beyond the threshold where extraction is cost-free and called them *Under-exploiters*. Hey et al. (2009) and Tasneem et al. (2019) identify similar behaviors, which they interpret as a manifestation of prudence.

Figure 2.6 reports the evolution of the average resource stock of the different categories identified. The solid blue line represents the players classified as significantly *Optimal* and the dotted black line nearby represents the theoretical trajectory of the socially optimal solution. As can be seen, even though these players behaved optimally, they did not let the resource increase fast enough. More specifically, on average, they reached the threshold of 20 after 101 seconds when, in theory, it should be reached

¹⁶ The individual curves of each of the 51 players are available at <https://tinyurl.com/h45z7hrz>

after 20 seconds. Also, their steady-state level was slightly higher than the theoretical level.

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

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

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

To complete the analysis we look at the efficiency of players’ decisions by calculating the ratio of their payoff to the maximum possible payoff, as is common practice in the literature. With our set of parameters, a perfectly optimal player would have achieved a payoff of 215 ECUs.¹⁸ The average ratio, with all categories included, is 0.78 (Std Dev. 0.23, Median 0.86), which is lower than in Tasneem et al. (2019) (0.85) and Suter

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

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

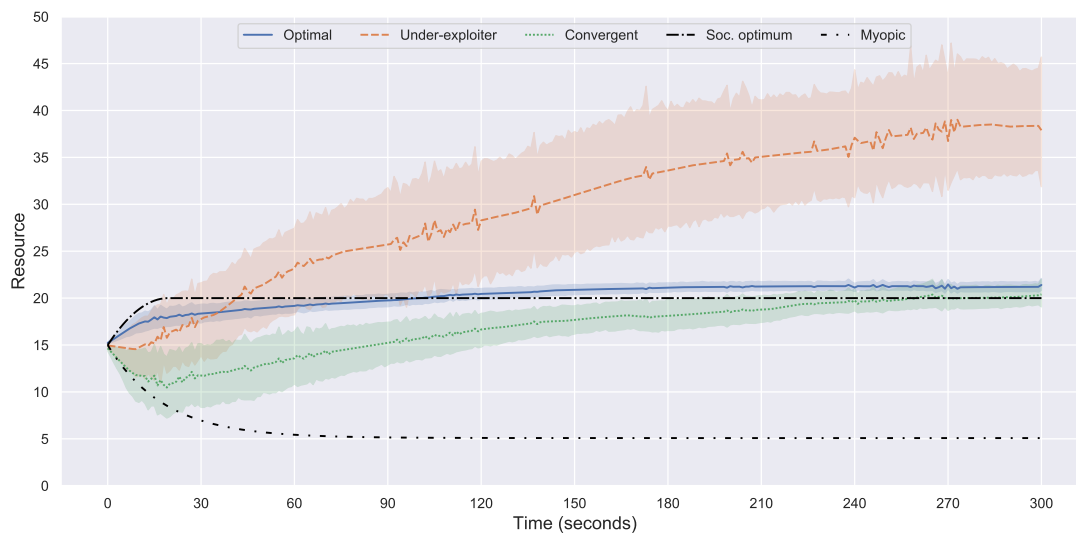


FIGURE 2.6 – Average resource stock of players classified as *Optimal*, *Convergent* and *Under-Exploiter*. Area represent the 95% confidence interval around the mean.

et al. (2012) (0.95). A possible explanation is that in Tasneem et al. (2019) the game lasted only 2 minutes and stopped after 30 seconds without any movement from the player, whereas Suter et al. (2012) implemented a discrete-time experiment. On average, the efficiency rate in the *Optimal* player category is 0.97 (Std Dev. 0.02), which is significantly higher than the other categories (Mann-Whitney p-value < 0.001 for each test performed), of 0.79 (Std Dev. 0.17) for *Convergent*, 0.79 (Std Dev. 0.19) for *Under-Exploiter* and 0.58 (Std Dev. 0.27) for *Undetermined*.

Figure 2.7 reports the ratios of each player in the experiment, taking care to separate the categories we just defined. The Figure shows that the *Optimal* category is very close to the ratio of 1, with low variance, which suggests the empirical strategy we proposed is very relevant for this exercise. We can also observe that some players who belong to the other categories also succeeded in achieving a high ratio of efficiency, even if these categories clearly exhibit much more heterogeneity than the *Optimal* one.

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

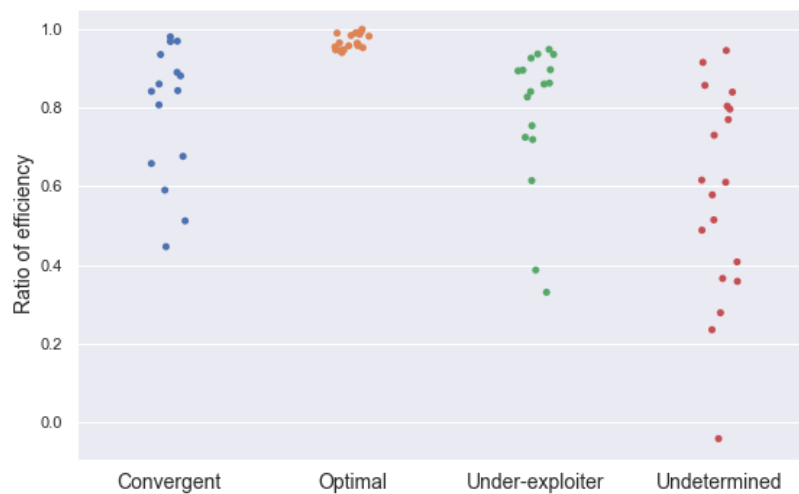


FIGURE 2.7 – Ratio of efficiency by category

three-quarters (72.46%) of the sample.

Game

As the game protocol is based on a within-subject design, the players were the same as in the optimal control problem but were grouped in pairs in which both extracted the same resource. Figure 2.8 reports the location of groups with respect to the conditional MSD_{op} and MSD_{my} . Based on this criterion, 32 groups are closer to the optimal than the myopic pattern, and 3 groups are, by contrast, closer to the myopic than the optimal pattern. However, after the application of the regression filter, we find that 7 groups out of 35 are significantly *Optimal* (olive markers in Figure 2.8) and the remaining (28) are *Undetermined*, that is, neither significantly *Feedback* nor *Myopic* (brown markers in Figure 2.8). In other words, 20% of groups were able to adopt the cooperative socially optimal solution.

A visual inspection of the extraction and resource curves of the 28 *Undetermined* groups¹⁹, lead us to identify 9 groups that converged toward the optimum (*Convergent*), 5 groups that let the resource increase to a very high level (*Under-Exploiter*) and 6 groups that, by contrast, overexploited the resource (*Over-Exploiter*). There are still 9 groups we could not classify, and these therefore remained in the *Undetermined* cate-

¹⁹Curves for each group separately are available at <https://tinyurl.com/2ztchw6x>

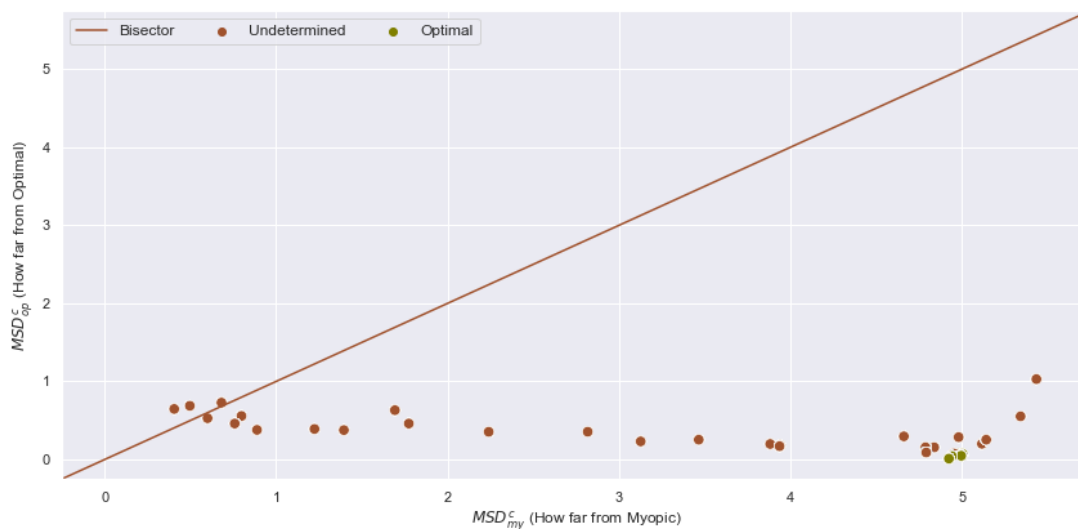


FIGURE 2.8 – MSD position of groups in the game. Colors represent the identified profiles after the regression filter.

gory. Figure 2.9 reports the evolution of the average resource stock for each category, as well as the three theoretical trajectories. Groups that behaved as significantly *optimal* are represented by the dotted blue line. On average, they started with a trajectory very close to the theoretical path, but after a few seconds, they maintained the resource stock at a slightly higher than optimal level.

As in the optimal control problem, the *Convergent* category (solid red line) differs from the *Optimal* category in that at the beginning of the game, the extraction level is too high, and thereafter the trajectory toward the equilibrium value of 20 is slow; it is reached after 177 seconds compared to fewer than 12 seconds by the *Optimal* groups (a significant difference, Mann-Whitney p-value=0.001). Like the *Optimal* groups, the *Under-Exploiter* groups (solid blue line) let the resource stock grow quickly, on average after 29 seconds (not significantly different from *Optimal*, Mann-Whitney p-value=0.503). However, those in this category maintain the growth path almost to the end, which is not optimal. We do not know why they do not stop under-extracting the resource once the steady-state level is reached. We did not include control tasks in the experiment, for example, to capture the attitude toward risk or impatience. As a result, we are unable to provide any explanatory insights. What is new in this multiple-agent setting is the *Over-Exploiter* category. On average, with some variation, groups

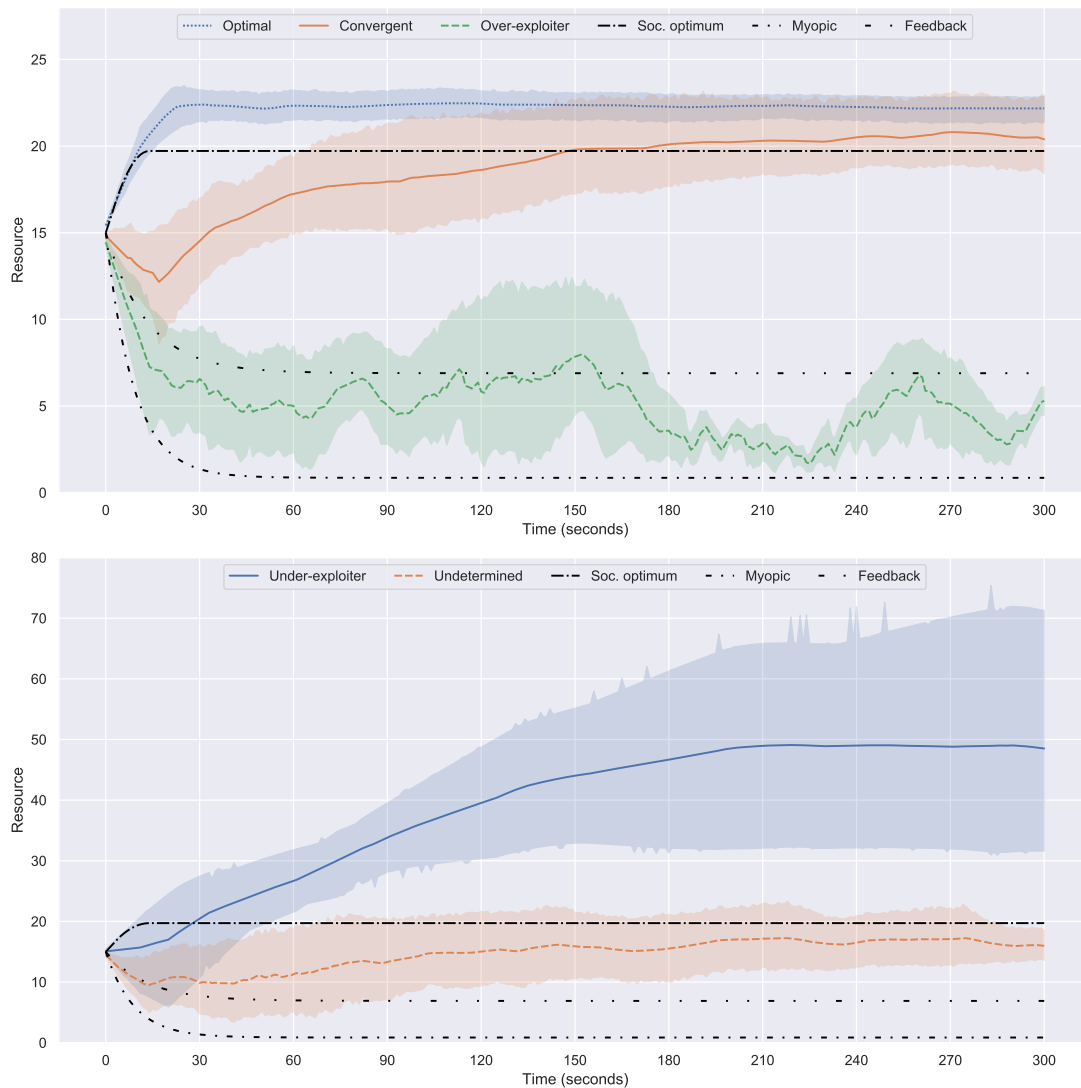


FIGURE 2.9 – Average resource stock of groups classified as *Optimal*, *Convergent* and *Over-Exploiter* (graph at the top of the figure), and *Under-Exploiter* and *Undetermined* (graph at the bottom of the figure). Area represent the 95% confidence interval around the mean.

in this category started with a trajectory close to the feedback solution. However, in the second part of the play, they fall between feedback and myopic behavior, which is why the regression filter failed to conclude significant feedback behavior. If we look at these groups individually (file referenced in footnote 19), they seem to be characterized by a high frequency of alternation between high and low levels of extraction,

revealing a difficulty within the group in agreeing on a path or strategy.

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

The maximum combined payoff the group could achieve is 240 ECUs. We first calculated the efficiency ratio at the group level by summing the payoff at the last instant of the two members of the pair. The average ratio of efficiency, for all categories combined, is 0.68 (Std Dev. 0.28, Median 0.77). Those in the *Optimal* category reach an average efficiency ratio of 0.98, followed by the *Convergent* (0.80), the *Under-Exploiter* (0.79), and the *Undetermined* (0.58) categories, and, in a distant last place the *Over-Exploiter* (0.22) category. Figure 2.10 reports on the left side the ratio of efficiency at the group level and on the right side at the individual level. For the calculation of the individual efficiency ratio, we compared the final individual payoff to 120 ECUs, half of the maximum the group could achieve. It was nevertheless possible for a player to obtain more than 120 ECUs, when the other member of their pair extracted a smaller quantity. As a result, it was possible to achieve an efficiency ratio greater than 1. This happened to one player in the *Undetermined* groups and to three in *Convergent*, four in *Under-Exploiter* and five in the *Optimal* groups. The latter number means that in groups that behaved according to the theoretical social optimum, individual behaviors were not symmetric. That is, one player has benefited from the low extraction of the other.

Group Behavior According to the Profiles in the Control

The within-subjects design allows us to analyze how groups are composed in terms of profiles identified in the control problem. Table 2.3 reports the contingency table of

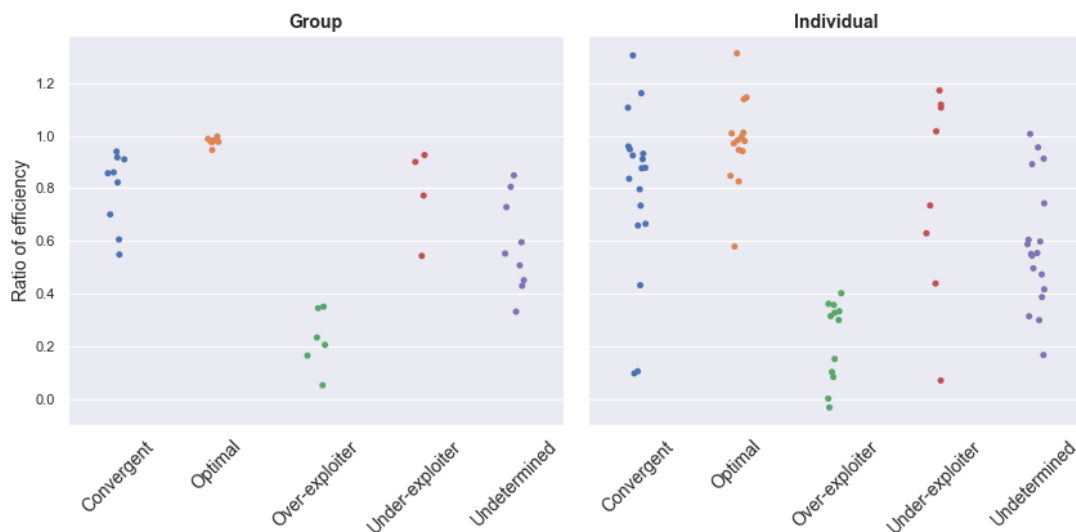


FIGURE 2.10 – Ratio of efficiency by category

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

In Table 2.4, we detail, for each identified category of groups, the group composition in terms of profiles identified in the control problem. Remember that we did not control for the group composition; this was done randomly by the server at the beginning of

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

TABLE 2.3 – Contingency table of players’ profile in the control and groups in the game

the game. If we read the table by rows we see that 13 of the 17 groups (76.47%) with at least one *Optimal* player had a trajectory identified either as significantly *Optimal* or *Convergent*; having an *Optimal* player in the pair increases the likelihood that the group cooperates. This is confirmed by reading the table by columns : of the *Optimal* groups, 6 out of 7 include at least one player that behaved as *Optimal* in the control problem.

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

TABLE 2.4 – Contingency table of groups’ profiles and groups’ composition in terms of profiles in the control

2.6 Conclusion

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

horizon in the laboratory, and comparing individual and collective decisions to the full set of standard theoretical solutions (Optimal, Feedback, and Myopic).

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

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

Most players who seemed to understand that their long-term payoff maximizing trajectory, when playing alone, required letting the resource increase until the level at which the extraction was cost-free pursued their reasoning in the game ; this was the case even if not always successful, depending on the behavior of their counter-

part. Therefore, if our goal were to foster cooperation in the multiple-agent setting, we would recommend starting with an intervention that helps players understand how to maximize their long-term payoff in the context of a single-agent scenario.

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

In the next chapter, we present the results of an experiment comparing continuous time to discrete time over an infinite horizon, in the study of the extraction behaviors of groundwater users. We also distinguish the situation without strategic interaction from the one involving strategic interaction.

Chapitre 3

Continuous vs. Discrete Time in Dynamic Common Pool Resource Game Experiments

Abstract:

We study the impact of discrete versus continuous time on the behavior of agents in the context of a dynamic common pool resource game. To this purpose, we consider a linear quadratic model in which agents exploit a renewable resource with an infinite horizon and conduct a lab experiment. We use a differential game for continuous time and derive its discrete time approximation. When the agent is the sole owner of the resource, we fail to detect on a battery of indicators any difference between discrete and continuous time. Conversely, in the two-player setting, significantly more agents can be classified as myopic and end up with a low resource level in discrete time. Continuous time seems to allow for better cooperation and thus greater sustainability of the resource than does discrete time. Also, payoffs are more equally distributed in the continuous time setting.

Keywords: Common Pool Resource; Differential Games; Experimental Economics; Continuous Time; Discrete Time

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

Résumé :

Nous étudions l'impact du temps discret versus temps continu sur le comportement

des agents dans un jeu dynamique de ressources communes. À cette fin, nous considérons un modèle linéaire quadratique dans lequel les agents exploitent une ressource renouvelable sur un horizon infini et menons une expérience de laboratoire. Nous utilisons un jeu différentiel en temps continu et déduisons son approximation en temps discret. Lorsque l'agent est le seul propriétaire de la ressource, nous ne parvenons pas à détecter sur une batterie d'indicateurs une quelconque différence entre temps discret et temps continu. Inversement, dans le cadre de deux joueurs, un nombre significativement plus élevé d'agents peuvent être classés comme myopes et se retrouvent avec un faible niveau de ressources en temps discret. Le temps continu semble permettre une meilleure coopération et donc une plus grande durabilité de la ressource contrairement au temps discret. De plus, les gains sont distribués de manière plus égale en temps continu.

Mots-clés : Ressources Communes ; Jeux Différentiels ; Économie Expérimentale ; Temps Continu ; Temps Discret

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

3.1 Introduction

On many issues, we have the possibility of taking decisions at any moment in time, and asynchronously with other agents : sending a message, extracting water from a groundwater table, reducing prices, etc. Many of the interactions we engage in have a real-time aspect. How does this ability to rapidly and asynchronously adjust actions shape our behavior? This question has been of deep interest for behavioral and experimental economists over the past decade. Indeed, many questions that were initially analyzed in discrete time in laboratory experiments can today be analyzed using continuous time protocols that allow researchers to compare the behavior of agents in discrete versus continuous time.

Previous articles find that continuous time can foster cooperation, but only under certain conditions. When presenting prisoner's dilemma games to two-person groups in three treatments, one in continuous time, one in static time (one-shot) and one in discrete time, [Friedman & Oprea \(2012\)](#) find a higher median cooperation rate in continuous time. [Bigoni et al. \(2015\)](#) combine elements of the design of [Bó \(2005\)](#) and of [Friedman & Oprea \(2012\)](#) to study cooperation in repeated prisoner's dilemma. They

find that contrary to previous results in discrete time, cooperation is easier to achieve in continuous time with a deterministic time horizon than with a stochastic time horizon. [Oprea et al. \(2014\)](#) study subjects' contributions in a public good game played in groups of five people. They find players contribute higher amounts in continuous time than in discrete time but only when a rich communication protocol among participants is included. Introducing new laboratory methods in order to eliminate inertia in a subject's decision in continuous time experiments, [Calford & Oprea \(2017\)](#) find strikingly different behaviors in continuous vs. discrete time in a simple timing game where two participants compete to enter a market. Finally, [Leng et al. \(2018\)](#) study the evolution of cooperation by crossing time protocols (continuous vs. discrete time) and information feedback (group minimum effort level vs. effort level of each member of the group) in a minimum effort coordination game played in groups of six people. Among the four treatments, the authors find that the average payoff increases only when continuous time is associated with the provision of information on the effort level of each member of the group.

Although studying interactions in the prisoner's dilemma, public good, timing, or minimum effort coordination games is extremely useful, these games abstract from a feature relevant to many economic applications, the presence of a state variable that makes the impact of any decision to persist through time, which is the case in common pool resource (CPR) games ([Vespa, 2020](#)). The vast majority of the CPR literature that combines theory and experimentation is in discrete time. A possible explanation is that discrete time is easier to implement in the lab and can be compared to a static repeated game in which the state variable evolves from one period to the other ([Herr et al., 1997](#); [Gardner et al., 1997](#); [Mason & Phillips, 1997](#); [Hey et al., 2009](#); [Suter et al., 2012](#), for instance). Nevertheless, [Tasneem et al. \(2017\)](#) recently tested a CPR differential game in the lab using a continuous time protocol. Focusing on Markov's perfect equilibrium strategy, they tried to determine the relevance of the nonlinear equilibria in a two-player common property resource game. [Janssen et al. \(2010\)](#) have also studied the role of communication and punishment in a CPR game in continuous time. They find that punishment can foster cooperation only when combined with communication. The authors do not present the formal theoretical model underlying their experiment.¹

¹Note also that some authors such as [Noussair et al. \(2015\)](#) conduct their experiments in discrete time, while their theoretical model is in continuous time, which poses the question of to what theoretical

In this paper we build on the previous literature to study the impact of the nature of time in a two-person common pool resource (CPR) problem. Several important differences with previously tested games (prisoner's dilemma, public good, timing, and minimum effort coordination games) can lead to a different impact of the nature of time. First, the presence of the state variable makes the impact of any decision persist through time (Vespa, 2020), which can, for instance, generate dynamic free riding (Battaglini et al., 2016).² Moreover, as opposed to the prisoner's dilemma, where payoffs can be directly read from a matrix, dynamic games are more difficult to handle. These two elements can make the optimal solution harder to reach in the case of CPR games. Reversely, infinite horizon can provide strategic opportunities to endogenously support cooperative outcomes (Battaglini et al., 2016). In addition, using dynamic CPR games allows us to explicitly derive equilibrium paths for three well identified types of behavior – myopic, feedback and optimal. How does the nature of time affect strategic interactions in this context? Can continuous time still foster cooperation? Does the nature of time affect the equilibrium path to which participants are the closest?

To analyze these questions, we consider a simple linear quadratic model, based on Gisser & Sanchez (1980); Negri (1989), and Rubio & Casino (2003), in which agents exploit a renewable resource with an infinite horizon. The resource can be assimilated to a groundwater basin but other interpretations of CPR are possible. We use a differential game for continuous time and propose a discretization of the CPR game so that the equilibrium paths for myopic, feedback and optimal behaviors are almost identical in the discrete and continuous time models. For the implementation in the lab we choose to lead a non-contextualized experiment in a between-subject design with four treatments. We cross the nature of time (discrete versus continuous) and the number of subjects exploiting the resource (one versus two). In the continuous time treatments, we follow the literature and mimic continuous time by allowing the agent to change

predictions should we compare lab results : those from discrete or those from continuous time models? Moreover, Tasneem et al. (2019) study the ability of a single economic agent to exploit a renewable resource efficiently. To do that they test in the laboratory an optimal control problem with an infinite horizon in continuous time and show that extraction behavior results in a steady state of the resource only 56% of the time.

²Battaglini et al. (2016) define dynamic free-riding this way : "an increase in current investment by one agent [which] typically triggers a reduction in future investment by all agents". In the context of a CPR, a decrease in extraction level can be seen as an investment to obtain a higher resource level, and thus greater benefits in the future.

his extraction rate every second. In the discrete time treatments, the agent can change his extraction level every 10 seconds. About one hundred subjects participated in each treatment.³

Presenting subjects with the simplest setting, i.e., a single agent exploiting the resource, allows us to test whether the ability to manage a resource differs in continuous and discrete time. Indeed, the greater number of decisions potentially taken in continuous time could facilitate a trial and error process to reach optimal management of the resource. It is important to establish this baseline because, as explained earlier, dynamic situations are complex problems to handle, and it is important to understand the impact of the nature of time without interactions. Our estimates indicating that only 37% of the agents play optimally, confirms this statement. Our results also show that in all aspects tested, a subject's ability is not affected by the nature of time in a single agent setting. This allows us to deduce that the differences observed in the multiplayer setting are due to the impact of the nature of time on the interactions.

When running the experiment in a multiplayer setting, we find significant differences between continuous and discrete time. For example, the average resource level is significantly lower in discrete time. There is a larger proportion of agents that can be classified as myopic and a larger proportion of agents that end up with a low resource level in discrete time, while the proportion of optimal and feedback agents are not significantly different between the discrete and continuous time. Continuous time seems to favor a more sustainable exploitation of the resource. Our underlying intuition for this result is similar to [Friedman & Oprea \(2012\)](#), [Oprea et al. \(2014\)](#) and [Leng et al. \(2018\)](#). Continuous time allows subjects to briefly switch to cooperative behavior, such as a socially optimal extraction rate, in order to incite the other player to do the same, or conversely to quickly increase extraction if the other player increases their extraction too much. The fact that we observe more stable extraction levels in continuous time and that extraction levels are more homogeneous within the group is consistent with this potential explanatory mechanism. It also results in less unequally distributed payoffs in continuous than in discrete time.

³One exception to this way of implementing continuous time in the laboratory is [Calford & Oprea \(2017\)](#). The authors propose a protocol where time freezes when one decision is taken in order to let the other player react to this decision without a delay in the game. This protocol is useful and easy to implement for timing games, such as the one studied by [Calford & Oprea \(2017\)](#), but is less appropriate for CPR games, as we explain in Section 3.3.

Through this work, we provide several contributions to the literature. We offer the first in-lab analysis of the impact of discrete versus continuous time in the lab in the case of CPR games. We contribute to the analysis of common pool resources using differential games, by being the first experimental paper to consider socially optimal and myopic strategies in a continuous time setting. We also make two secondary contributions. We present an experimental protocol allowing to compare continuous and discrete time models in the laboratory. Finally, to compare the behavior of subjects in the lab to theoretical projections, we combine mean-squared deviation statistics and linear regressions.

The next section of this paper presents the theoretical setting. Section 3.3 describes the experimental design used to test the theoretical model. Section 3.4 is devoted to the empirical strategy, and results are analyzed in Section 3.5. The final section provides a discussion and conclusion.

3.2 The Model

We consider a simple linear quadratic model in continuous time, in which two agents, i, j exploit a renewable resource over an infinite horizon. The resource can be assimilated to a groundwater table. Water pumped provides agents revenue $B(w)$ depending only on the extraction w . Agents also incur a cost $C(H, w)$, which depends negatively on the level of the groundwater H . The parameters a, b, c_0 and c_1 are positive. An agent's instantaneous payoff is given by the difference between revenue and cost, as shown by equation (3.1) :

$$aw - \frac{b}{2}w^2 - \underbrace{\max(0, c_0 - c_1H)}_{C(H,w)} w. \tag{3.1}$$

We need to have a positive the marginal or unitary cost $c(H)$ to prevent the cost to become a subsidy. Thus it is important to adopt a piecewise marginal cost function :

$$c(H) = \begin{cases} (c_0 - c_1H) & \text{if } 0 \leq H < \frac{c_0}{c_1}. \\ 0 & \text{if } H \geq \frac{c_0}{c_1}. \end{cases}$$

In the model, agents have to choose an extraction that maximizes their instantaneous payoff. The problem differs between continuous time and discrete time, in continuous time, decisions are made at each instant t in real time and the resource evolves continuously, while in discrete time, decisions are made at each period n and the resource evolves from one period to the next. Whether in continuous or discrete time, the behavior of agents is analyzed in two settings. First, in an optimal control problem, where a sole agent exploits the groundwater, we characterize both the myopic and the optimal behaviors. Second, the behavior of agents can be analyzed in a game, where strategic interaction is introduced by considering two identical and symmetrical agents in the exploitation of the groundwater. A feedback equilibrium path can be defined, in addition to the myopic and optimal equilibrium paths in the game.

Social optimum can be defined as a behavior in which an agent's extraction decision allows him to maximize his discounted payoffs in order to maintain the resource at an efficient level. The social optimum is also called the "cooperative solution" in the game. In that case the resource is maintained at an efficient level by maximizing the joint discounted payoff of all agents. The myopic solution is where the agent is only interested in the maximization of his current payoff (equation (3.1)), regardless of the evolution of the groundwater. The feedback equilibrium can be seen as a scenario in which agents adopt non-cooperative behavior, maximizing their own discounted net payoffs while also taking into account the evolution of the groundwater.

In continuous time, the discounted payoff (with r the discount rate) for player i is :

$$\int_0^{\infty} e^{-rt} \left[aw_i(t) - \frac{b}{2} w_i(t)^2 - \max(0, c_0 - c_1 H(t)) w_i(t) \right] dt, \quad (3.2)$$

and the dynamics is given as :

$$\left\{ \begin{array}{l} \dot{H}(t) = R - \alpha(w_i(t) + w_j(t)), \\ H(0) = H_0 \text{ and } H_0 \geq 0, H_0 \text{ given,} \\ H(t) \geq 0, \\ w_i(t) \geq 0. \end{array} \right.$$

In discrete time, the discounted payoff (with $1 - r\tau$ the discount factor) and the dynamics for player i are given as :

$$\sum_{n=0}^{\infty} (1 - r\tau)^n \left[aw_i(n) - \frac{b}{2} w_i(n)^2 - \max(0, c_0 - c_1 H(n)) w_i(n) \right] \tau. \quad (3.3)$$

s.t

$$\begin{cases} H(n+1) = H(n) + \tau (R - \alpha(w_i(n) + w_j(n))), \\ H(0) = H_0 \text{ and } H_0 \geq 0, H_0 \text{ given}, \\ H(n) \geq 0, \\ w_i(n) \geq 0. \end{cases}$$

In Appendix C.1 of Chapter 3, we explain how we discretized the continuous time model in order to obtain its discrete time equivalent. The discrete time model converges towards the continuous time model when the discretization step τ tends toward zero.

The discretization rate τ chosen in discrete time provides a good approximation of the continuous time problem, and optimal solutions can be found by means of the Hamiltonian operator. The Nash feedback equilibrium in continuous time can be found by means of the Hamilton Jacobi Bellman (HJB) equation, by applying the guessing method to guess a quadratic value function and in discrete time by means of the Bellman equation. Finally, myopic solutions are obtained by means of a simple first-order derivative. They can also provide a feedback representation of the solutions when considering the constraints.⁴ When w_j is dropped from the dynamics, one is able to solve the optimal control maximization problem (the sole-agent setting). See Appendix C.1 of Chapter 3. The complete theoretical proofs are available in Appendix C.2 of Chapter 3.

3.3 The Experimental Design

We used a between-subject design in which participants in the sole-agent treatments were different from the ones in the multiple-agent treatments. The experiment took place at the Experimental Economics Laboratory of Montpellier (LEEM). From December 2019 to February 2020, a total of 200 students from the University of Montpellier participated in the first part of the experiment. This part was devoted to data collection for the single agent condition. It included a total of 17 sessions, 11 where subjects took decisions in a continuous-time treatment and 6 in a discrete-time one.⁵ From Novem-

⁴The feedback representation is obtained when the solution is written according to the state variable, instead of according to time.

⁵Since the continuous time condition involves higher network traffic, we limited the number of participants per session to a maximum of 14, which explains the greater number of sessions for this treatment.

ber to December 2020, a total of 190 subjects participated in the second part of the experiment, which was devoted to data collection for the two-players game. The experiment involved 20 sessions of continuous and discrete time treatments for groups of two players, so that we had 49 groups in continuous time and 46 groups in discrete time.⁶ It was a non-contextualized experiment, using the oTree platform (Chen et al., 2016), in which subjects participated in a ten-minute training phase of the game, followed by a ten-minute effective phase of the game which counted for their remuneration. The experimental currencies (ECU) accumulated by subjects in the experiment were converted into cash payments with the conversion rate of 10 ECUs to 0.5 euro.⁷ Each experimental session lasted around an hour.

We begin by giving a global overview of the experiment, then we describe the parametrization. Finally, we explain how we implemented continuous time and infinite horizon.

3.3.1 Global Description

In the sole-agent treatments, instructions explained the dynamics of the resource, the decision-making process and its consequences on the available resource, the cost of extraction and the payoff. After an initial individual reading, an experimenter proceeded to an out loud reading of the instructions. Next, subjects answered a digital questionnaire to make sure they understood the evolution of the resource as well as the computation of payoffs. They were also invited to ask questions by raising their hands.

To familiarize subjects with the graphical interface, they participated in a 10-minute training phase before a 10-minute paid phase. At the beginning of each phase, subjects had to choose an initial extraction between 0 and 2.8 by moving their cursor on a graduated slider, which displayed values up to two decimal points. Due to the quadratic nature of our revenue function, any extraction level led to a positive revenue. Figure B.1 in the Appendix C.3 of Chapter 3 shows a concave revenue curve with a maximum revenue reached for an extraction of 1.4. Figure B.2 in the Appendix C.3 of Chapter 3 also shows the unitary cost function, which decreases as the available resource in-

⁶ORSEE (Greiner, 2015) is the platform used by the LEEM to manage the subject pool.

⁷ECU means Experimental Currency Unit.

creases and vanishes when the level of the available resource is above 20.

In the continuous time instructions, the extraction refers to an extraction rate, while in the discrete time instructions it refers to an extraction level. In addition, a distinction is made between the differential equation representing the dynamics of the resource in continuous time and the difference equation representing the dynamics of the resource in discrete time. However, for the sake of simplification, we explain the dynamics in continuous time rather than writing the differential equation. Once the subjects chose an initial extraction level, a new screen appeared and subjects were able to see the dynamics of the resource along with their payoff, which included the cumulative and continuation payoffs, updated every second in the continuous time treatment and every period in the discrete time treatment.

Adapted instructions were provided to subjects in the multiple-agent treatments. Environments remained the same as in the sole agent treatments, except that subjects extracted the resource in groups of two. The layout of the user interface was slightly different from that of the sole agent treatments, with an additional curve showing the pair's total extraction. Complete instructions for the four treatments can be found in the supplementary materials.

3.3.2 Parameters

Table 3.1 reports the parameters used. To get comparable results, parameters were the same in continuous time and discrete time for both the sole- and multiple-agent treatments.

TABLE 3.1 – Parameters for the experiment

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
$c_0 - c_1H$	Marginal or unitary cost	$2 - 0.1H$
r	Discount rate in continuous time	0.005
$\beta = (1 - r\tau)$	Discount factor in discrete time	0.995
R	Natural recharge (rain)	0.56
α	Return flow coefficient	1
H_0	Initial resource level	15
τ	Discretization step	0.1 & 1

Figure 3.1 and 3.2 below show the theoretical time paths for the extraction and resource levels in continuous time for 100 seconds. The theoretical time paths in discrete time are almost identical to those in continuous time. See for instance Appendix C.1 of Chapter 3 for the feedback equilibrium (continuous version with $\tau = 0.1$ and discrete version with $\tau = 1$).

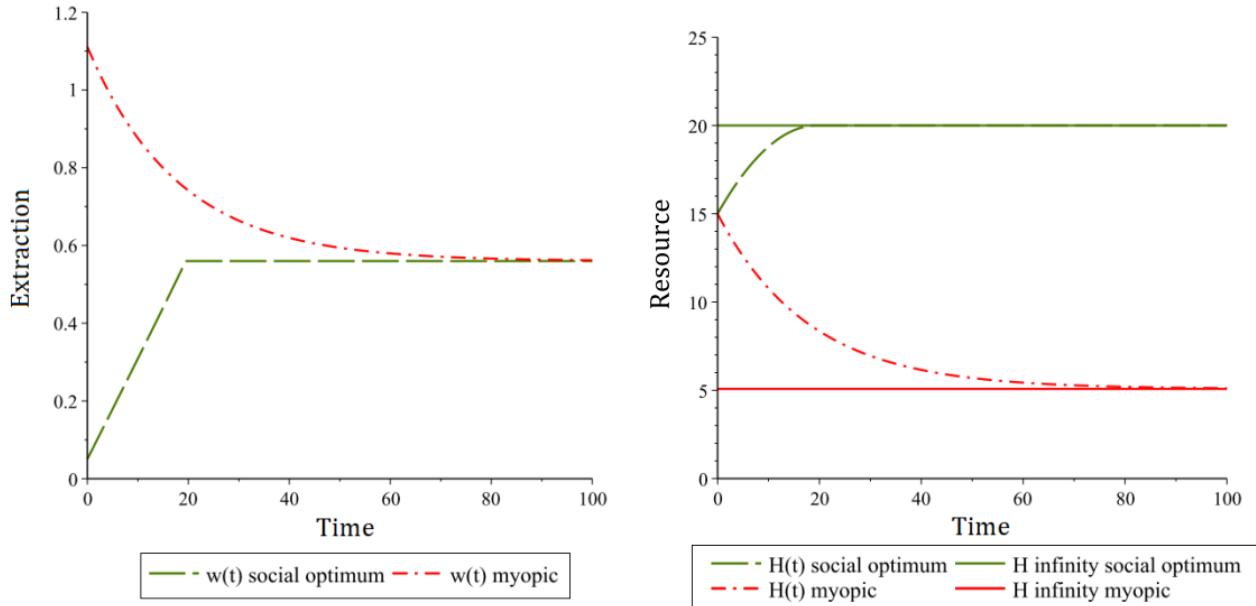


FIGURE 3.1 – Extraction behaviors and resource levels in sole-agent continuous time

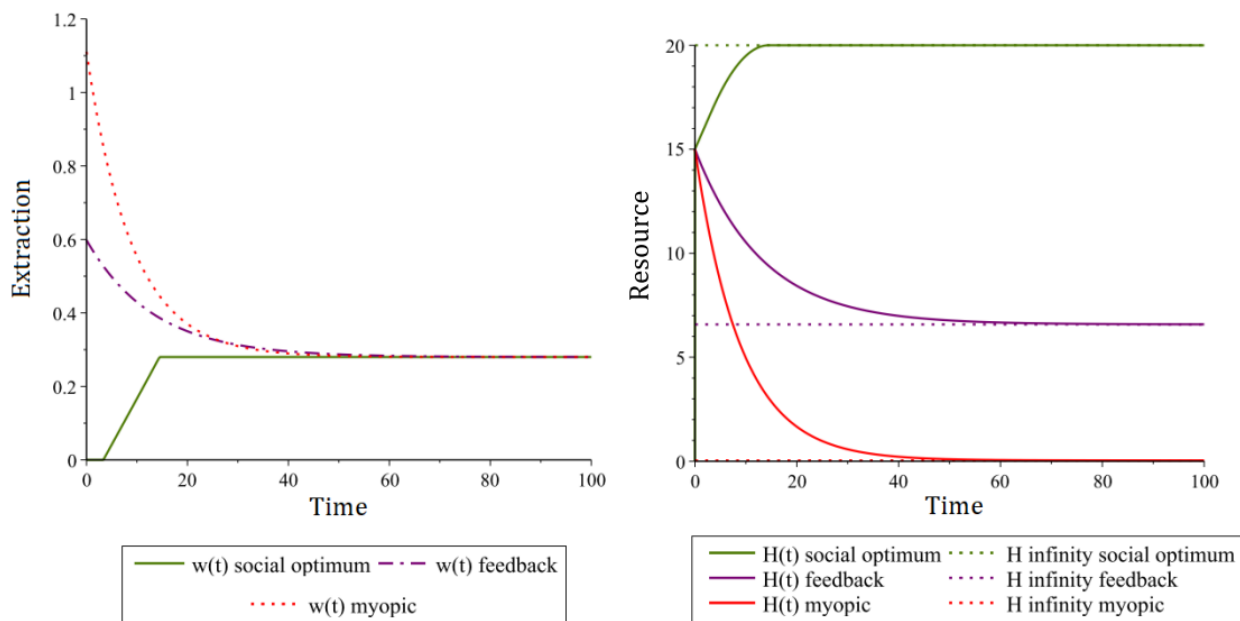


FIGURE 3.2 – Extraction behaviors and resource levels in multiple-agent continuous time

The infinite horizon requires us to set a small discount rate r to capture subjects’ attention on the sustainability of the resource. The corresponding discount factor in discrete time is β . We also chose these parameters so that the steady state level of the resource in the socially optimal case is strongly separated from other cases. The socially optimal behavior leads to a high level of the groundwater, while the myopic behavior results in low groundwater levels (see the right sides of figures 3.1 and 3.2).

Both the natural recharge R and the return flow coefficient α were designated at a small enough size to capture the renewable nature of the resource, simulate real life conditions and avoid floods in the model.⁸

In situations where a subject’s extraction is higher than the available resource, the rule was to set the extraction to zero until she changed her decision or until the amount of the resource increased enough to allow for a new extraction. This rule was chosen because it is easy to implement in the lab and because setting an allocation rule for the extraction in proportion to the available resource would have led to a multiplicity of equilibria, which would have greatly complicated the empirical strategy

⁸The return flow coefficient is the quantity of water returning to the groundwater after each extraction.

needed to compare lab results to equilibrium paths without revealing any (particularly) interesting information on the behavior of agents.

3.3.3 Decision Timing in Continuous and Discrete Time

One of the main challenges of our experimental protocol is the implementation of continuous time in the lab. The computer is naturally unable to implement "pure" continuous time in the sense that time doesn't stop and that decisions can be taken at literally any moment. Most previous experiments implement continuous time by letting people change their decisions very frequently, every second or less, in order to mimic continuous time (Friedman & Oprea, 2012; Oprea et al., 2014; Bigoni et al., 2015; Leng et al., 2018).

One exception to this way of implementing continuous time is presented by Calford & Oprea (2017) with a timing game where two firms compete to enter a market. The authors distinguish two types of continuous time in their experiment : (realistic) inertial continuous time and perfectly continuous time. In (realistic) inertial continuous time, subjects are allowed to enter the market at any time, but both firms cannot do so at the exact same time. Indeed, subjects take a brief moment to consider whether to enter or not, which generates natural inertia in decision making. To eliminate this inertia, Calford & Oprea (2017) freeze time following the the first firm's decision to enter the market. If the other firm enters during the frozen time window, the decisions of the two players are considered as simultaneous. Otherwise, the game continues as in inertial continuous time. The authors call this perfectly continuous time.

Calford & Oprea (2017)'s protocol is interesting and easy to implement with timing games that involve one decision (e.g., entering a market). In CPR games like ours, where up to 600 decisions can be taken, this approach would become cumbersome. In our experiment we follow the literature first mentioned in (Friedman & Oprea, 2012; Oprea et al., 2014; Bigoni et al., 2015; Leng et al., 2018) and let subjects change their extraction level very frequently. In practice, the time that elapses between two instants must be short enough that the subject in the experiment experiences it as continuous. We chose to set a one-second time interval between two instants. It is not the shortest possible interval we could implement in the laboratory, but it is intuitive and easy to understand for subjects. Moreover, enough time elapses between two seconds for computers to

perform calculations and exchange information across the network.^{9,10}

To be implemented in the lab, the continuous time model thus has to be discretized. We explain how to discretize the continuous time model in order to obtain its discrete time equivalent in Appendix C.1 of Chapter 3. To provide an experiment that is as close as possible to continuous time, one has to choose a discretization step that is as small as possible. We choose $\tau = 0.1$ to capture the specific characteristic of continuous time, i.e., its uninterrupted evolution. This means that in our continuous time treatment, one second of real time corresponds to 0.1 instant in the model. Thus, 10 minutes of experiment are equal to 600 seconds and equivalent to 60 instants. In the discrete time treatment, we have chosen a larger but reasonable discretization rate, $\tau = 1$. With this rate, 1 period equals 1 instant in the model. Therefore, subjects participated in a 60-period dynamic environment. In addition, in order to ensure a similar duration in both treatments, we gave the subject exactly 10 seconds in each period to take her decision, which means that the play time was also 10 minutes in discrete time.

The graphical user interface was divided into four areas. On the top left, a graph showed the evolution of the player's extraction. At the top right, a graph displayed the evolution of the resource, and at the bottom left there was a graph showing the evolution of the payoff. Finally, at the bottom right, a text box presented the same information as the graphs but in text form. Figure B.3 in Appendix C.3 of Chapter 3 shows a screenshot of the user interface for the sole agent treatment in continuous time. In the multiple agent treatments, the user interface was identical except that an additional curve in the upper left graph showed the evolution of the group's total extraction.

⁹In the sole agent continuous time treatment, subjects were able to change their extraction rate at any moment by simply moving the graduated slider displayed on their computer. Every second, the computer transmitted the slider value to the server, which then performed the computations (resource and payoff) and updated the values displayed on the computer's graph and text interfaces.

¹⁰In the two-player continuous-time treatment, player 2's computer sent the cursor value to the server as soon as it changed, while player 1's computer transmitted the cursor value to the server every second, which triggered the server to continuously broadcast the updated values to both players. Thus, every second, the server took player 1's current extraction and player 2's most recent extraction (i.e. the last one transmitted by his computer). In this way, the time was synchronized between the two members of the group, since only one player was triggering the continuous updating of the information. This also reduced network traffic because as long as the second player did not change his extraction, his computer did not transmit a new value.

3.3.4 Infinite Horizon

Several ways of modelling the infinite horizon have been proposed in the literature. In repeated games, a heavily used solution is random termination. [Fr chet te & Yuksel \(2017\)](#) compare variations of this solution. With dynamic CPR games, an alternative to random termination is to use a continuation payoff. For our experiment we opted for continuation payoffs, as implemented by [Tasneem et al. \(2017\)](#) and [Tasneem et al. \(2019\)](#), because it allows subjects to see directly what they would earn if the game went on forever. Moreover, in a two-player game with random termination, the players may have different beliefs about the last period or instant. Continuation payoff avoids this problem.¹¹

In both continuous and discrete time, the payoff is composed of two elements : (i) a cumulative payoff from the first instant of play ($t = 0$) to the present instant ($t = p$), and (ii) a continuation payoff, which is computed as an integral of payoffs from the present instant ($t = p$) to infinity ($t = \infty$), assuming that the player's extraction remains unchanged. In the two-player game, the continuation payoff was calculated assuming that both players' extraction remained unchanged.

The cumulative payoff in continuous time corresponds to the discounted integral of the instantaneous payoffs from the beginning of the experiment up to the present instant. Thus, the discount rate is $r = 0.5\%$ and means that the payoff of instant t is multiplied by $e^{-0.005 \times t}$. The discounting principle allows subjects to understand that the same instantaneous payoff has a different discounted value according to the instant. In other words, as time goes on, the payoffs of the last instants have a lesser impact on the subject's total payoff for the experiment. Similarly, the cumulative payoff in discrete time corresponds to the discounted sum of each period's payoff from the beginning of the experiment up to the present period. Thus, the discount factor is $\beta = 0.995$ and means that the payoff of period n is multiplied by 0.995^n . The discounting principle allows subjects to understand that the same payoff has a different discounted value according to the period. In other words, in the experiment, the same instantaneous payoff contributes less to the total final payoff when it occurs in the later periods rather than in the earlier periods.¹²

¹¹[Noussair & Matheny \(2000\)](#) and [Brown et al. \(2011\)](#) show that in single-agent cases, behavior is not significantly different under random termination or continuation payoff.

¹²Note that while discounting allows us to implement the continuation payoff here, it has limited

3.4 Empirical Strategy

Two hundred subjects participated in the sole-agent (optimal control) experiment and 190 in the multiple-player (game) experiments. They took (paid) extraction decisions for 600 seconds during each session. We use these extraction decisions data to understand whether agents take different decisions in continuous vs. discrete time, and in the control vs. in the game. Through the empirical analysis, we use standard tests such as the Mann-Whitney and the Fisher exact proportion tests to compare our indicators among the different treatments. Furthermore, to determine whether agents demonstrated myopic or optimal behavior (or feedback behavior in the game), we use the empirical strategy presented in this section. For ease of understanding, the empirical strategy is first explained in detail for the sole-agent setting.

To identify which theoretical extraction pattern an agent's extraction comes closest to, a widely used statistics is the mean squared deviations (MSD, e.g., [Herr et al., 1997](#)). The minimum MSD gives the agent type. The MSDs are calculated for each agent such that :

$$\begin{aligned} MSD_{my}^{th} &= \frac{\sum_{t=1}^T (w(t) - w(t)_{my}^{th})^2}{T}, \\ MSD_{op}^{th} &= \frac{\sum_{t=1}^T (w(t) - w(t)_{op}^{th})^2}{T}, \end{aligned} \tag{3.4}$$

where $w(t)$ is the extraction of the agent at time t , $w(t)_{my}^{th}$ is the constrained myopic theoretical extraction at time t , and $w(t)_{op}^{th}$ is the optimal theoretical extraction at time t . Agents can be classified as myopic or optimal, depending on which MSD, MSD_{my}^{th} or MSD_{op}^{th} is the smallest. Comparing extractions of the agent to the theoretical constrained myopic and optimal extraction in this way is imperfect since an agent can make mistakes and begin adopting an optimal path after, say, 30 seconds, which will not be captured correctly by the method.

For instance, if an agent under-extracts for the first 30 seconds, the optimal extrac-

impact on the payoffs that are accumulated within the 10 minutes of the game. Given our parametrization, the optimal extraction rate when $R=20$ is equal to 0.56. At $t=18$ (first instant/period that $R=20$ with the optimal extraction path) it generates a payoff of 1.02 ECU, while at $t=60$ (the last instant/period), it generates a payoff of 0.82 ECU, a gap of only 20%.

tion at time 31, given the observed groundwater level H (called conditional, $w(31)_{op}^c$) will be greater than the optimal extraction at time 31 if the agent behaved perfectly optimally from time 0 ($w(31)_{op}^{th}$). Thus, in order to correctly identify an agent's behavior type - myopic or optimal - we compare observed extraction to conditional extractions throughout the remainder of the paper. Conditional extractions are computed with respect to the $t - 1$ actual groundwater level. Thus, we compute the following MSDs :

$$\begin{aligned} MSD_{my}^c &= \frac{\sum_{t=1}^T (w(t) - w(t)_{my}^c)^2}{T}, \\ MSD_{op}^c &= \frac{\sum_{t=1}^T (w(t) - w(t)_{op}^c)^2}{T}, \end{aligned} \quad (3.5)$$

where $w(t)_{my}^c$ is the conditional constrained myopic extraction of the agent at each second (every ten seconds for discrete time), and $w(t)_{op}^c$ is the conditional optimal extraction of the agent. Agents are classified as myopic or optimal depending on which MSD, MSD_{my}^c or MSD_{op}^c is the smallest.

The inconvenient of a classification of agents based on the MSD alone is that an agent will always be classified, even if he doesn't follow the theoretical patterns studied at all.¹³ To overcome this flaw, we add a second criteria based on a regression analysis. Supposing that for a given agent, we have :

$$\begin{aligned} w(t)_{my}^c &< w(t)_{op}^c, \quad or \\ w(t)_{my}^c &> w(t)_{op}^c, \end{aligned} \quad (3.6)$$

then we run the following regression :

$$\begin{aligned} w(t) &= \beta_0 + \beta_1 w(t)_{my}^c + \varepsilon_t, \quad or \\ w(t) &= \beta_0 + \beta_1 w(t)_{op}^c + \varepsilon_t. \end{aligned} \quad (3.7)$$

We consider an agent to be significantly myopic (or optimal) if β_1 is positive and significantly different from 0. This allows us to categorize the agents as : myopic, optimal,

¹³To take a concrete example, instead of comparing the agent's extraction $w(t)$ to the conditional constrained myopic and conditional optimal extraction, $w(t)_{my}^c$ and $w(t)_{op}^c$, we could compare it to the temperature in Moscow and Istanbul from day 1 to day 600, and we would find that our agent's extraction is closer to the temperature either in Moscow or in Istanbul, because one MSD will always be smaller than the other, even if completely irrelevant.

or undetermined.¹⁴ Regarding the econometric time series treatments, we implement an augmented Dickey-Fuller test to detect the presence of unit roots in the series. In case of non-stationarity of the variables, we run our regressions on a differentiated series. Serial correlation of the error terms is dealt with using Newey-West standard errors, and sensitivity tests using 1, 5, and 10 lags are implemented.¹⁵

We follow exactly the same strategy to analyze experimental data for the game, but this time for three instead of two predicted behaviors, namely : myopic, optimal and feedback. Note that the continuous time framework provides us with 600 decisions per agent, while the discrete time framework provides us with only 60. This greatly impacts our empirical strategy as β -coefficients would have more chances to be significant in continuous time - a greater number of observations leading to a lower minimum effect size. To avoid this issue, we keep only one observation every ten seconds when running the regressions in continuous time.

3.5 Results

Figure 3.3 presents an overview of our results. We plotted the mean resource by treatment along with the 95% confidence interval around the estimated mean. It seems we have close average resource levels in the two time treatments in the control, but different ones in the game. Also, the average resource level increases in the control and decreases in the game.

¹⁴An alternative is proposed by [Suter et al. \(2012\)](#), who run a similar regression (without the constant term) and consider that an agent follows a given behavior if the coefficient is not significantly different from 1. A natural way to do this is to implement a Wald test with :

$$\begin{cases} H_0 : \beta_1 = 1, \\ H_A : \beta_1 \neq 1, \end{cases} \quad \text{and} \quad W = \frac{(\hat{\beta}_1 - 1)^2}{\text{var}(\hat{\beta}_1)} \rightarrow F_{(1,300)}.$$

In this case, a very imprecisely estimated coefficient β_1 (very large $\text{var}(\hat{\beta}_1)$) will lead us to reject H_A and classify the agent as myopic or optimal, although he follows neither an optimal or myopic path. This is the reason why we propose the aforementioned alternative rule for classification.

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

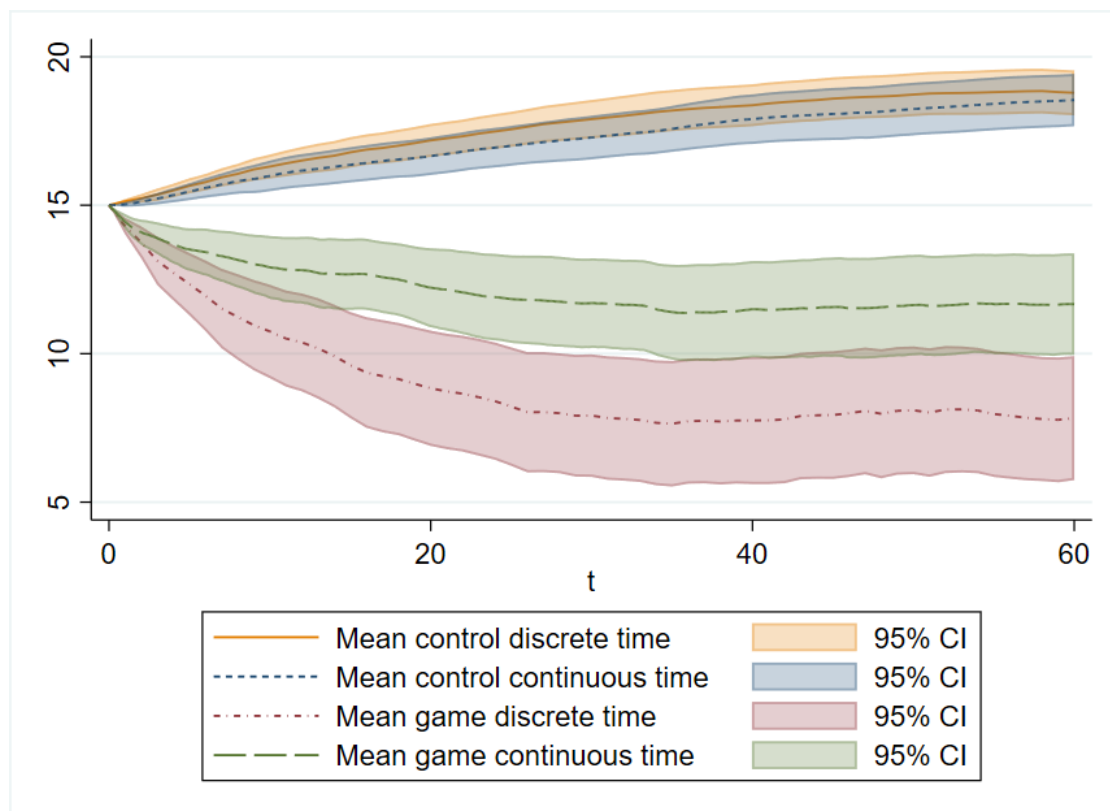


FIGURE 3.3 – Evolution of mean resource level by treatment

In the rest of the section we take a closer look at what happens within each treatment. We first compare the agents in the control setting. Second, we compare the average behaviors in the control and in the game. Third, we thoroughly study behaviors in the game. Finally, we build specific indicators to examine the potential mechanism at play. Note that through the rest of the paper, the term ‘agents’ is used to refer to subjects in the control, the term ‘players’ to subjects in the game, and the term ‘groups’ to groups of two subjects that were paired in the game.

3.5.1 Analysis of the Optimal Control

Table 3.2 compares continuous and discrete time over various indicators. The average resource level is not significantly different between the two treatments. About 40% of the players reach a resource level greater than 20 in each treatment (the optimal steady state resource level) and at approximately the same time. Only three agents in

each treatment end up with a resource level below ten. Finally, the average extraction level is around 0.50 in both treatments and, perhaps more surprisingly, the number of times the players change their extraction level is not significantly different between the continuous and discrete time treatments, while in theory they had the possibility to change it 61 times in discrete time and 601 times in continuous time.

TABLE 3.2 – Continuous versus discrete time in the control

	Average agent's resource level			Mann-Whitney test	
	Mean	S.D.	N	Z-stat	Exact prob
Discrete time	17.572	2.639	98	-0.98	0.328
Continuous time	17.144	3.297	102	-	-
			Agents reaching R=20		Fisher exact test
	Yes	No	N	Odds ratio	Exact prob
Discrete time	39	59	98	0.983	0.535
Continuous time	41	61	102	-	-
			Time agents reach R=20		Mann-Whitney test
	Mean	S.D.	N	Z-stat	Exact prob
Discrete time	23.795	13.546	39	-0.563	0.577
Continuous time	23.115	15.460	41	-	-
			Agents ending up with R<10		Fisher exact test
	Yes	No	N	Odds ratio	Exact prob
Discrete time	3	95	98	1.042	0.640
Continuous time	3	99	102	-	-
			Average agents extraction		Mann-Whitney test
	Mean	S.D.	N	Z-stat	Exact prob
Discrete time	0.497	0.064	98	0.992	0.322
Continuous time	0.501	0.075	102	-	-
			Number of agents extraction change		Mann-Whitney test
	Mean	S.D.	N	Z-stat	Exact prob
Discrete time	34.122	17.603	98	-0.304	0.762
Continuous time	44.902	47.515	102	-	-
			Agents with smaller MSD_{my}^c than MSD_{op}^c		Fisher exact test
	Yes	No	N	Odds ratio	Exact prob
Discrete time	6	92	98	0.446	0.087
Continuous time	13	89	102	-	-

The fact that we observe a substantial share of agents reaching a resource level above 20 and very few ending up with a resource level below ten is consistent with the fact that the average resource level in the control observed in Figure 3.3 is closer to the optimal than to the myopic path. This is confirmed by the MSDs map Figure 3.4,

which presents the location of agents with respect to the MSD_{op}^c on the y axis and the MSD_{my}^c on the x axis. Agents located above the bisector can be considered as more myopic ($MSD_{op}^c > MSD_{my}^c$) and vice versa. Very few agents have a greater MSD_{op}^c than the MSD_{my}^c , i.e., 19 over 200. This proportion is slightly lower in discrete than in continuous time (see the last test in Table 3.2).

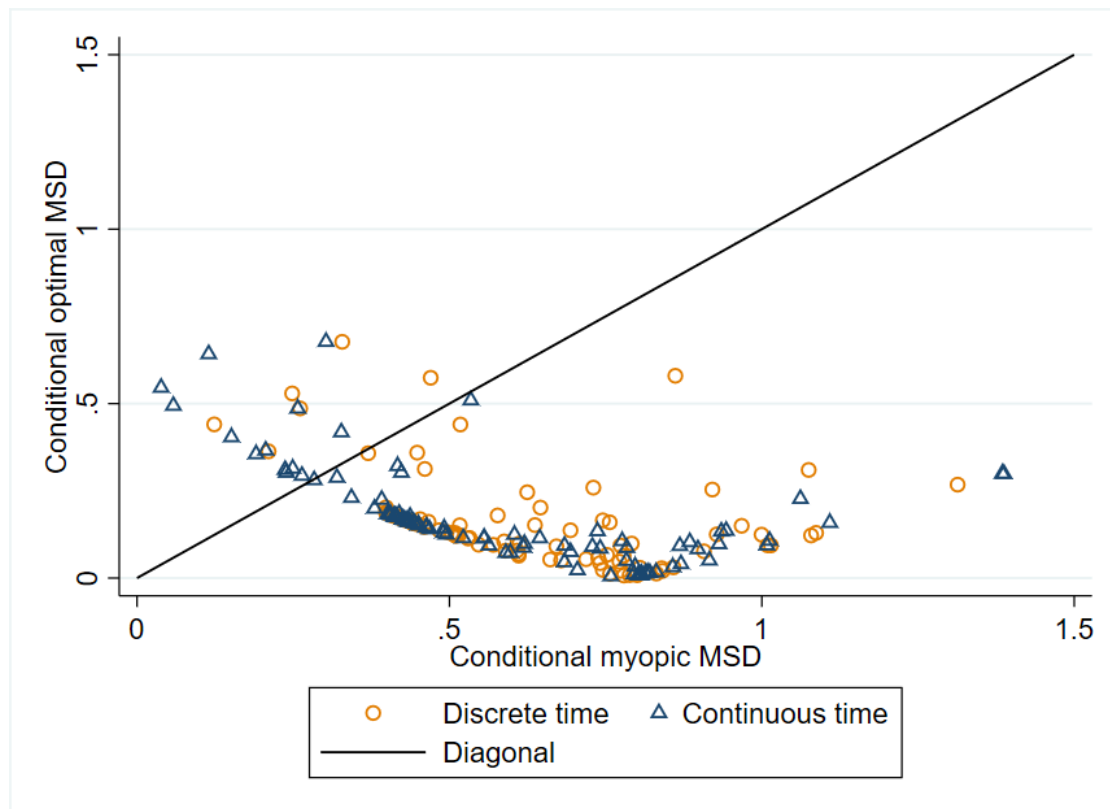


FIGURE 3.4 – Map of conditional MSDs in the control

As we explained in Section 3.4, using the MSD alone is unsatisfactory, because we want to know if agents are significantly optimal or myopic. Applying the regression filter presented in the previous section leads us to find that in discrete time 33 agents can be classified as significantly optimal and one as myopic, and 41 can be considered optimal and four as myopic in continuous time. Proportions of optimal and myopic agents are not significantly different between the two treatments. As expected, average payoffs are not significantly different either (see Table 3.3). The proportion of optimal agents seems comparable to the experiment of [Tasneem et al. \(2019\)](#) who found that

extraction behavior results in a steady state of the resource 56% of the time, with the mode of the distribution being optimal.¹⁶ Also, the average efficiency ratio (individual payoff over the optimal payoff, here 220 ECUs) is 83% in [Tasneem et al. \(2019\)](#)'s study while it is 88% in ours. [Suter et al. \(2012\)](#) found a slightly higher efficiency ratio in the optimal control in a discrete time experiment, about 95%.

TABLE 3.3 – Classification and payoffs in the control

	Proportion of optimal agents			Fisher exact test	
	Yes	No	N	Odds ratio	Exact prob
Discrete time	33	65	98	0.755	0.209
Continuous time	41	61	102	-	-
	Proportion of myopic agents			Fisher exact test	
	Yes	No	N	Odds ratio	Exact prob
Discrete time	1	97	98	0.253	0.198
Continuous time	4	98	102	-	-
	Average agents payoffs			Mann-Whitney test	
	Mean	S.D.	N	z-stat	Exact prob
Discrete time	191.370	38.497	98	-0.755	0.452
Continuous time	196.605	16.878	102	-	-

To summarize, in a control setting, both continuous and discrete times lead to similar choices by participants. Having made this first observation we now study how the nature of time affects strategic interactions between players.

3.5.2 The Control Versus the Game

The first observation that can be made by looking at [Figure 3.3](#) is that the average level of the resource is lower in the game than in the control and decreases over time, whereas the resource level was increasing over time in the control. Mann-Whitney tests reported in [Table 3.4](#) confirm that, compared to the control, the average resource level in the game is significantly lower and the average extraction level significantly higher. This is consistent with what one would expect if agents had unlimited rationality, since they would play optimal in the control and feedback in the game. In addition, we observe that agents change their extraction levels more often in the game than in the

¹⁶A more precise comparison of the results is not possible since the authors use a different empirical strategy.

control.

TABLE 3.4 – Control versus game

	Agent and group average resource levels			Mann-Whitney test	
	Mean	S.D.	N	Z-stat	Exact prob
Control	17.354	2.993	200	9.720	0.000
Game	1.653	5.406	95	-	-
	Agent and group average extraction levels			Mann-Whitney test	
	Mean	S.D.	N	Z-stat	Exact prob
Control	0.499	0.069	200	-10.025	0.000
Game	0.652	0.012	95	-	-
	Number of agents and groups extraction changes			Mann-Whitney test	
	Mean	S.D.	N	Z-stat	Exact prob
Control	39.62	36.415	200	-5.541	0.000
Game	60.658	56.041	190	-	-
	Agents and groups with smaller MSD_{my}^c than MSD_{op}^c			Fisher exact test	
	Yes	No	N	Odds ratio	Exact prob
Control	19	181	200	0.207	0.000
Game	32	63	95	-	-

Finally, the MSDs map reported in Figure 3.5 shows that, compared to Figure 3.4, significantly more agents have a smaller MSD_{my}^c than MSD_{op}^c in the game than in the control (32 groups over 95, see Fisher test in Table 3.4).

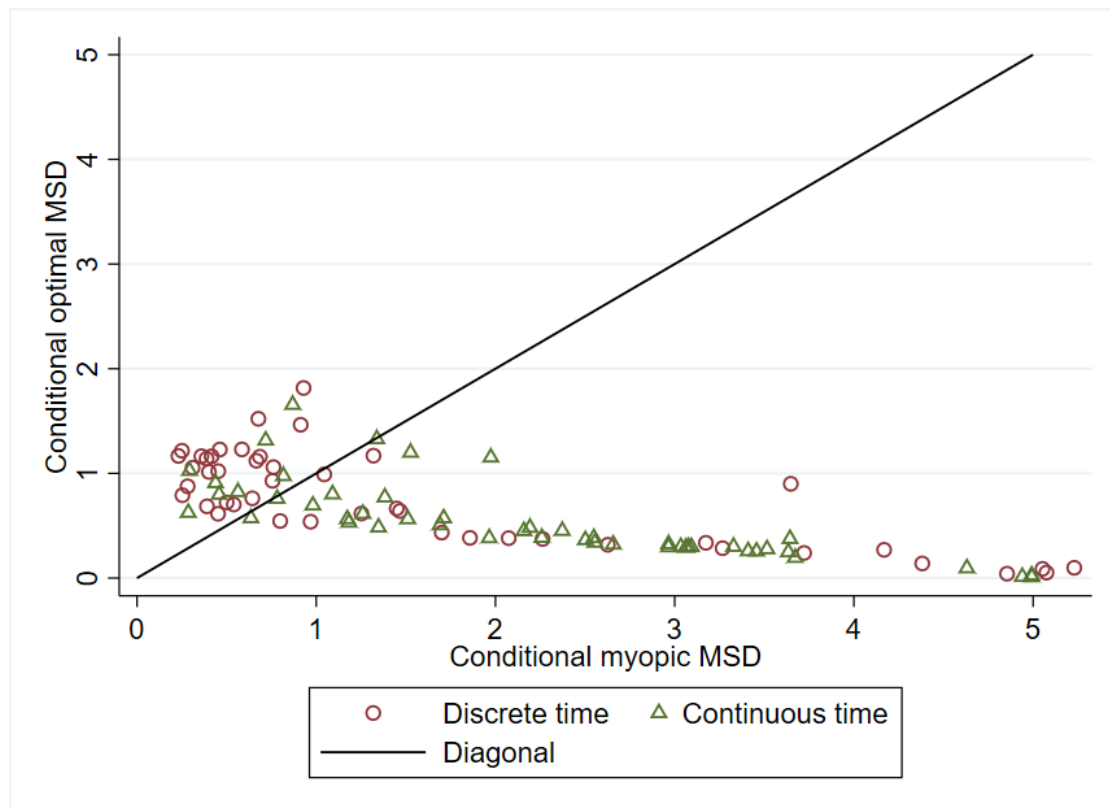


FIGURE 3.5 – Map of conditional group MSDs in the game

3.5.3 Analysis of Behaviors in the Game

Table 3.5 compares the decisions in discrete and continuous time in the game over various indicators. The average resource level is significantly lower in discrete time and the average extraction significantly higher. Very few groups reach a resource level greater than 20 – only five in each treatment, and at approximately the same time. The big difference with the control is that now a large number of groups end up with a resource level below ten and in a significantly larger proportion in discrete time. Introducing strategic interaction thus leads to an over-exploitation of the resource, as the theory predicted, but to a greater extent in discrete time, suggesting that continuous time allows for better cooperation between players. Finally, the number of times the agents change their extraction level is now significantly greater in continuous time.

Continuous time offers more opportunities to change one’s extraction level. This possibility can be used to test the reaction of the other players and perhaps to try to

induce a change in their behavior. For example, one player can temporarily lower his extraction level to see if the other player will do the same. This type of test is less expensive in continuous time than in discrete time. Indeed, in discrete time, the player can only make one decision per period and this corresponds to one instant, whereas in continuous time, the player can make one decision per second and this corresponds to only 0.1 of an instant. In other words, the opportunity cost of testing a strategy, in terms of payoff, is much lower in continuous time, because only a fraction of the payoff is given up during the temporary test strategy. This mechanism through which continuous time can foster cooperation was also advanced by [Friedman & Oprea \(2012\)](#), [Oprea et al. \(2014\)](#) and [Leng et al. \(2018\)](#). [Oprea et al. \(2014\)](#) calls this "pulse behavior" and sees it as a non-verbal form of communication. It can be used as a way to incite the other player to decrease extraction up to the optimal level or to retaliate if the other players increase their extraction level too much.

TABLE 3.5 – Continuous versus discrete time in the game

	Average group resource			Mann-Whitney test	
	Mean	S.D.	N	Z-stat	Exact prob
Discrete time	9.06	5.884	46	2.867	0.004
Continuous time	12.149	4.477	49	-	-
	Groups reaching R=20			Fisher exact test	
	Yes	No	N	Odds ratio	Exact prob
Discrete time	5	41	46	1.073	0.589
Continuous time	5	44	49	-	-
	Time required for groups to reach 20			Mann-Whitney test	
	Mean	S.D.	N	Z-stat	Exact prob
Discrete time	27.8	12.911	5	0.314	0.314
Continuous time	32.46	14.622	5	-	-
	Groups ending up with R<10			Fisher exact test	
	Yes	No	N	Odds ratio	Exact prob
Discrete time	31	15	46	3.89	0.001
Continuous time	17	32	49	-	-
	Average players extraction			Mann-Whitney test	
	Mean	S.D.	N	Z-stat	Exact prob
Discrete time	0.345	0.129	92	-2.352	0.019
Continuous time	0.308	0.114	98	-	-
	Number of extraction changes by players			Mann-Whitney test	
	Mean	S.D.	N	Z-stat	Exact prob
Discrete time	40.674	16.202	92	4.203	0.000
Continuous time	79.418	71.68	98	-	-

Applying the regression filter presented in Section 3.4 leads us to find that 14 groups (28 players) can be classified as significantly myopic in discrete time versus three groups in continuous time, making the proportion of myopic behavior significantly larger in discrete time. Six groups are classified as feedback in the two treatments, and we find only two optimal in discrete time and one in continuous time. Proportion of optimal and feedback agents are not significantly different between discrete and continuous time. Note that the presence of optimal groups is consistent with [Battaglini et al. \(2016\)](#)'s argument that infinite horizon can provide strategic opportunities to endogenously support cooperative outcomes.

As a result, we observe significantly higher average individual payoffs in continuous time than in discrete time. Efficiency ratios in the game are lower than in the

control, and lower in discrete time (48%) than in continuous time (64%).¹⁷

TABLE 3.6 – Analysis of types in the game

	Proportion of optimal groups			Fisher exact test	
	Yes	No	N	Odds ratio	Exact prob
Discrete time	2	44	46	2.182	0.476
Continuous time	1	48	49	-	-
	Proportion of feedback groups			Fisher exact test	
	Yes	No	N	Odds ratio	Exact prob
Discrete time	6	40	46	1.075	0.575
Continuous time	6	43	49	-	-
	Proportion of myopic groups			Fisher exact test	
	Yes	No	N	Odds ratio	Exact prob
Discrete time	14	32	46	6.708	0.002
Continuous time	3	46	49	-	-
	Average individual payoffs			Mann-Whitney test	
	Mean	S.D.	N	Z-stat	Exact prob
Discrete time	57.987	46.233	92	3.184	0.002
Continuous time	76.806	41.897	98	-	-

Finally, Figure 3.6 provides an overview of the results of the classification by type by plotting the cumulative density functions (c.d.f.) of the resource levels. The distribution of the observed resource levels rank as expected, with the myopic groups experiencing the lowest resource levels, followed by the feedback and optimal groups. The undetermined group displays a high level of heterogeneity, which could be of interest in further research.

¹⁷The maximum group payoff is 240 ECUs, so we computed the individual efficiency ratio by halving this value. Nevertheless, it is possible to get "more than your own share". Obviously, if one of the two members of the pair extracts a very small amount of groundwater, the other member can obtain more than 50% of the total maximum payoff.

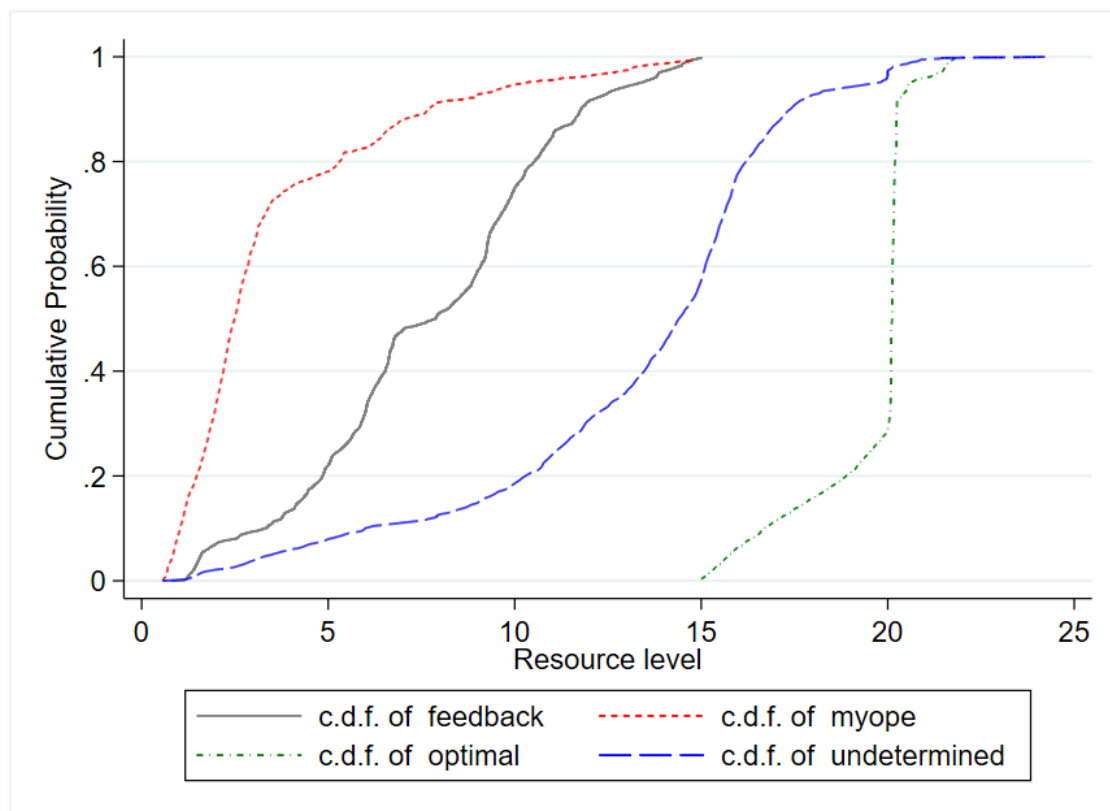


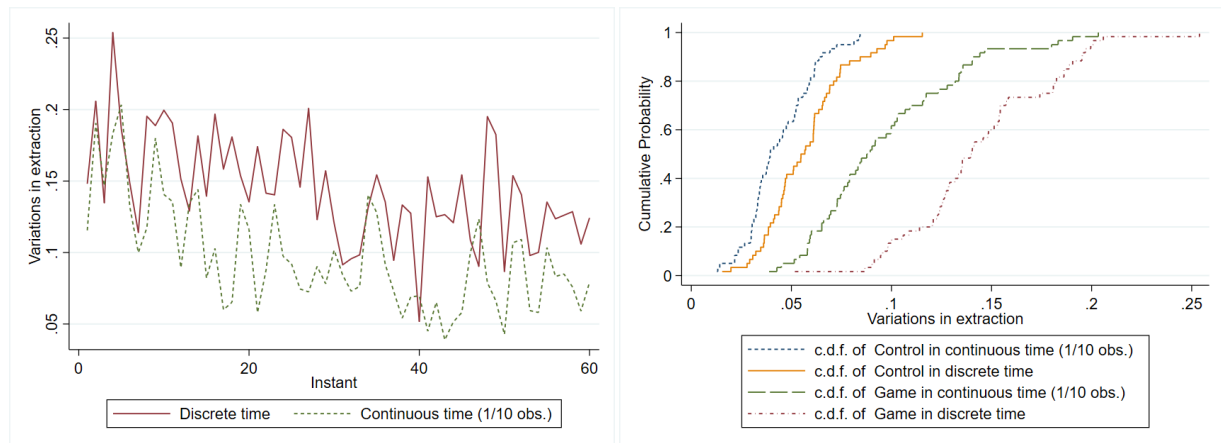
FIGURE 3.6 – Cumulative density functions of the resource levels by type

3.5.4 Potential Mechanism at Play

Our results show that continuous time fosters cooperation and allows for more sustainable management of the resource than does discrete time. Our intuition is that continuous time offers the possibility to induce cooperation at a lower opportunity cost, by lessening one’s own extraction to incite the other player to do the same or to retaliate against them for over-extracting. If this mechanism actually applies, the threat of immediate sanction should make extraction patterns more stable and extraction levels should be more homogeneous, resulting in a more even distribution of payoffs within groups. To test this reasoning, we compute several statistics.

First, for each player we compute the absolute value of the difference of extraction between two consecutive instants ($|E_t - E_{t-1}|$) and calculate the average value over

time by treatment, as did Oprea et al. (2014).¹⁸ As shown by Figures 3.7.a and 3.7.b, continuous time leads to greater stability than does discrete time, and, not surprisingly, playing alone leads to greater stability than playing with someone else.¹⁹



(a) Evolution through time in the game

(b) Cumulative density functions

FIGURE 3.7 – Variations in players' extraction levels (w)

Second, we compute the absolute value of the difference in extraction levels between two players (A and B) of the same group at each point in time ($|E_{tA} - E_{tB}|$). We then take the average value over each period of time, by treatment.²⁰

Figure 3.8.a shows that the average difference in extraction inside groups is almost always greater in discrete time, which is confirmed by the c.d.f. displayed in Figure 3.8.b.²¹ Also, although extraction level differences decrease over the course of the game, it remains an issue until the end. Indeed, at the last instant the average difference in extraction levels still represents two-thirds of the average player's extraction.²²

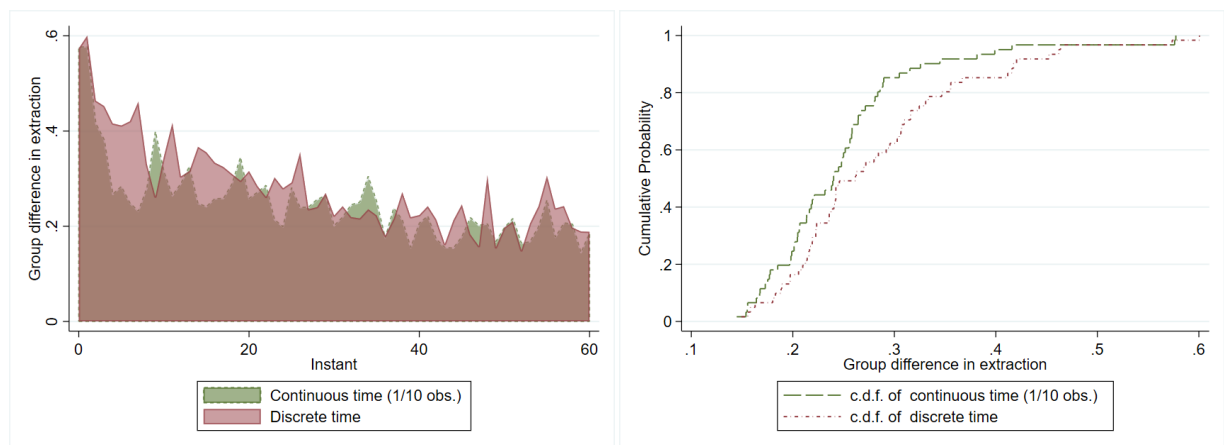
¹⁸To make continuous and discrete time comparable, we take the difference between two decisions separated by ten seconds in continuous time.

¹⁹In Figure 3.7.a we also see an increase in stability over time for both treatments. Note, however, that the greater instability in the beginning of the play time can be explained by the game setting. Indeed, players need first to either let the resource grow or deplete it before reaching a steady state, depending on their preferred equilibrium.

²⁰To make continuous and discrete time comparable, we use only one decision every ten seconds in continuous time.

²¹The c.d.f. are statistically different according to the Kolmogorov-Smirnov test (p-value < 0.05).

²²The average difference in extraction between players of the same group at the end of the game equals 0.18, while the average player's extraction level equals 0.27.



(a) Evolution through time

(b) Cumulative density functions

FIGURE 3.8 – Difference of extraction levels (w) within groups

To see whether or not within-group differences in extraction levels results in more unequal distribution of payoffs, we compute the Lorenz curves of individual final payoffs in the game. We can see in Figure 3.9.a that final payoffs are more unequally distributed in discrete time. More precisely, 50% of the poorest players share 28% of the payoffs in continuous time while they share 17% in discrete time. The Lorenz curves in Figure 3.9.a are easily readable but here unequal distribution can come from between-group inequalities and within-group inequalities. To take a closer look at within-group inequalities we compute the difference between individual final payoffs within a group and plot the corresponding Lorenz curves (Figure 3.9.b). Payoff distribution is more unequal in the discrete time setting. If within-group payoff differences were the same for all groups, the Lorenz curves would be confounded with the diagonal. Here we see that large payoff-differences represent a greater proportion of total payoff differences in discrete time than in continuous time, as the Lorenz curve for discrete time is further from the diagonal than the Lorenz curve for continuous time.²³

²³Concentration (Gini) indexes are significantly different whether we use the standard, Erreygers or Wagstaff indexes (O'Donnell et al., 2016).

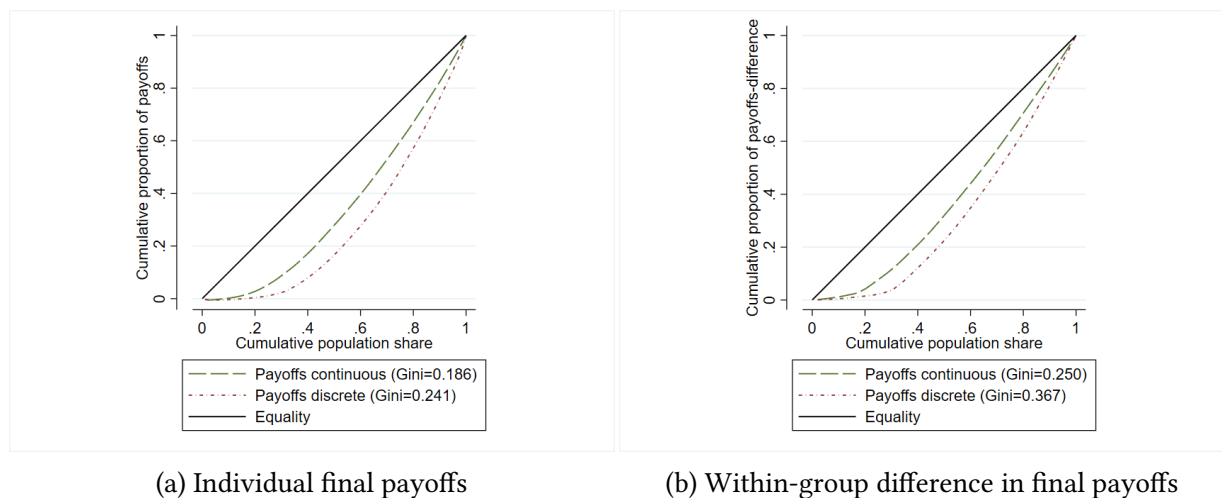


FIGURE 3.9 – Lorenz curves

To summarize, even if we cannot prove the mechanism at play, the fact that extractions are more stable and that within-group differences in final payoffs are lower in continuous time is consistent with the fact that continuous time offers a less costly opportunity to influence the other player’s decisions. As a result, continuous time seems to reduce inequality in payoff distribution, in addition to favoring more sustainable resource exploitation.

3.5.5 Behavior at the End of the Game

Given the way we model the infinite horizon, one might expect the last period/instant decisions would be greatly informative about players’ behavior and equilibrium selection in the multi-player treatments. Graphs previously displayed, and those presented in Appendix C.4 of Chapter 3, do not support this conjecture. Indeed, the average resource level remains stable (see Figure 3.3). Final payoffs and resource levels are aligned with expectations regarding player profiles over the course of the game, with optimal players earning the highest payoffs, followed by feedback and myopic players (see Figures B.4 and B.5 in Appendix C.4 of Chapter 3). Regarding extraction levels, we do not observe any specific changes during the final instants/periods. The percentage of subjects who change their extraction level during the last instants/periods is not greater than during the rest of the play time (see Figure B.6 in Appendix C.4 of Chapter 3), nor is the variation in extraction levels (see Figures 3.7 and 3.8). Finally the analysis of the

last instant/period extraction level by group of subjects is not particularly informative (see Figures B.7 in Appendix C.4 of Chapter 3). We observe that ten groups end up with an extraction level greater than the natural recharge R (implying a depletion of the resource in the long run) in discrete time and ten in continuous time. Among these groups, five are classified as myopic, one as feedback and fourteen as undetermined (see Table C.1 in Appendix C.4 of Chapter 3). It appears that equilibrium selection is determined over the whole course of the game, as many decisions influence the resource level, and that the last instants/periods are not specifically informative about subjects' behavior. This suggests that the use of continuation payoffs to simulate the infinite horizon works well in our context and do not lead to strategic behaviors during the last instants/periods.

3.6 Discussion and Conclusion

In this paper, we attempted to determine the impact of the nature of time, discrete or continuous, on the behavior of agents in the context of a dynamic CPR game. To this end, we considered a simple linear quadratic model in which agents exploit a renewable resource over an infinite time horizon. Starting from a differential game, we proposed a discretization such that the equilibrium paths for the myopic, feedback and optimal behaviors are almost identical in discrete and continuous time. We then took on the challenge of implementing continuous time and infinite horizon in the lab, allowing participants to make extraction decisions every second, and adding continuation payoffs to cumulative payoffs to simulate an infinite horizon.

To determine whether the nature of time has an impact on the ability of agents to manage a resource, we first looked at the situation where the resource is owned by a single agent. Observations showed no difference between discrete and continuous time, based on a battery of indicators, including the average level of the resource, the average level of extraction, the proportion of myopic agents, and the proportion of optimal agents. Furthermore, about 35% of the subjects could be classified as significantly optimal and the average resource level increased over time, as is the case with the optimal solution.

In the context of a two-player game, the results were dramatically different. First, unlike what we observed with a single agent, the average resource level decreased over

time, as is the case with the myopic and feedback equilibrium paths. Furthermore, only 2% of the groups behaved according to the optimal (cooperative) path. The competitive nature of the game when multiple players simultaneously extract the same resource explains the difficulty in adopting a sustainable path. Second, we observed significant differences between discrete and continuous time settings. In particular, the discrete time setting led to the observation of a larger number of agents exhibiting myopic behavior, thus leading to a much lower average resource level than that observed in the continuous time setting. The continuous time environment seems to allow for better cooperation within groups and thus greater resource sustainability. Although our experimental design does not allow us to prove the exact mechanism at play, our intuition is consistent with [Friedman & Oprea \(2012\)](#), [Oprea et al. \(2014\)](#) or [Leng et al. \(2018\)](#) : compared to discrete time, continuous time allows for rapid and adaptive strategic choices that promote the emergence of cooperation, either by attempting to influence the other or by retaliating against their tendency to over-exploit the resource. The observed greater stability of continuous-time extraction, as well as the greater homogeneity within groups in this environment, is consistent with this explanatory mechanism.

We voluntarily used a very simple design, as to our knowledge we are the first paper to test the impact of the nature of time in dynamic CPR games. Consequently, many extensions are possible. We hope our work can offer a basis for future works examining, for instance, whether continuous time can still foster cooperation when increasing the group size, as the continuous time frame by itself was able to induce cooperation compared to the discrete time frame in a two-person prisoner's dilemma in [Friedman & Oprea \(2012\)](#), but not in a five-person public good game as in [Oprea et al. \(2014\)](#) or a six-person minimum effort game as in [Leng et al. \(2018\)](#). Also, many refinements of the underlying theoretical model and of the game setting are possible. In particular, the role of major mechanisms such as rewards, punishments and communication settings in the continuous versus the discrete time frame remain to be examined.

In the next chapter, we present the results of a continuous time experiment over an infinite horizon, in which we propose non-monetary instruments belonging to the class of nudges, to induce groundwater users to adopt pro-environmental behavior.

Chapitre 4

Nudging Behaviors in a Dynamic Common Pool Renewable Resource Experiment

Abstract:

The seminal papers of [Gordon \(1954\)](#) and [Hardin \(1968\)](#) show the need for regulation to insure a better management of common pool resources. Thus, in recent decades, in addition to traditional monetary policies, new non-monetary instruments called nudges have emerged to guide individuals to efficient decisions. This paper aims to test the influence of nudges based on a descriptive social norm, as well as on an injunctive social norm, in the management of dynamic common pool resources, with a particular interest on differential games. Our results suggest that the highest efficiency is provided by the injunctive nudge, but should be interpreted sparingly.

Keywords: Dynamic Optimization; Experimental Economics; Renewable Resources; Nudges

Codes JEL : C91; C92; Q20; Q58

Résumé :

Les articles fondateurs de [Gordon \(1954\)](#) et [Hardin \(1968\)](#) montrent la nécessité d'une réglementation pour assurer une meilleure gestion des ressources communes. Ainsi, au cours des dernières décennies, en plus des politiques monétaires traditionnelles, de nouveaux instruments non-monétaires appelés nudges sont apparus, afin de

guider les individus dans les prises de décisions efficaces. Cet article vise à tester l'influence de nudges basés sur une norme sociale descriptive, ainsi que sur une norme sociale injonctive, dans la gestion de ressources communes dynamiques, avec un intérêt particulier pour les jeux différentiels. Nos résultats suggèrent que le nudge injonctif procure une efficacité plus élevée, mais ils devraient être interprétés avec précaution.

Mots-clés : Optimisation Dynamique ; Économie Expérimentale ; Ressources Renouvelables ; Nudges

Codes JEL : C91 ; C92 ; Q20 ; Q58

4.1 Introduction

The management of environmental resources is an issue that has a major impact in recent decades, especially since [Hardin \(1968\)](#) considered that in the absence of regulation, common pool resources (CPRs) are doomed to overexploitation. This is mainly due to their rival and non-excludable nature. The key question that economists ask themselves in order to solve this problem is how to encourage resource users to behave in a way that respects the exploited resource. The most common methods to incentivize people to behave this way has long been the use of monetary instruments, such as taxes. Ambient tax/subsidy is commonly applied in the control of nonpoint source pollution (NPSP). It consists of a taxation mechanism combining a system of reward for water quality above a given target (for instance, the social optimum level) and a system of penalty under this target ([Segerson, 1988](#); [Xepapadeas, 1991](#); [Cochard et al., 2005](#)). However, tax-based incentives are not without crowding out individuals in their willingness to make efforts in favor of the environment. In order to limit this crowding out effect, policy makers are increasingly turning to either non-monetary incentives or a mix of monetary and non-monetary incentives.

Among the non-monetary instruments, we distinguish "nudges", which are defined by [Thaler & Sunstein \(2009\)](#) as a choice architecture, a special case of libertarian paternalism where a planner guides individuals to make the choices they consider to be the best, while preserving their freedom of choice. Praised for their low cost, non-binding nature and ease of implementation, nudges have attracted growing interest in recent years. In the United States, President Obama signed in 2009 a memorandum to clarify the role of behavioral sciences in regulatory policy formulation. In the Uni-

ted Kingdom, David Cameron also created the Behavioral Insights Team (the "nudge unit") within Prime Minister Services, to analyze the efficiency of behavioral instruments like nudges (Croson & Treich, 2014). In his book entitled "Green Nudges", Singler (2015) mentioned his willingness to spread the word about the nudges approach, which according to him is a formidable lever for action to promote sustainable development, but which is still very little used in France. Finally, international institutions such as the World Bank, also share the idea that nudges are a new way to promote sustainable behavioural changes, as described in the World Bank's "Mind, Society, and Behavior" report (Bank, 2014).

The question is therefore to know how we can use non-monetary instruments to improve cooperation in order to induce a pro-environmental behavior when the dynamic nature of the exploited resource is considered. To answer this question, we start from a dynamic framework in continuous time, in which the resource evolves continuously over an infinite horizon. We assimilate the renewable resource to a groundwater basin, but other types of resources can be considered. The implementation of continuous time in the laboratory is very recent and very challenging, as it allows subjects to make their decisions at any time during the experiment, which requires continuous updating of the data. We must therefore distinguish "quasi-continuous" experiments, which are based on extensive form games, from "continuous time" experiments, which are based on dynamic games. In quasi-continuous experiments, studies sometimes refer to the prisoner's dilemma (Friedman & Oprea, 2012; Bigoni et al., 2015), public goods games (Oprea et al., 2014) or minimum effort games (Leng et al., 2018).¹ To our knowledge, the only continuous time experiments applied to renewable common pool resources are those proposed by Tasneem et al. (2017, 2019); Djiguemde et al. (2021). In this study, the continuous time model is based on the one proposed by Djiguemde et al. (2021), to compare continuous to discrete time in a dynamic common pool resource experiment. They found that the trajectories adopted by experimental subjects in the game were different between continuous and discrete time. Continuous time plays an important role in fostering cooperation, as it allows a fast adjustment of players decisions. Moreover, it allows to simulate the real world evolution of common pool resources.

¹The implementation of continuous time in the laboratory, has also required the consideration of spatial and temporal aspects in order to simulate the real life evolution of social ecological systems (Janssen et al., 2010; Cerutti, 2017).

The main objective of this study is to guide the greatest number of players towards the cooperative solution, i.e., the social optimum, by means of paternalistic mechanisms such as nudges. Among the different categories of nudges, we consider those exploiting social norms, as it is the most widespread category whether in the field of food, energy, transportation or more recently, common pool resources. In addition to be intuitive for the subjects, who very often tend to follow the crowd, their implementation seems to be simple. Social norms constitute the moral rules of a group and we can distinguish descriptive norms from injunctive norms. According to [Cialdini et al. \(1991\)](#), descriptive or popular norms characterize the perception of what most people do. They inform behavior, i.e., they specify "**what is done**". Injunctive or prescriptive norms characterize the perception of what most people approve or disapprove. They enjoin behavior, i.e., they specify "**what ought to be done**". The second objective is to investigate which kind of norm among the descriptive norm and the injunctive norm will lead to more cooperation and more pro-environmental behavior.

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.

4.2 The Literature

Our paper is related to the growing literature on experiments dealing with non-monetary instruments such as nudges, to foster pro-environmental behavior. Nudges have many applications in the three areas of sustainable consumption, namely food, energy and transportation, where they are most implemented. However, in recent years we have witnessed the emergence of nudges in the field of public goods and renewable common pool resources. Faced with this profusion of nudges, their classification sometimes differs according to the authors, but [Lehner et al. \(2016\)](#) as well as [Schubert \(2017\)](#) have nevertheless managed to propose a synthetic classification ranging from three to four categories. We can thus distinguish :

- Nudges that **exploit defaults**. This category of nudges is based on laziness or the tendency of individuals to procrastinate. The best known example is the default

double-sided printing

- Nudges that **change the physical environment**. [Kallbekken & Sælen \(2013\)](#) found that by reducing the plate size from 24 cm to 21 cm food waste was reduced by 19.5%
- Nudges that capitalize on consumers' desire to maintain an **attractive self-image** through "green" behavior. This category includes the simplification of information, to reduce the cognitive costs necessary for the exercise of self-control (e.g : eco-labels). It also includes the framing of information through contextualization and the exploitation of people's private sense of social identity through emulation, which stimulates competition for social status ²
- Nudges that **exploit social norms**. It is the most widespread category of nudges and it plays on the tendency of individuals to imitate peers, i.e., to follow the most socially widespread behavior. For instance, [De Castro \(2000\)](#) show an increase in total food consumption with the number of people around the table. While a meal shared with one person increases total consumption by 33%, a meal shared with seven or more people results in a doubling of consumption

The following papers analyze the decision-making processes of individuals under both a tax-based incentive (or a deterrence-based incentive) and a nudge-based incentive. In a repeated public good game, [Festré et al. \(2019\)](#) compare the impact of an advice to that of a collective sanction.³ The experiment was repeated over 10 periods with groups of four players, where an additional player called the third-party was introduced. Their results show that the advice significantly increase cooperation, but this positive effect vanishes over time, while sanction as well as the threat of sanction has a significant impact on contributions to the public good, with no crowding out effects.⁴ Moreover, [My & Ouvrard \(2019\)](#) analyzed subjects' voluntary contribution to

²For instance, the website of stickK offers challenges based on personal commitment to help participants achieve their goals (weight loss, green initiatives, etc.). The website is available at : <https://www.stickk.com/>

³See [Festré et al. \(2017\)](#) for the english working paper version of their article.

⁴The Advice treatment can be considered as a combination of descriptive, injunctive social norms and engaging communication, in which subjects were allowed to receive an advice from the third-party, on any desirable level of individual contribution.

a stochastic public good i.e., the reduction of pollution. The authors first measured subjects' environmental sensitivity by means of the General Ecological Behavior Scale (Kaiser, 1998), to classify them into two categories of players. For each category, they formed groups of four players to participate in a 15 periods public goods game. The main results were that the reaction to the nudge directly depends on subjects' environmental sensitivity, and that contrary to the tax treatment, the effect of the nudge vanishes over time.⁵ Using a static common pool resource experiment, Buckley & Llerena (2018) tried to incentivize consumers to reduce their energy consumption during peak periods. Groups of four players participated in a repeated CPR game over 10 periods. They found that although the nudge is more effective than the tax, it is not enough in itself. They also found in line with My & Ouvrard (2019) that the reaction to the nudge depends on subjects' environmental sensitivity, but also depends on their altruism.⁶ In the management of recreational fisheries, deterrence-based approaches (fines, loss of licenses or in extreme cases, imprisonment) are not sufficient to solve the problem of non-compliance, which consists in fishing more than the allowed quantities. In this context, Mackay et al. (2020) used in addition to these approaches, a nudge based on a descriptive social norm to tackle non-compliance. Groups of six players participated in a static one-shot framed CPR game. Their results show a 10% increase in compliance, when using the descriptive social norm with a low deterrence. Although a high level of deterrence increases compliance by 30%, adding a descriptive social norm increases compliance by only 33%.⁷

Our paper is related to the literature on nudge based on social norms. Although we are getting closer to the papers on public goods games and renewable resources, we differ from them in that we use a dynamic CPR in continuous time and infinite horizon. Another difference is that we compare two types of social norms, i.e., a descriptive social norm and an injunctive social norm.

⁵The nudge belongs to the class of injunctive social norms, and consisted of an announcement of the optimal contribution at the beginning of each period, in the form : "The best solution for the environment and your group is to invest X tokens in the environmental account".

⁶The nudge combine both information on suggested play and social approval from the regulator, who uses a smiley face or a sad face to inform subjects if they consume less or more than the optimal amount. This social approval can be considered as a kind of injunctive norm. In the suggested play, subjects were told that "one way to avoid power cuts is to ask consumers to lower their consumption during peak periods".

⁷A 20% probability of being randomly inspected for low deterrence and of 50% for high deterrence.

4.3 The Model

We consider a simple continuous time linear quadratic model in which two farmers use simultaneously a renewable groundwater basin. Each farmer i make his/her 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 B.1 and B.2 in Appendix C.3 of Chapter 3 show a farmer's revenue function and the marginal cost function. Equation (4.1) denotes an agent's instantaneous payoff, which is given by the difference between revenue and costs :

$$\overbrace{aw - \frac{b}{2}w^2}^{B(w)} - \underbrace{\max(0, c_0 - c_1H)}_{C(H,w)} w. \quad (4.1)$$

where the marginal cost $c(H)$ is given by Equation (4.2) :

$$c(H) = \begin{cases} (c_0 - c_1H) & \text{if } 0 \leq H < \frac{c_0}{c_1}, \\ 0 & \text{if } H \geq \frac{c_0}{c_1}. \end{cases} \quad (4.2)$$

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 :

$$V(H_0) = \max_{w_1(t), w_2(t)} \int_0^\infty e^{-rt} \sum_{i=1}^2 \left[aw_i(t) - \frac{b}{2}w_i(t)^2 - \max(0, c_0 - c_1H(t))w_i(t) \right] dt, \quad (4.3)$$

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

The Nash feedback equilibrium is found by solving the previous maximization problem without the sum, while the myopic maximization equilibrium is found by solving only the equation in brackets. By considering the constraints, the myopic solutions provides a feedback representation.⁸

4.4 Experimental Design and Procedures

We conducted three treatments at the Experimental Economics Laboratory of Montpellier (LEEM) : the baseline and two nudge treatments. The baseline was conducted from November to December 2020 during 10 sessions, with 98 subjects. The two nudge treatments were conducted in July and September 2021 and involved 114 subjects. Table 4.1 shows information about each treatment. Groups of two subjects participated in a non-contextualized experiment, using the oTree software (Chen et al., 2016). Each session lasted between an hour and an hour and a half. At the end of each session, the experimental currencies (ECUs) accumulated during the experiment were converted into cash payments at the rate : 10 ECUs = 0.5 Euros.

Treatments	Number of sessions	Number of subjects	Number of groups
Baseline	10	98	49
Injunctive Norm	5	62	31
Descriptive Norm	7	68	34
Total	22	228	114

TABLE 4.1 – Information per treatment

⁸The feedback representation is obtained when the solution is written according to the state variable, instead of according to time.

It was a between-subject design, in which subjects participated in several tasks. After an individual reading, an experimenter proceeded to a loud relecture of the instructions. Then, subjects answered a computerized comprehension questionnaire to ensure they understood the evolution of the resource as well as the computation of payoffs. They were allowed to ask questions at any time by rising their hands. To get familiar with the graphical interface and the dynamics of the game, subjects played a ten-minute training phase, before playing the ten-minute paid phase.

In each treatment and at the beginning of each phase, groups of two subjects had to individually choose an initial extraction rate between 0 and 2.8 units by moving a graduated slider, which allows values with two decimals. Groups were randomly formed for each phase. Following the choice of the initial extraction rate, a new screen allowed subjects to see the evolution of their extraction rate, as well as that of the total extraction rate of the group. They can see in addition the dynamics of the resource and their payoff, as shown by the user's interface on Figure B.16 in Appendix C.6.1 of Chapter 3. An additional box presented the same information as the curves in text form and at any time during the experiment, subjects could read the experimental instructions by clicking on the "Review Instructions" button on the upper right corner of their screens. They also had the possibility to change their extraction rate whenever they wanted by moving the slider. In all the treatments except the baseline, subjects completed a General Ecological Behaviour (GEB) Scale questionnaire (Kaiser, 1998), in order to measure their environmental sensitivity and distinguish groups who are more sensitive to those who are less sensitive to the environment.⁹ A demographic questionnaire concluded the experiment in all treatments.

All the information were updated every second to simulate continuous time. More specifically, one second of real time in our treatments, corresponds to 0.1 instant in the model, so that 10 minutes of experiment are equal to 600 seconds and are equivalent to 60 instants. The infinite horizon is simulated through the payoffs, which are composed of: (i) a cumulative payoff since the beginning of the experiment to the present instant, to which is added (ii) a continuation payoff from the present instant until infinity, by assuming that the player's extraction rate and that of his partner's remain constant.

⁹There was no GEB questionnaire in the baseline because the baseline was conducted before the nudge treatments and the research question was different (continuous vs. discrete time).

The discounting principle behind the cumulative payoff implies that as time goes, the less important the instantaneous payoff. Table 4.2 reports the parameters used in the experiment.¹⁰

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
$c_0 - c_1H$	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 4.2 – Parameters for the experiment

4.4.1 The Nudge Treatments

The proposed nudges consist in graphic information. The first nudge is an injunctive social norm, in which subjects were given the theoretical time paths for the resource, resulting from our three benchmarks, with the corresponding payoffs in experimental currencies. The details of this treatment are available in Appendix D.1.2 of Chapter 4. The second nudge is a descriptive social norm, in which subjects were given the time paths for the resource, resulting from the behaviors observed in the baseline treatment, along with the frequency of the observed groups and the corresponding average individual payoffs in experimental currencies. More details on this treatment are provided in Appendix D.1.3 of Chapter 4. These graphical information was displayed after the training phase. Subjects had the possibility to review them, by clicking on the "Information" button, located next to the button allowing to review the instructions, as shown by Figure B.3 in Appendix D.1 of Chapter 4. Subjects were also informed that they are free to follow this information or not.

¹⁰For more details on the model, the implementation of continuous time and the infinite horizon, as well as the choice of the parameters, one can refer to (Djigumde et al., 2021).

The two treatments with social norms differ in several elements. First, the curves presented in the injunctive norm are obtained theoretically in an infinite horizon model while in the descriptive norm the infinite horizon is approximated by a scrap value as explained in the description of the payoff. Moreover, we specify in the injunctive norm that these are theoretical results obtained with symmetrical players, while in the descriptive norm, these are the results of the baseline for which the players are not necessarily symmetrical. Finally, in the descriptive norm there is an additional curve which does not exist in the injunctive norm, because this type of behavior is not explained by the theory. The descriptive norm also presents in detail the share of the population associated with each resource level. Given these differences in presentation, we made some conjectures about the potential behaviors in our different treatments.

Conjecture 1 *Behaviors in nudge treatments will result in more resource preservation than in the baseline.*

We believe that having more information about the best behavior to adopt or even the most adopted behavior, could lead to better management of the resource, as players have a benchmark to decide what to do.

Conjecture 2 *The injunctive social norm will lead to more cooperation than the descriptive social norm*

We expect that, because the injunctive norm is based on theoretical results, which are very well optimized by considering perfectly symmetrical players, excluding free-riding problems in the group. Furthermore, in their field experiment to examine littering in public places, [Cialdini et al. \(1991\)](#) found that human behavior can be powerfully affected by social norms. They also found that three of these norms (descriptive, injunctive and personal norms) can be effective, but once the injunctive norm is activated, it can benefit the greatest number of populations.¹¹

Conjecture 3 *High environmentally sensitive groups will consume less, allowing the resource to grow*

¹¹Personal norms "...guide one's behavior via the perception of how one would approve/disapprove of one's own conduct."

We believe that the most sensitive groups are naturally focused on the preservation of the resource, and will manage to do so, regardless of the fact that preserving the resource brings them significant payoffs. Moreover, Buckley & Llerena (2018) found in their nudge treatment, that high environmental sensitive subjects significantly consume less electricity. This Conjecture is also in line with My & Ouvrard (2019), who found in their nudge treatment, that high environmentally sensitive individuals significantly increase their contributions to the public good.

4.5 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.

4.5.1 Descriptive Statistics

Results are presented at the group level. Figure 4.1 shows the evolution of the average resource over time in the three treatments and the colored area is the 95% confidence interval. The first part of Table 4.3 shows the overall and average initial extraction rates, as well as the overall and final resource levels. The second part of the table displays the corresponding Student test p-values. The average resource levels are decreasing, with more dispersion in the nudge treatments. They are very close between the baseline and the injonctive nudge treatment, and we found no significant difference between these treatments as shown by Table 4.3. The average resource in the descriptive nudge treatment deviates from the other trajectories around 200 seconds and is rather increasing.

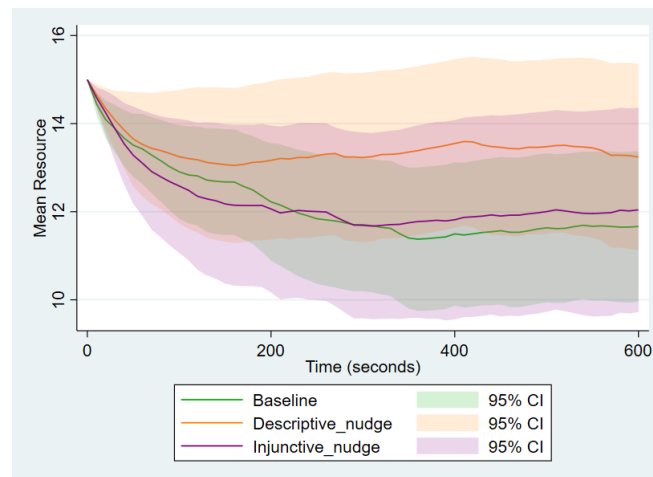


FIGURE 4.1 – Average resources by treatment

Since the nudge is an information about theoretical or observed trajectories, we expect it to have an impact on the first instants of the game, compared to the baseline where no information was given. That is why we are interested in the initial extraction rates and the final resource levels. We found no significant difference on average initial extraction rates between the descriptive and the injunctive nudge ($p\text{-value} = 0.690$), between the baseline and the descriptive nudge ($p\text{-value} = 0.279$), and between the baseline and the injunctive nudge ($p\text{-value} = 0.488$), nor on final resource levels for these treatments. However, considering the overall duration of the game, the average resource levels are significantly different between the descriptive and the injunctive nudge ; and between the baseline and the descriptive nudge (all $p\text{-value} < 0.001$).

	Groups	Initial Extraction	Average Extraction	Final Resource	Average Resource
Baseline	49	1.154 (0.919)	0.621 (0.441)	11.665 (5.959)	12.166 (4.983)
Descriptive nudge	34	0.947 (0.735)	0.591 (0.354)	13.241 (6.074)	13.423 (5.041)
Injunctive nudge	31	1.019 (0.703)	0.614 (0.388)	12.043 (6.320)	12.240 (5.347)
Student test (Between treatment p-values)					
Baseline = Descriptive		0.279	0.012	0.243	< 0.001
Baseline = Injunctive		0.488	0.568	0.788	0.625
Descriptive = Injunctive		0.690	0.059	0.439	< 0.001

*Standard deviations in brackets.

TABLE 4.3 – Summary statistics per treatment

Therefore, our results are partially in line with Conjecture 1, as the descriptive nudge leads to a significant higher final resource level than the baseline, which is not the case with the injunctive nudge. Thus, contrary to our expectations for Conjecture 2, it seems to be the descriptive social norm that leads to more cooperation. However, there is also another way to better understand the behaviors in the different treatments, by looking at the distribution of group profiles.

4.5.2 Group Profiles According to Treatments

In order to determine which theoretical predictions the groups are closest to, we computed in each treatment and for each theoretical prediction, the conditional mean squared deviation (MSD^c) between the observed extractions, $w_i(t)$, and the conditional theoretical extractions, $w_i(t)^c$. The conditionnal theoretical extraction takes into account the fact that groups can constantly readjust their choices throughout the experiment.

$$MSD^c = \frac{\sum_{t=1}^T (w_i(t) - w_i(t)^c)^2}{T}. \tag{4.4}$$

The behavior associated to each group (myopic, optimal, feedback) is thus given

by the lowest MSD^c . In order to provide robust and significant results, we combine this with regressions :

$$w_i(t) = \beta_0 + \beta_1 w_i(t)^c + \varepsilon_t. \quad (4.5)$$

where $w(t)_i^c$ is the conditionnal extraction associated to each behavior. A group will be significantly myopic or feedback or optimal, when β_1 is positive and significantly different from zero. We also checked for the presence of unit roots through an augmented Dickey-Fuller test. Serial correlation of the errors is dealt by means of Newey-West standard errors and sensitivity tests were implemented using one lag. More details about the conditional MSD is provided in Chapter 3.

Results are summarized by Figures 4.2 and 4.3. As in the baseline, we also see the appearance of a new profile in the nudge treatments, that we called "undetermined", because they do not fit into any of the three types of behavior predicted by the theory. These are groups that have not succeeded in increasing the resource as suggested by the optimal behavior. However, their extraction rates are sufficiently low, allowing the resource to remain above its observed level in the case of feedback or myopic behavior. They also seem to keep a stable resource throughout the game. Whether without information (baseline) or with (descriptive nudge), we found almost the same proportion of undetermined groups between the two treatments (almost 80%). Perhaps that is why [Cialdini et al. \(1991\)](#) stated that descriptive norms "will be effective prosocially only when most individuals already do behave in a socially desirable way". They must have thought that since very few groups succeed in reaching the social optimum, staying in an intermediate behavior would be advantageous to them in terms of payoffs, but also in terms of conservation of the resource.

Moreover, although the information given in the injunctive nudge did not exhibit any undetermined behavior, our results still suggest that 64.52% of the groups belong to this category. The undetermined profile seems to correspond to a focal point towards which, the majority of groups converge. We believe that the information provided in the nudges had an effect on the behaviors adopted in the groups. Therefore, a more thorough analysis on this type of behavior would be necessary, by trying for instance to take into account some visual aspects or some behavioral insights (cognitive

biases, misperception of the feedback due to the dynamic environment). An example of these type of analysis is already provided in Chapter 2. There are fewer undetermined groups in the injunctive nudge than in the other treatments and 3.23% of optimal groups. Nevertheless, we notice the existence of more myopic and feedback groups, as suggested by the theory. Unfortunately, this tends to reduce the average resource in the injunctive nudge treatment, as suggested in Table 4.3. A Chi2 test on the distribution of profiles according to treatments suggests no significant difference. Between the descriptive and the injunctive nudge, we found a p-value of 0.435. The p-value was equal to 0.825 between the baseline and the descriptive nudge, and finally, we found a p-value of 0.520 between the baseline and the injunctive nudge. As a conclusion, nudges did not change behavior significantly.

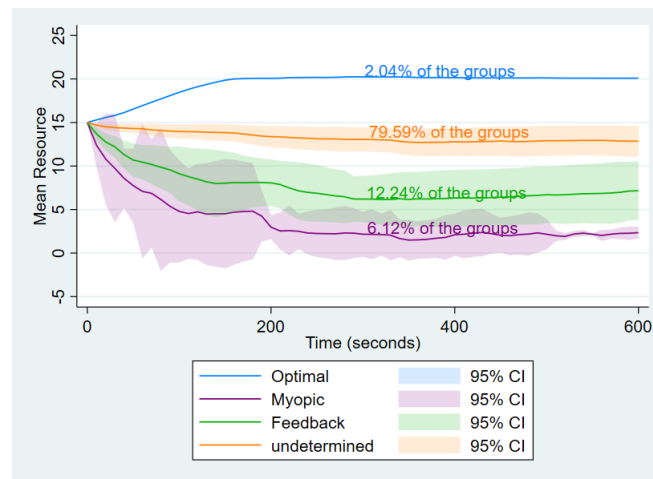


FIGURE 4.2 – Profiles in the baseline

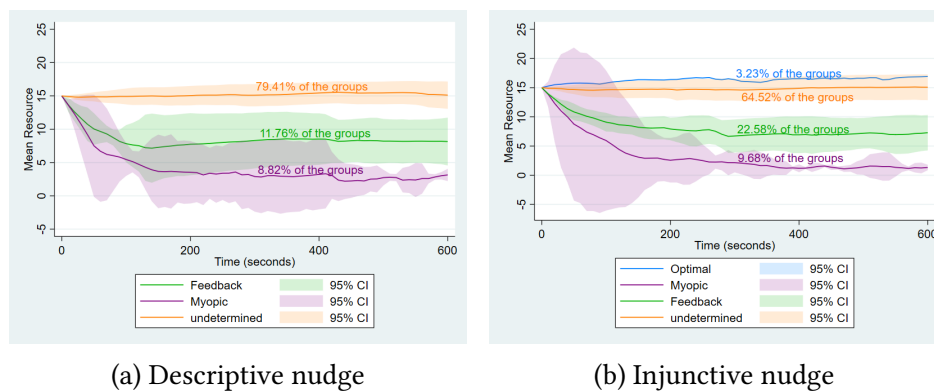


FIGURE 4.3 – Profiles in the descriptive and in the injunctive nudge

We complete the analysis by looking efficiency at the group level for each treatment. The maximum payoff a group could achieve is 240 ECUs. We compute the efficiency ratio by applying the total payoff of the two members of the group, over the maximum group payoff. The highest efficiency was achieved in the injunctive nudge (72.07%), followed by the average efficiency observed in the descriptive nudge, which is 69.02%. The average efficiency ratio in the baseline is 64.34%. However, we found no significant difference between the average efficiency by treatments, as shown by Students p -values in Table 4.4. We found greater efficiency in injunctive nudge than in descriptive nudge. Greater efficiency indicates the presence of optimal groups that have been able to cooperate. This could mean that our results support Conjecture 2. However, our results are not significant to allow us to draw this conclusion.

To investigate the within-group inequalities, we compute the difference between individual final payoffs within each group. The corresponding Lorenz curves are displayed on Figures 4.4 and 4.5. The Lorenz curves would be confounded with the equality curve, if the differences in within-group payoffs were identical for all groups. The differences in payoffs is larger in the baseline than in the nudge treatments, as the Lorenz curve for the baseline is more distant from the diagonal than those of the nudge treatments. Even with no significant difference between the average efficiencies, within-group differences in final payoffs are lower in the injunctive nudge, meaning that this nudge seems to reduce inequality in payoffs distribution.

	Groups	Average Efficiency
Baseline	49	64.34 (30.57)
Descriptive nudge	34	69.02 (27.73)
Injunctive nudge	31	72.07 (24.40)
Student test (Between treatment p-values)		
Baseline = Descriptive		0.479
Baseline = Injunctive		0.238
Descriptive = Injunctive		0.640

*Standard deviations in brackets.

TABLE 4.4 – Summary statistics for efficiency

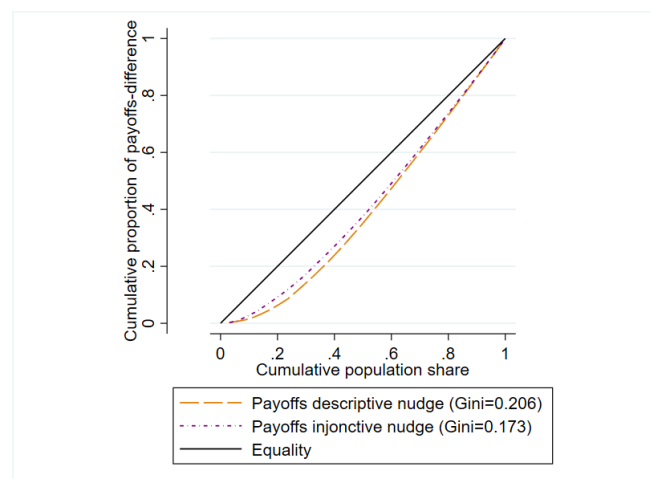


FIGURE 4.4 – Lorenz curves - Within-group difference in final payoffs for nudge treatments

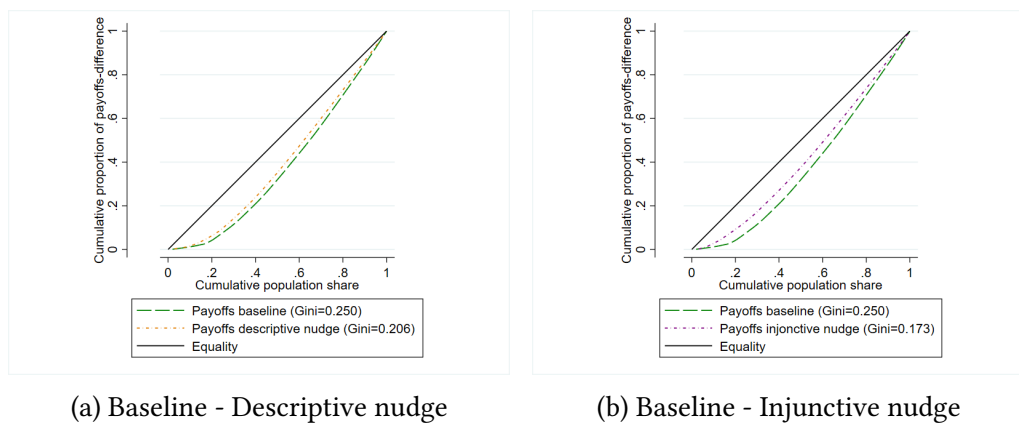


FIGURE 4.5 – Lorenz curves - Within-group difference in final payoffs

4.5.3 The General Ecological Behavior Scale

The General Ecological Behavior (GEB) scale aims to measure subjects' environmental sensitivity. Indeed, [Schultz & Zelezny \(2003\)](#) and [Costa & Kahn \(2010\)](#) show that certain personality traits such as altruism, political sensitivity, environmental sensitivity are relevant indicators of good reactivity to nudges. Appendix D.3 of Chapter 4 presents the GEB questionnaire used in the experiment. We implemented the short version with 28 items proposed by [Davis et al. \(2009, 2011\)](#).¹² These items only include ecological garbage removal, water and power conservation, ecologically aware consumer behavior, garbage inhibition and ecological automobile use. 17 items are formulated positively and the remaining 11 items 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", either a yes/no response format is also possible ([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.

¹²One 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.

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 $\alpha = 0.74$, the GEB scale is acceptable, in line with that found in the literature.¹³ To determine the environmental sensitivity of players, we computed the mean total score in both nudge treatments ($M = 102.28$ with $SD = 11.50$).¹⁴ Players whose score was below the mean, was considered as low environmental sensitive, while players whose score was greater than the mean was considered as high environmental sensitive. This allowed us to have three categories of environmental sensitivity at the group level, based on the environmental sensitivity of each of the members in the group. We thus note "High-High", groups where both members have high environmental sensitivity. "Low-Low" are groups in which both members have low environmental sensitivity and "High-Low" are groups in which one member has high environmental sensitivity, while the other has low environmental sensitivity. Results are presented at the group level and Tables 4.5 provide a summary of environmental sensitivity in the nudge treatments.

Treatment	Sensitivity			Total
	High-High	High-Low	Low-Low	
Descriptive nudge	10	18	6	34
Injunctive nudge	5	15	11	31
Total	15	33	17	65

TABLE 4.5 – Environmental sensitivity by treatment

Table 4.5 shows that in both treatments, there is a great number of mixed groups.¹⁵ Figure 4.6 shows the average resource according to environmental sensitivity. We note that the resource level of the high environmentally sensitive groups is higher than those of the low environmentally sensitive, as well as the mixed groups. A kruskal-Wallis test on the average resource by environmental sensitivity in the groups show

¹³The 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 $\alpha = 0.73$.

¹⁴My & Ouvrard (2019) found a mean total score $M = 104$.

¹⁵At an individual level, we found that 51.54% of the players were classified as low environmental sensitive, while 48.46% were highly sensitive to the environment.

a significant difference (p -value < 0.001) in the three categories of environmental sensitivity. This is confirmed by a Student test on couples of environmental sensitivity in the group (all p -values < 0.001) on Table 4.6, thus, our results are in line with Conjecture 3.

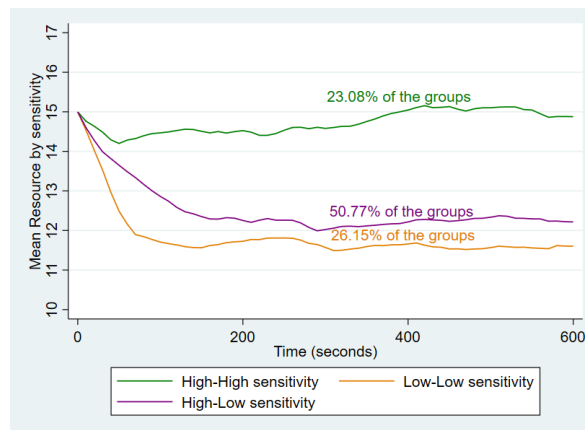


FIGURE 4.6 – Average resource by environmental sensitivity in nudge treatments

	Average Resource High-High	Average Resource High-Low	Average Resource Low-Low
Nudge Treatments	14.731	12.525	11.855
Kruskal Wallis test (p-values)			
High-High = High-Low = Low-Low	< 0.001		
	Student test (p-values)		
HH = HL	< 0.001		
HL = LL	< 0.001		
HH = LL	< 0.001		

TABLE 4.6 – Environmental sensitivity in nudge treatments

Figure 4.7 provides an overview of groups environmental sensitivity inside each treatment. We found a significant difference between groups classified as High-High with Low-Low groups, as well as between High-High with High-Low groups. This confirms that our results are always in line with Conjecture 3, regardless of the treat-

ment. However, there was no significant difference between High-Low and Low-Low groups.

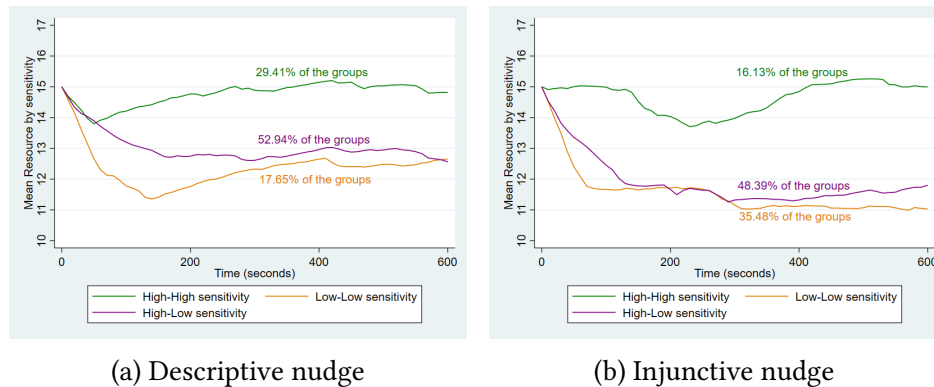


FIGURE 4.7 – Average resources by environmental sensitivity per treatment

By looking environmental sensitivity at an individual level, we found that more players were classified as high environmental sensitive in the descriptive nudge than in the injunctive nudge, as shown by Table 4.7. At the individual level, we found 3 optimal players in the baseline, 2 in the descriptive nudge and 4 in the injunctive nudge. However, by being paired at random with players from other profiles, most of the groups failed to maintain optimal behavior, especially in the descriptive nudge.

Profiles	Sensitivity		
	High	Low	Total
Feedback	3	2	5
Myopic	1	2	3
Optimal	1	1	2
Undetermined	33	25	58
Total	38	30	68

(a) Descriptive nudge

Profiles	Sensitivity		
	High	Low	Total
Feedback	3	7	10
Myopic	3	2	5
Optimal	3	1	4
Undetermined	16	27	43
Total	25	37	62

(b) Injunctive nudge

TABLE 4.7 – Individual environmental sensitivity

Finally, we found a great number of mixed groups in terms of environmental sensitivity and a great number of players classified as high environmental sensitive in the descriptive nudge than in the injunctive nudge. However, applying a chi-squared test (χ^2), show that the distribution of environmental sensitivity at the group level is independent of the treatments (p-value= 0.194). The same results was also observed at

the individual level (p-value= 0.076). This could be the consequence of the random matching in the game and could explain the low number of optimal groups in the injunctive nudge. A solution would be to perform more experiments, to have at least the same number of observations in both treatments, to be able to formulate consistent conclusions.

4.6 Discussion and Conclusion

The purpose of this study was to use nudge based instruments to induce more resource friendly behavior. To this end, we considered a dynamic model in continuous time and over an infinite horizon, to study the extraction decisions of groups of two players. We carried out three treatments using a between-subject design, where the first treatment was the baseline. In the two other treatments, we implemented a nudge based on a descriptive social norm and an injunctive social norm, because we expect them to be effective in changing behaviors. We used the results of the baseline as a benchmark, given as information to subjects in the descriptive social norm treatment. More precisely, they were given a figure representing the time paths for the resource, as well as the corresponding average individual payoffs. In the injunctive social norm treatment, subjects were given the theoretical time paths for the resource, as well as the corresponding payoffs.

A first general comparison of the three treatments through the average resource levels indicates that the descriptive nudge achieves a significantly higher resource level than the other two treatments. This allows us to partially support our Conjecture 1, which suggests that nudges preserve the resource better than the baseline. However, contrary to our expectations our results do not converge towards Conjecture 2, as a higher level of resource in the descriptive nudge suggests more cooperation in this treatment than in the injunctive nudge. In addition, by classifying the profiles observed in the groups within each treatment, we found only 3.23% of optimal groups in the injunctive nudge and a more equal distribution of payoffs within the groups, as well as promoting greater efficiency. The lowest efficiency was recorded in the baseline. However, the distribution of profiles in the treatments was not significantly different to allow us to conclude that the nudge treatments have a real impact on the beha-

viors observed in the groups. We finally measured players environmental sensitivity in the nudge treatments and found that regardless of the treatment, high environmental sensitive groups succeeded in maintaining a high resource level than low and mixed environmental sensitive groups, in line with Conjecture 3. However, we found at the group and at the individual level, more environmental sensitive players in the descriptive nudge than in the injunctive nudge. We expect it could be the consequence of the random matching in the game, explaining the low number of optimal groups in the injunctive nudge.

We are aware that our work has limitations and can be improved. For example, it would be necessary to look further to understand the undetermined behavior, which seems to be a focal point in the different treatments, regardless of whether an information is provided or not. Moreover, checking whether there are behavioral biases that could provide more information about this profile could be considered. In addition, more data could also be collected to solve the random matching, perhaps clearer results would be found. In terms of public policy recommendations, we cannot really conclude that nudge treatments provide more effective results than the baseline or that the injunctive nudge is more efficient than the descriptive nudge, even if the highest efficiency ratio was found in this treatment. We believe that additional observations will help us to conclude. Some extensions are also possible and it could be interesting to test communication mechanisms such as cheap talk, to see how this will affect the nudge treatments. Other category of nudges such as default options could also be investigated.

General Conclusion

The first goal of this thesis was to study and test in the laboratory, considering a dynamic framework in continuous time and over an infinite horizon, the behaviors of common pool renewable resources users. It then aimed at proposing non-monetary instruments such as "nudges" to guide resource users towards optimal decisions. In this perspective, we have adopted an approach that combines modeling, experimentation and analysis of the behaviors observed in the laboratory. In **Chapter 1**, which presents studies on the management of common pool resources in a dynamic framework, it was found that the implementation of dynamic models in continuous time in the laboratory is very weak. This is the reason why **Chapter 2** focused on the implementation of an experimental protocol in continuous time and over an infinite horizon, which is faithful to the theoretical model. It allowed us to identify the theoretical behaviors for which the experimental subjects are closest when they exploit the resource alone, and then when they are two to exploit the resource.

In **Chapter 3**, we tried to see how to present the dynamic model in continuous time in the laboratory, in the simplest possible way and easily understandable. Since real continuous time is impossible to implement in laboratory, a discrete approximation almost similar to the theoretical continuous time has been proposed. Then, depending on the discretization parameter chosen, we could implement experiments close to continuous time and experiments close to discrete time. Our results suggest that without strategic interaction, the behaviors of experimental subjects are quite similar, regardless of the nature of time (continuous vs. discrete). Strategic interaction, leads to more cooperation in continuous time. However, we found in Chapters 2 and 3 that

the introduction of strategic interaction strongly leads to an over-exploitation of the resource, in line with the literature. **Chapter 4**, studies the effect of a nudge based on social norms, by comparing descriptive social norms and injunctive social norms. These nudges consisted in providing experimental subjects with graphical information on the equilibrium paths of the exploited resource. These equilibria were related to theoretical benchmarks in the case of injunctive norms and to the benchmarks observed in the baseline for descriptive norms. Our results suggest that the classification of groups in the nudge treatments appears to be consistent with the nature of the information displayed to the experimental subjects. Moreover, our results are quite mixed between the two types of nudges, with however a greater efficiency in the injunctive nudge.

We are aware that our work also has limitations and could be improved. First, the use of students as experimental subjects could be a limitation, as they are not necessarily representative of the target population of our study and are sometimes more motivated by their payoffs than by resource conservation. The interpretation of our results should therefore be done with caution. Moreover, the experiment in Chapter 2 was the first experiment we conducted. A discretization of the dynamics with a discretization parameter $\tau = 1$ seemed to us to be sufficient to approach the continuous dynamics. On the other hand, when we wanted to know in Chapter 3 if a discrete presentation of the continuous time model would be easier to understand in the laboratory, we realized that a finer approximation of continuous time should be proposed, in order to keep the two approaches comparable, i.e. sufficiently close to the theoretical model in continuous time. This is why we have considered in this chapter $\tau = 0.1$ for continuous time and $\tau = 1$ for discrete time.

Moreover, we literally explained the evolution of the resource in the instructions of Chapter 3 by excluding formulas, unlike Chapter 2 where a discrete formula was given (the discretization with $\tau = 1$, allowing a fairly simple interpretation of the evolution). This difference in the presentation of the instructions did not allow us to compare the experiments of Chapter 2 with those of Chapter 3 in continuous time. It would have been very interesting, because it would have allowed us to compare the effect of information, since in Chapter 2 subjects first play the problem without strategic interaction.

Finally, considering the analysis of experimental data, our subject methodology of classification results in a very large number of "undetermined" individuals, whose behavior is intermediate between two theoretical benchmarks. This type of individuals has been discussed in Chapter 2, where they were again classified according to visual criteria. It would therefore be necessary to recourse to finer analysis methods or to think about theoretical models able to explain such behavior.

However, several extensions can be drawn from the different results. For the moment we have limited to two players in strategic interaction situations. However, in the literature, it is shown that the Tragedy of the Commons is more exacerbated with the number of players, both in continuous and discrete time. It could be useful to increase the number of players to check this result and try to understand the learning process of subjects when they are in a dynamic environment, by comparing the results of the game (several players), with and without the optimal control phase (only one player). The ability of continuous time to induce cooperation is very mixed, as it sometimes requires additional mechanisms such as communication, punishment, feedback to be effective (Oprea et al., 2014; Leng et al., 2018). One way would be to introduce these mechanisms in Chapter 3 to check how the results evolve in continuous time compared to discrete time; or in Chapter 4, to see if they induce the emergence of cooperation.

Another approach would be to give information on the dynamics of costs instead of the dynamics of the resource. Even if theoretically the same results are obtained in both situations, results could differ in the laboratory. We believe that individuals would be more sensitive to variations in costs and would focus more on their payoffs than on the preservation of the resource.

Finally, in Chapter 4, it might be useful to test other categories of nudges such as default options. This could be a real challenge with our dynamic framework. It would also be possible to test monetary instruments or a combination of monetary and non-monetary instruments in order to determine the most efficient instrument for optimal resource management.

Conclusion Générale

Cette thèse avait pour but dans un premier temps, d'étudier et tester en laboratoire, dans un cadre dynamique en temps continu et sur un horizon infini, les comportements des utilisateurs de ressources communes renouvelables. Elle visait ensuite à proposer des instruments non-monétaires de type "nudges" pour guider les utilisateurs de ressources vers des décisions optimales. Dans cette perspective, nous avons adopté une démarche qui combine modélisation, expérimentation et analyse des comportements observés en laboratoire. Dans le **Chapitre 1** qui présente des études portant sur la gestion des ressources communes dans un cadre dynamique, il est ressorti que l'implémentation en laboratoire des modèles dynamiques en temps continu est très peu répandue. C'est la raison pour laquelle le **Chapitre 2** s'est penché sur la mise en place d'un protocole expérimental en temps continu et sur un horizon infini, qui soit fidèle au modèle théorique. Cela nous a permis d'identifier les comportements théoriques pour lesquels les sujets expérimentaux se rapprochent le plus lorsqu'ils exploitent seuls la ressource, puis lorsqu'ils sont deux à exploiter la ressource.

Dans le **Chapitre 3**, nous avons essayé de voir comment présenter en laboratoire le modèle dynamique en temps continu, de la manière la plus simple possible et facilement compréhensible. Le vrai temps continu étant impossible à implémenter en laboratoire, une approximation discrète quasiment similaire au temps continu théorique a été proposée. Ensuite, selon le paramètre de discrétisation choisi, nous pouvions implémenter des expériences proches du temps continu et des expériences proches du temps discret. Nos résultats suggèrent qu'en l'absence d'interaction stratégique, les comportements des sujets expérimentaux sont assez similaires, indépendamment de la nature

du temps (continu vs. discret). La présence de l'interaction stratégique entraîne cependant plus de coopération en temps continu. Toutefois, on constate dans les Chapitres 2 et 3 que l'introduction des interactions stratégiques conduit fortement à une sur-exploitation de la ressource, en accord avec la littérature. Le **Chapitre 4**, étudie l'effet d'un nudge basé sur les normes sociales, en comparant norme sociale descriptive et norme sociale injonctive. Ces nudges consistaient à fournir aux sujets expérimentaux, des informations graphiques sur les sentiers d'équilibres de la ressource exploitée. Ces équilibres portaient sur les benchmarks théoriques dans le cas des normes injonctives et sur les benchmarks observés dans la baseline pour les normes descriptives. Nos résultats suggèrent que la classification des groupes dans les traitements nudges semble consistante avec la nature de l'information présentée aux sujets expérimentaux. Par ailleurs, nos résultats assez mitigés entre les deux types de nudges, avec cependant une efficacité plus importante dans le nudge injonctif.

Nous sommes conscient que notre travail comporte aussi des limites et pourraient être amélioré. D'abord, le fait d'avoir eu recours à des étudiants comme sujets expérimentaux pourrait constituer une limite, car ils ne sont pas forcément représentatifs du public visé par notre étude et sont parfois plus motivés par leurs gains que par la préservation de la ressource. L'interprétation de nos résultats devrait donc se faire avec précaution. Par ailleurs, l'expérience du Chapitre 2 fut la première expérience que nous avons réalisée. Une discrétisation de la dynamique avec un paramètre de discrétisation $\tau = 1$ nous a alors paru largement suffisante pour approcher la dynamique continue. Par contre, en voulant savoir dans le Chapitre 3 si une présentation discrète du modèle en temps continu serait plus facile à comprendre en laboratoire, nous avons réalisé qu'une approximation plus fine du temps continu devrait être proposée, afin de garder les deux approches comparables, c'est-à-dire suffisamment proches du modèle théorique en temps continu. C'est ainsi que le choix de considérer dans ce chapitre $\tau = 0.1$ pour le temps continu et $\tau = 1$ pour le temps discret a été fait.

De plus, nous avons opté pour une explication littéraire de l'évolution de la ressource dans les instructions du Chapitre 3 en excluant les formules, contrairement au Chapitre 2 où une formule discrète était donnée (la discrétisation avec $\tau = 1$, permettant une interprétation assez simple de l'évolution). Cette différence de présentation des instructions ne nous a pas permis de comparer les expériences du Chapitre 2 à

celles du Chapitre 3 en temps continu. Chose qui aurait été très intéressante, car aurait permis de comparer l'effet de l'information, puisque dans le Chapitre 2 les sujets jouent d'abord le problème sans interaction stratégique.

Enfin, du point de vu de l'analyse des données expérimentales, notre méthodologie de classification des sujets résulte en un très grand nombre d'individus "indéterminés", dont le comportement est intermédiaire entre deux benchmarks théoriques. Ce type d'individus a d'ailleurs retenu notre attention dans le Chapitre 2, où ils ont à nouveau été classés suivant des critères visuels. Il serait donc nécessaire d'avoir recours à d'autres méthodes d'analyses plus fines ou encore de réfléchir à des modèles théoriques capables d'expliquer de tels comportements.

Toutefois, plusieurs extensions peuvent se dégager des différents résultats. Pour l'instant nous nous sommes limités à deux joueurs dans la prise en compte de l'interaction stratégique. Or dans la littérature, il est démontré que la Tragédie des Communs est davantage exacerbée avec le nombre de joueurs, que ce soit en temps continu, qu'en temps discret. Il pourrait être utile d'augmenter le nombre de nos joueurs pour vérifier ce résultat et essayer de comprendre le processus d'apprentissage des sujets lorsqu'ils sont dans un environnement dynamique, en comparant les résultats du jeu (plusieurs joueurs), avec et sans la phase en contrôle optimal (un seul joueur).

La capacité du temps continu à induire la coopération est très mitigée, car nécessite parfois des mécanismes supplémentaires comme la communication, la punition, des retours d'information pour être efficace (Oprea et al., 2014; Leng et al., 2018). Une piste serait également d'introduire ces mécanismes dans le Chapitre 3 pour vérifier comment évoluent les résultats en temps continu comparativement au temps discret; ou encore dans le Chapitre 4, pour voir s'ils constituent un plus dans l'émergence de la coopération. Une autre piste serait de donner des informations sur la dynamique des coûts à la place de la dynamique de la ressource. Même si théoriquement on obtient les mêmes résultats dans les deux situations, les résultats pourraient diverger en laboratoire. Nous pensons en effet que les individus seraient plus sensibles aux variations des coûts et se concentreraient davantage sur leurs gains au détriment de la ressource.

Enfin, dans le Chapitre 4, il pourrait être utile de tester d'autres catégories de nudges comme par exemple les options par défauts. Ce qui pourrait constituer un véritable challenge avec notre cadre dynamique. Il serait également envisageable de tester

des instruments monétaires ou encore une combinaison d'instruments monétaires et non-monétaires afin de déterminer l'instrument le plus efficace pour une gestion optimale de la ressource.

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Appendices

Appendix A

Appendices for Chapter 1

A.1 Description of variables

In this survey, **extraction**, **harvesting**, **pumping**, **catch** or **fishing** refer to the same concept.

Table A.1 – Variables for single agents articles

Variables	Description
x_t	Agent's extraction (or extraction rate in continuous time)
S_t	Stock of the resource
$F(S_t)$	Logistic growth function
n	Number of users
i	Index of users
T	Finite time horizon
r	Discount rate
ρ	Discount factor (in discrete time)
\exp^{-r}	Discount factor (in continuous time)
R	Recharge rate or replenishment rate or intrinsic growth
K	Carrying capacity
MSY	Maximum Sustainable Yield

Table A.2 – Variables for multiple agents articles

Variables	Description
x_{it}	Agent i 's extraction (or extraction rate in continuous time)
x_{jt}	Agent j 's extraction rate (or extraction rate in continuous time)
X_t	Total group extraction
B_{it}	Benefit function
π	Profit
C_{it}	Total extraction cost function
c_t	Marginal cost
c_0	Cost parameter
c_f	Fixed costs
c_{op}	Opportunity cost
c_1	Static crowding externality
c_2	Dynamic externality
P	Price
k	Incremental cost parameter
V	Value function
d_t	Depth to water
s	Parameter on the size and configuration of the aquifer
S_t	Stock of the resource
S_{th}	Threshold stock
$F(S)$	Logistic growth function
n	Number of users
i	Index of users
T	Finite time horizon
r	Discount rate
ρ	Discount factor (in discrete time)
\exp^{-r}	Discount factor (in continuous time)
R	Recharge rate or replenishment rate or intrinsic growth rate
K	Carrying capacity
MSY	Maximum Sustainable Yield
E	Extraction effort
E_0	Per period effort endowment
\bar{E}	Maximum amount of extraction effort
α	Extraction technology
\bar{p}	Marginal value of an extracted resource unit
AS	Area times storativity of the aquifer
Tr	Transmissivity
$v(g, h)$	Radial distance between well g and well h
$w(t, v)$	The well function

Appendix B

Appendices for Chapter 2

B.1 The Optimal Control Problem

B.1.1 Social Optimum Solution

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

$$\max_{w(t)} \int_0^{\infty} e^{-rt} \left[aw(t) - \frac{b}{2}w(t)^2 - \max(0, c_0 - c_1H(t))w(t) \right] dt, \quad (\text{B.1})$$

s.t

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

Condition 1 : We suppose that:

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

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

smaller than $\frac{c_0}{c_1}$.

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

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

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

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

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

$$\max_w \int_0^{\infty} e^{-rt} \left[aw - \frac{b}{2}w^2 - (c_0 - c_1H)w \right] dt, \quad (\text{B.2})$$

s.t

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

is

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

Proof 1 : The associated Hamiltonian is:

$$\text{Hamiltonian} = aw - \frac{b}{2}w^2 - (c_0 - c_1H)w + \lambda(R - \alpha w),$$

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

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

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

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

$$\max_w \int_0^\infty e^{-rt} \left[aw - \frac{b}{2}w^2 \right] dt, \quad (\text{B.3})$$

s.t

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

The associated Hamiltonian:

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

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

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

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

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

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

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

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

$$L = aw - \frac{b}{2}w^2 - (c_0 - c_1 H)w + \lambda(R - \alpha w) + \mu \left(\frac{c_0}{c_1} - H \right) + \nu w, \quad (\text{B.4})$$

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

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

$$L = aw - \frac{b}{2}w^2 + \lambda(R - \alpha w) + \mu \left(H - \frac{c_0}{c_1} \right). \quad (\text{B.5})$$

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

B.1.2 The Constrained Myopic Solution

The constrained myopic problem faced by the farmer is:

$$\max_{w(t)} \left[aw(t) - \frac{b}{2}w(t)^2 - \max(0, c_0 - c_1 H)w(t) \right]. \quad (\text{B.6})$$

This problem provides a feedback representation of the solution $w(H)$, under the following constraints:¹

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

Condition 2 : We suppose that

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

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

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

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

¹ The feedback representation is obtained when the solution is written according to the state variable, instead of according to time.

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

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

$$H_{my}^\infty < H_{op}^\infty. \quad (\text{B.7})$$

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

$$H(t) = H_{my}^\infty + (H_0 - H_{my}^\infty)e^{-\frac{\alpha c_1}{b}t}, \quad (\text{B.8})$$

with the steady-state that is:

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

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

B.2 The Case of Multiple Agents: Game

B.2.1 The Social Optimum Solution

The social optimum or the cooperative maximization problem is given by:

$$V(H_0) = \max_{w_1(t), w_2(t)} \int_0^\infty e^{-rt} \sum_{i=1}^2 \left[aw_i(t) - \frac{b}{2}w_i(t)^2 - \max(0, c_0 - c_1H(t))w_i(t) \right] dt, \quad (\text{B.9})$$

s.t

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

Condition 3 : We suppose that

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

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

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

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

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

B.2.2 The Nash Feedback solution

The Nash Feedback maximization problem for each farmer is:²

$$\max_{w_i(t)} \int_0^\infty e^{-rt} \left[aw_i(t) - \frac{b}{2} w_i(t)^2 - \max(0, c_0 - c_1 H(t)) w_i(t) \right] dt, \quad (\text{B.10})$$

s.t

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

Condition 4 : We suppose that

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

²In the Nash Feedback equilibrium, we consider only the case of linear strategies.

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

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

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

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

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

To prove theorem 4, we consider $H_0 \leq \frac{c_0}{c_1}$ and $H_0 > \frac{c_0}{c_1}$:

When $H_0 \leq \frac{c_0}{c_1}$, condition 3 guarantees the positivity of the extraction path for all t and that the Nash feedback trajectory remains in the region where $H < \frac{c_0}{c_1}$. The Nash equilibrium can be found by solving the Hamilton-Jacobi-Bellman (HJB) equation :

$$rV_{R_1}^i(H) = \max_{w_i} \left[(aw_i - \frac{b}{2}w_i^2 - (c_0 - c_1H)w_i - (V_{R_1}^i)'(H)(R - \alpha(w_i + w_j(H))) \right].$$

By using the guessing method to guess a quadratic value function and a linear strategy, one can easily find the Nash feedback equilibrium. Thus, proposing:

$$\begin{cases} V_{R_1}^i(H) = A_1 + A_2H + \frac{A_3}{2}H^2, \\ w_j(H) = a_iH + b_i. \end{cases}$$

One can find A_1, A_2, A_3, a_i, b_i , where A_3 is obtained by solving the following equation:

$$-\frac{3\alpha^2}{2b}A_3^2 + \frac{rb + 4c_1\alpha}{2b}A_3 - \frac{c_1^2}{2b} = 0, \quad (\text{B.11})$$

with the condition $-c_1 + \alpha A_3 < 0$, and we have :

$$\left\{ \begin{array}{l} a_1 = \frac{c_1 - \alpha A_3}{b}, \\ b_1 = \frac{a - c_0 - \alpha A_2}{b}, \\ A_2 = \frac{(a - c_0)(-c_1 + 2\alpha A_3) - RbA_3}{-rb - 2c_1\alpha + 3A_3\alpha^2}, \\ A_1 = \frac{3\alpha^2 A_2^2 + 2Rb - 4\alpha(a - c_0)A_2 + (a - c_0)^2}{2br}. \end{array} \right.$$

The evolution of the water table for H_0 is also given by:

$$H(t) = e^{-\frac{2\alpha(-c_1 + \alpha A_3)t}{b}} (H_0 - H_f^\infty) + H_f^\infty, \quad H_f^\infty = \frac{Rb + 2\alpha^2 A_2 - 2\alpha(a - c_0)}{2\alpha(c_1 - \alpha A_3)}.$$

When $H_0 > \frac{c_0}{c_1}$ the problem is a bit different, because the following facts must be taken into account : first, there is no stationary steady state in the regime where $H > \frac{c_0}{c_1}$. As a consequence, the Nash feedback solution will decrease from this regime to the steady state H_f^∞ . Second, our problem is an autonomous problem, thus the solution in this case is also the solution of an HJB equation of the form:

$$rV_{R_2}^i(H) = \max_{w_i} \left[(aw_i - \frac{b}{2}w_i^2 - (V_{R_2}^i)'(H))(R - \alpha(w_i + w_j(H))) \right]. \quad (\text{B.12})$$

For the first point, the solution of this last HJB equation is constrained to the condition:

$$V_{R_2}^i\left(\frac{c_0}{c_1}\right) = V_{R_1}^i\left(\frac{c_0}{c_1}\right). \quad (\text{B.13})$$

The first order condition for equation (B.12) gives:

$$w_i(H) = \frac{a - \alpha(V_{R_2}^i)'(H)}{b}. \quad (\text{B.14})$$

Replacing (B.14) in equation (B.12) and taking into account that $w_j(H) = w_i(H)$, we obtain the following differential equation for $V_{R_2}^i(H)$:

$$V_{R_2}^i(H) = \frac{C}{2} [(V_{R_2}^i)'(H)]^2 + B (V_{R_2}^i)'(H) + A, \quad (\text{B.15})$$

where,

$$\begin{cases} A = \frac{a^2}{2br}, \\ B = \frac{Rb - 2a}{br}, \\ C = \frac{-\alpha^2 + 4\alpha}{br}. \end{cases}$$

Differentiating (B.15) with respect to H , one must finally solve:

$$U(H) = B U'(H) + C U(H)U'(H), \quad \text{with} \quad U(H) = (V_{R_2}^i)'(H). \quad (\text{B.16})$$

The solution of equation (B.16) is given by:

$$U(H) = e^{-\frac{-H + BLambertW(x) - cte}{B}}, \quad x = \frac{H}{Ce\frac{H}{B} + \frac{cte}{B}}, \quad (\text{B.17})$$

where *LambertW* is the Lambert *W* function and the constant *cte* is found using (B.13).

B.2.3 The Constrained Myopic solution

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

$$\max_{w_i(t)} \left[aw_i(t) - \frac{b}{2}w_i(t)^2 - \max(0, c_0 - c_1H)w_i(t) \right]. \quad (\text{B.18})$$

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

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

Condition 5 : *We suppose that*

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

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

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

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

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

To finally prove the link between the steady states of the 3 types of behavior studied in the game, condition 4 gives:

$$\begin{aligned}
H_f^\infty &= \frac{Rb + 2\alpha^2 A_2 - 2\alpha(a - c_0)}{2\alpha(c_1 - \alpha A_3)} \\
&= \frac{Rb - 2\alpha(a - c_0)}{2\alpha c_1 - \alpha^2 A_3} + \frac{2\alpha^2 A_2}{2\alpha c_1 - \alpha^2 A_3} \\
&= \left[\frac{Rb - 2\alpha(a - c_0)}{2\alpha c_1} \times \frac{1}{1 - \frac{\alpha A_3}{c_1}} \right] + \frac{2\alpha^2 A_2}{2\alpha(c_1 - \alpha A_3)} \\
H_f^\infty &= \left[H_{my}^\infty \times \frac{1}{1 - \frac{\alpha A_3}{c_1}} \right] + \frac{2\alpha^2 A_2}{2\alpha(c_1 - \alpha A_3)}.
\end{aligned}$$

Thanks to the condition $-c_1 + \alpha A_3 < 0$, we can deduce that $c_1 - \alpha A_3 > 0$. Moreover, we have $A_2 > A_3$, so that:

$$\frac{2\alpha^2 A_2}{2\alpha(c_1 - \alpha A_3)} > 0, \quad \text{and} \quad \frac{2\alpha^2 A_2}{2\alpha(c_1 - \alpha A_3)} > \left[H_{my}^\infty \times \frac{1}{1 - \frac{\alpha A_3}{c_1}} \right].$$

Thus, one can say that $H_f^\infty > H_{my}^\infty$, and we can conclude from conditions 3 and 4 that in the game:

$$H_{my}^\infty < H_f^\infty < H_{op}^\infty. \tag{B.19}$$

Notice that conditions 1, 2, 3, 4 and 5 were decisive in the choice of the values of the parameters used for the experiment. A discussion of these conditions will be made in section 2.4.3.

B.3 An example of how the empirical strategy works

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

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

$$\begin{aligned} MSD_{my}^c &= 0.718, \\ MSD_{op}^c &= 0.011. \end{aligned} \tag{B.20}$$

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

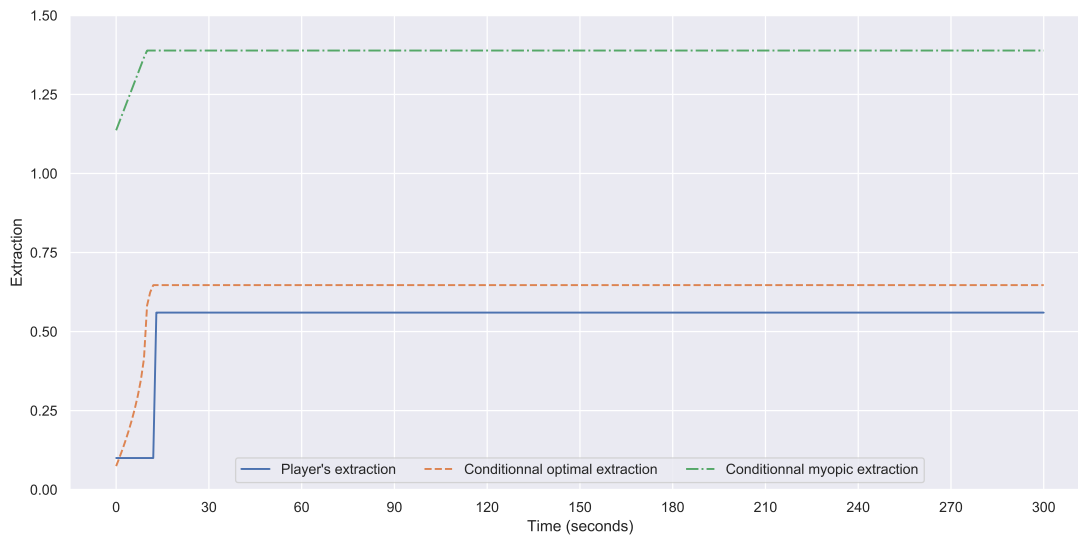


Figure B.1 – Player 58’s extraction path versus the conditional extraction path for the optimal control

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

Step 2 : Next, we regress player 58’s extractions from time $t = 0$ to $t = 300$ over its conditional optimal extraction path in the optimal control. Results are shown in Table B.1.

Table B.1 – Player 58's extraction in the optimal control

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

Newey-West standard errors with 5-period lags.

t statistics in parentheses.

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

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

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

$$\begin{aligned}
 MSD_{my}^c &= 5.004, \\
 MSD_{fb}^c &= 1.160, \\
 MSD_{op}^c &= 0.070.
 \end{aligned}
 \tag{B.21}$$

MSD_{op}^c is the smallest. Extraction and conditional extraction paths of group 29 are shown by Figure B.2.

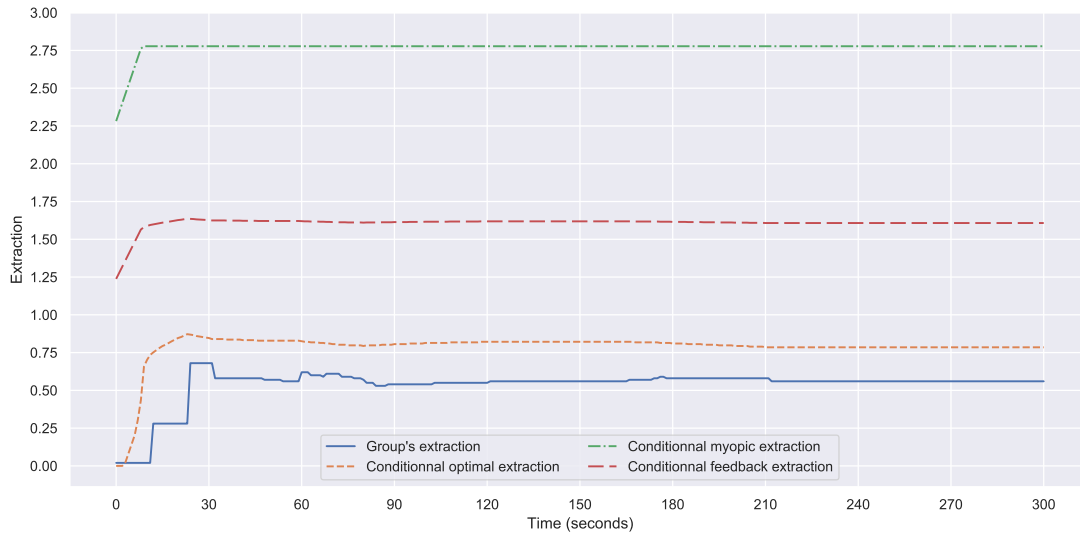


Figure B.2 – Group 29’s extraction path versus conditional extraction path for the game

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

Step 4 : Next, we regress group 29’s extractions from time $t = 0$ to $t = 300$ over their conditional optimal extraction path in the game. Results are shown in Table B.2.

Table B.2 – Group 29’s extraction in the game

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

Newey-west standard errors with 5-period lags.

t statistics in parentheses.

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

The coefficient is positive (0.770) and significant at 0.1%. Therefore, we consider

group 29 as being significantly optimal in the game.

B.4 Instructions

Translated from French

B.4.1 Optimal control

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

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

Part 1

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

General framework

You initially have 15 resource units. At any time, you can extract between 0 and 2.8 resource units with up to two decimal points of precision. This means that you are free to choose your extraction rate as 0, 0.01, 0.02 ... 2.79, 2.8. You will move a slider similar to that depicted in Figure B.3 to make your choice. The value displayed above

the slider is automatically taken into account when you release the slider and sent to the central computer which updates information.

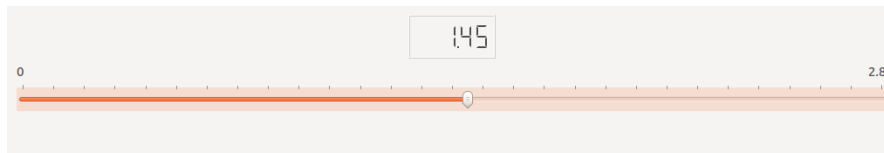


Figure B.3 – Slider for decision-making

Resource dynamics

The available resource continuously evolves. Its evolution depends on two elements: (i) your extraction rate at instant t denoted E_t and (ii) a fixed rate of 0.56 automatically added at each instant t .

By noting R_t the amount of resource available at instant t , the dynamics of the resource is then:

$$R_{t+1} = R_t - E_t + 0.56.$$

In the experiment, the instant is the second, which means that 1 second elapses between the instant t and the instant $t + 1$, thus, the resource evolves each second as described above.

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

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

Example

Suppose that at the instant t the amount of resource available is 15 units and that your extraction rate is 0.30 units. At the instant $t + 1$ the amount of resource available will then be: $R_{t+1} = 15 - 0.30 + 0.56 = 15.26$ units.

Payoff

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

Total revenue from extraction

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

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

Figure B.4 below shows the total revenue according to the extraction rate.

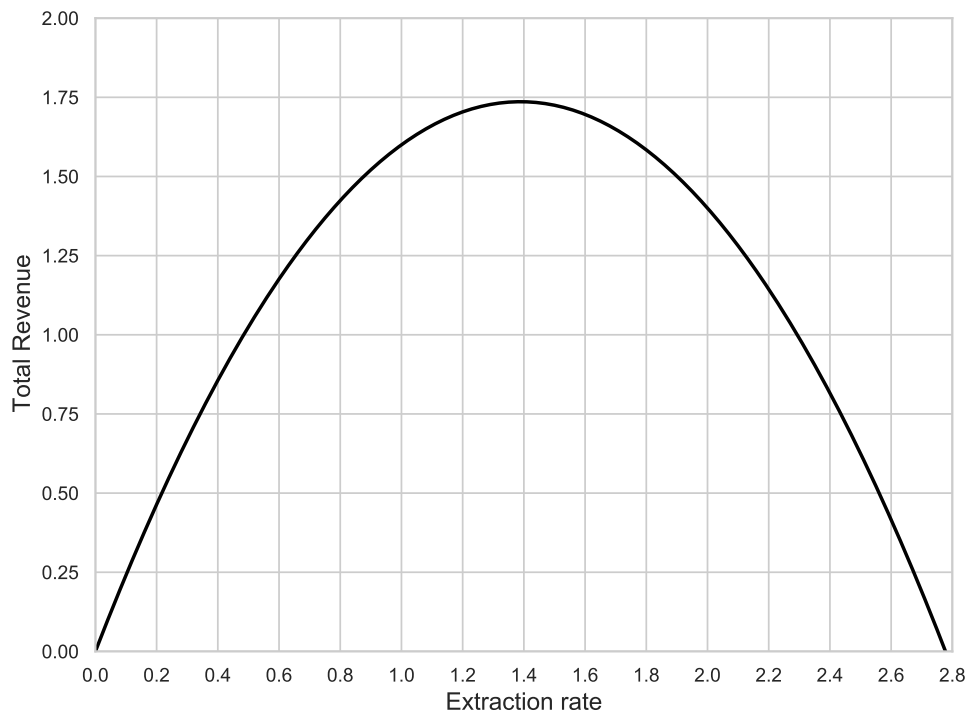


Figure B.4 – Total revenue from extraction

Cost of extraction

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

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

Thus,

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

Figure B.5 shows the unitary cost according to the available resource.

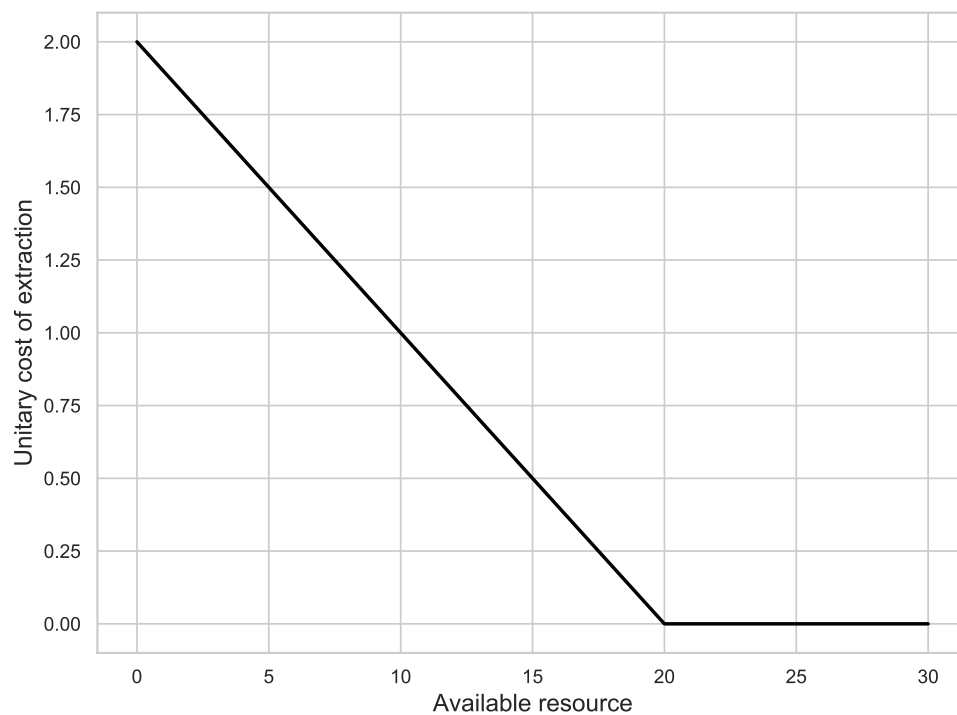


Figure B.5 – Unitary cost of extraction

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

$$C_t = E_t \times c_t.$$

Instant t payoff

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

Example

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

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

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

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

Discounted instantaneous payoff

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

Example

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

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

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

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

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

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

Payoff for the part

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

with your extraction rate being fixed to the present instant p .

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

How the part works

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

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

The decision screen includes four areas, in addition to the decision area with the slider. Three of these areas are graphic areas, and the fourth is a text area. Figure B.6 on page 170 gives you a depiction of the decision screen. Description of the areas is as follows:

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

Final details

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

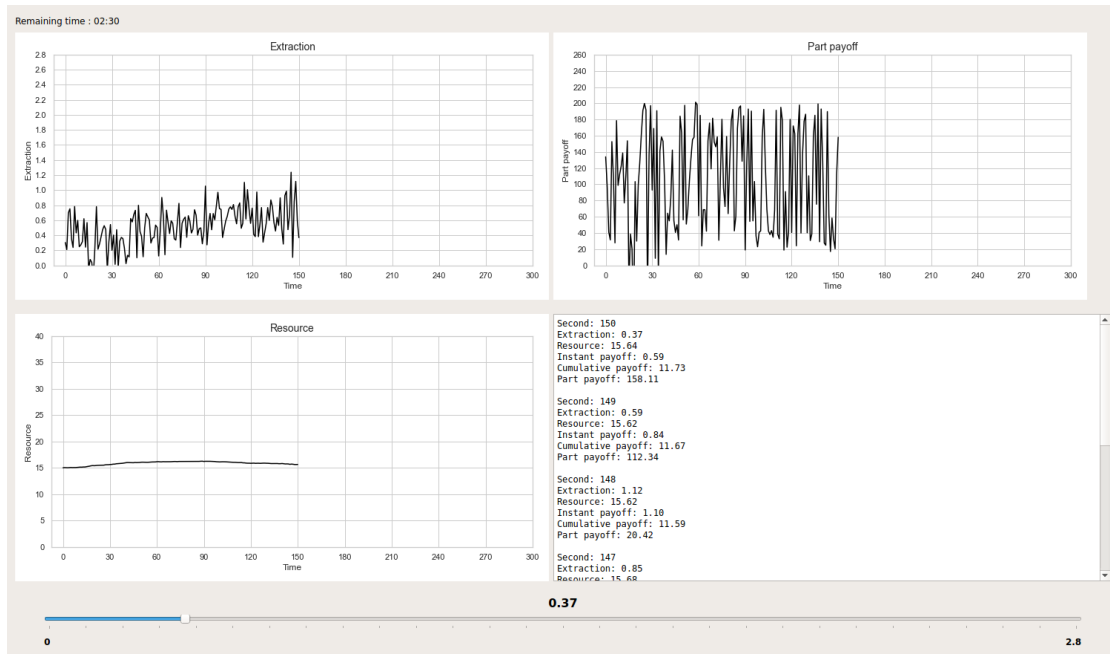


Figure B.6 – Decision-making screenshot. We follow a hypothetical subject who chooses his extraction rate at random

B.4.2 Game

Part 2

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

Resource dynamics

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

Thus the available resource at the instant $t + 1$ is equal to :

$$R_{t+1} = R_t - (E_{1,t} + E_{2,t}) + 0.56,$$

where $E_{1,t}$ is the amount extracted by player 1 of the pair and $E_{2,t}$ the amount extracted by player 2 of the pair.

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

Example

Suppose that at the instant t the amount of resource available is 15 units, that your extraction rate is 0.30 units and that the extraction rate of the other player of your pair is 0.22 units. At the instant $t + 1$ the amount of resource available will then be: $R_{t+1} = 15 - (0.30 + 0.22) + 0.56 = 15.04$ units.

Payoff

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

The calculation of the unitary cost is also identical, namely

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

Thus

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

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

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

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

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

How the part works

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

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

Last details

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

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

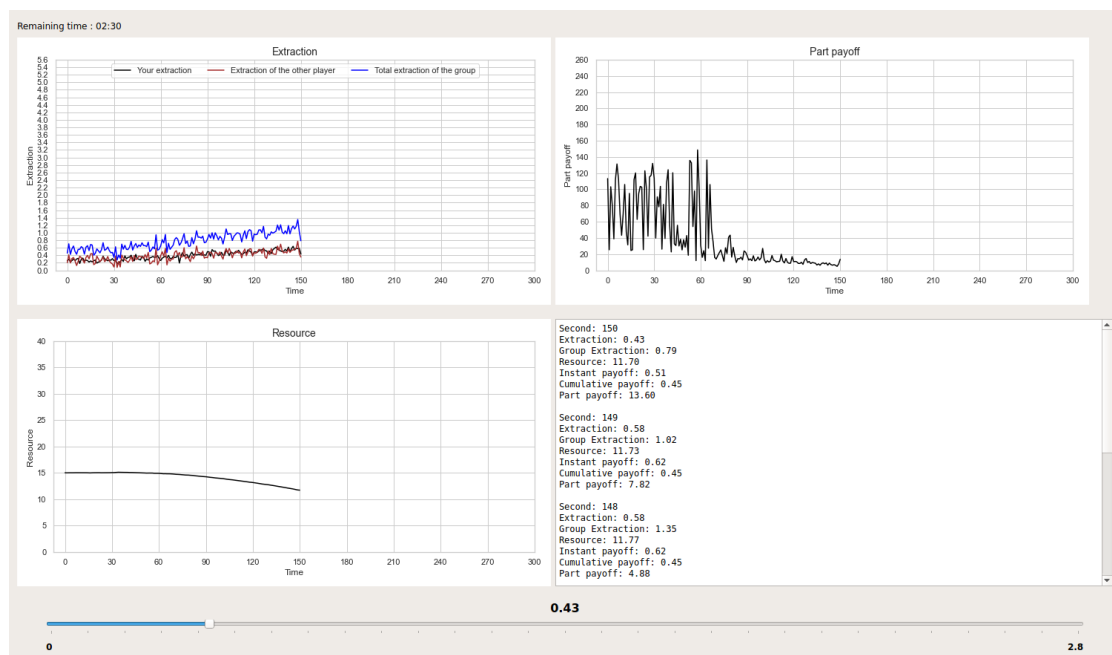


Figure B.7 – Decision-making screenshot. We follow two hypothetical subjects who choose their extraction rate at random

B.5 Comprehension questionnaire

Question 1 – The amount of available resource is updated every second :

true

false

Comment: Every second, the resource decreases by your extraction and increases by 0.56 units.

Question 2 – The payoff at time t depends on the amount of available resource :

true

false

Comment: The payoff at time t is the difference between benefit and cost at time t . Benefit only depends on the extraction rate (see figure 2 of the instructions), but the cost depends on the amount of available resource. The unitary cost (also equivalent to the marginal cost) or the total cost (unitary cost \times extraction rate) increases when the amount of resource decreases but becomes equal to 0 when the amount of 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 payoff at time t (difference between benefit and cost at time t) is given as information, but it is the discounted instantaneous payoff that is taken into account in the calculation of the cumulated payoff (and therefore is one of the two elements used to compute the payoff of the experiment).

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

true

false

Comment: Each time the computer gives you the payoff of the experiment as if the experiment was to immediately end with the two elements mentioned above. First the discounted cumulated payoff from the initial instant $t = 0$ to the present instant. Second 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 no longer change your extraction rate. Your payoff for the experiment is the payoff you would earn at time $t = 300$ (5 minutes of play).

Appendix C

Appendices for Chapter 3

C.1 The Discretization of the Continuous Time Model

This section presents the procedure adopted to discretize the continuous time model. Let's consider the following continuous time model:

$$\begin{aligned} \max_{w(t)} \int_0^{\infty} e^{-rt} f(w(t), H(t)) dt, \quad (C.1) \\ \text{s.t. } \begin{cases} \dot{H}(t) = R - \alpha w(t), \\ H(0) = H_0 \geq 0, H_0 \text{ given}, \\ H(t) \geq 0, \\ w(t) \geq 0. \end{cases} \end{aligned}$$

For the discretization of the model above, let's consider τ as the discretization step and n as a period. Time is discretized into intervals of length τ , such that the differential equation and the payoff are approximated in each interval $n\tau, (n + 1)\tau$.

Thus, the discretization of the objective function gives:

$$\begin{aligned}
\int_{n\tau}^{(n+1)\tau} e^{-rt} f(w(t), H(t)) dt &= \left[-\frac{e^{-rt}}{r} f(w(t), H(t)) \right]_{n\tau}^{(n+1)\tau} \\
&= -\frac{e^{-r(n+1)\tau}}{r} f(w(n), H(n)) - \left(-\frac{e^{-rn\tau}}{r} \right) f(w(n), H(n)) \\
&= \frac{e^{-rn\tau}}{r} (-e^{-r\tau} f(w(n), H(n))) + \frac{e^{-rn\tau}}{r} f(w(n), H(n)) \\
&= f(w(n), H(n)) \frac{e^{-rn\tau}}{r} (-e^{-r\tau} + 1) \\
\int_{n\tau}^{(n+1)\tau} e^{-rt} f(w(t), H(t)) dt &= f(w(n), H(n)) e^{-rn\tau} \left(\frac{1 - e^{-r\tau}}{r} \right).
\end{aligned}$$

Using Taylor's first order limited development of $e^{-r\tau}$ gives :

$$e^{-r\tau} \simeq 1 - r\tau.$$

Thus, the objective function becomes:

$$\begin{aligned}
\int_{n\tau}^{(n+1)\tau} e^{-rt} f(w(t), H(t)) dt &\simeq f(w(n), H(n)) (1 - r\tau)^n \left(\frac{1 - (1 - r\tau)}{r} \right) \\
&= f(w(n), H(n)) (1 - r\tau)^n \left(\frac{1 - 1 + r\tau}{r} \right) \\
\int_{n\tau}^{(n+1)\tau} e^{-rt} f(w(t), H(t)) dt &= f(w(n), H(n)) (1 - r\tau)^n \tau.
\end{aligned}$$

The discretization of the dynamics gives:

$$H(n+1) = H(n) + (R - \alpha w(n)) \tau.$$

The discrete time problem can be defined as:

$$\max_{w(n)} \sum_{n=0}^{\infty} (1 - r\tau)^n \left[a w(n) - \frac{b}{2} w(n)^2 - \max(0, c_0 - c_1 H(n)) w(n) \right] \tau, \quad (\text{C.2})$$

$$s.t \begin{cases} H(n+1) = H(n) + \tau(R - \alpha w(n)), \\ H(0) = H_0 \geq 0, H_0 \text{ given}, \\ H(n) \geq 0, \\ w(n) \geq 0. \end{cases}$$

The discrete time model therefore converges towards the continuous time model when the discretization step τ tends toward zero.

In order to see the degree of the approximations used in the experiment, with the parameters chosen in the model, Figure C.1 shows the feedback trajectory in continuous time and for the discretizations ($\tau = 0.1$ and $\tau = 1$).

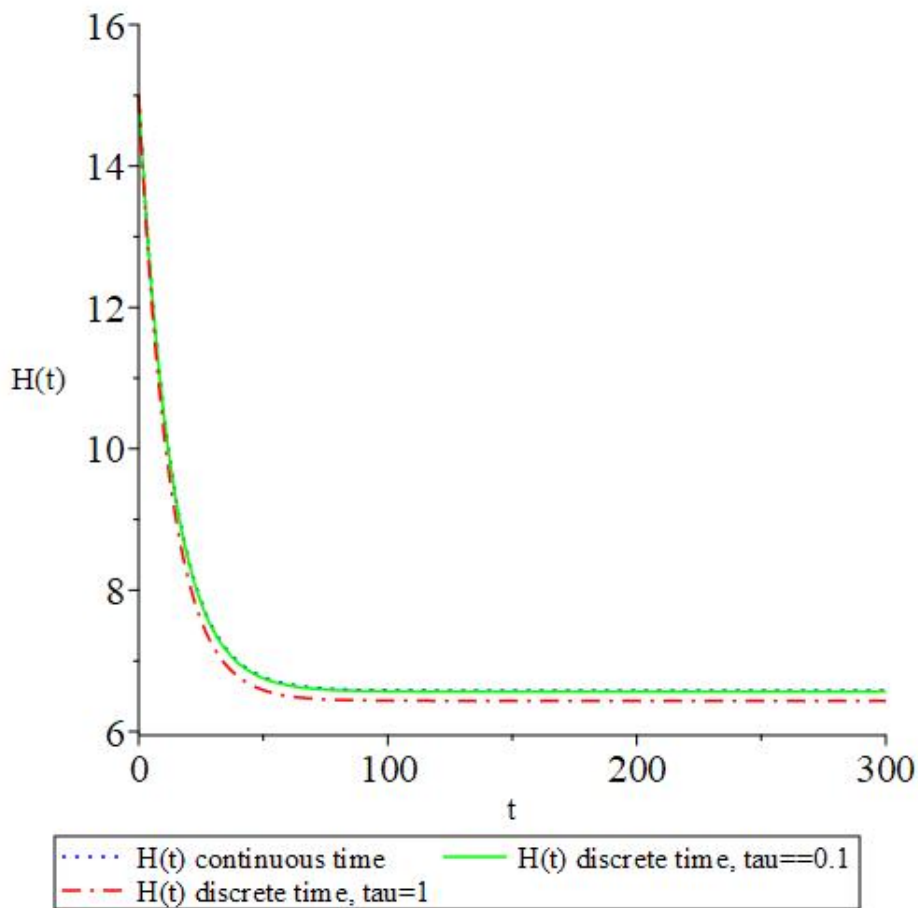


Figure C.1 – Feedback equilibrium in continuous and discrete time

C.2 Theoretical Solutions

Only continuous time solutions are presented because solutions for the discrete time model are similar. In the single agent (optimal control) problem, we describe the two types of behaviors farmers can exhibit: social optimum and myopic.

In the game, we consider two farmers exploiting the resource. Despite the evolution of the water table, payoffs and costs are the same than in the single farmer problem. They are also similar for both players. We consider two non-cooperative types of behaviors: a look-forward farmers, allowing to compute the feedback equilibrium, and myopic farmers. For sake of comparison we also consider the joint maximization problem i.e., the cooperative solution or the social optimum solution. We do that because we want to know if some kind of "tacit" cooperation can emerge without negotiation.

Solutions for the single agent and the game converges to those presented in Appendix B.1 and Appendix B.2 of Chapter 2 for the continuous time problem when the parameter of discretization goes to zero.

C.3 Figures from Experimental Instructions

Figure B.1 – Total revenue from extraction

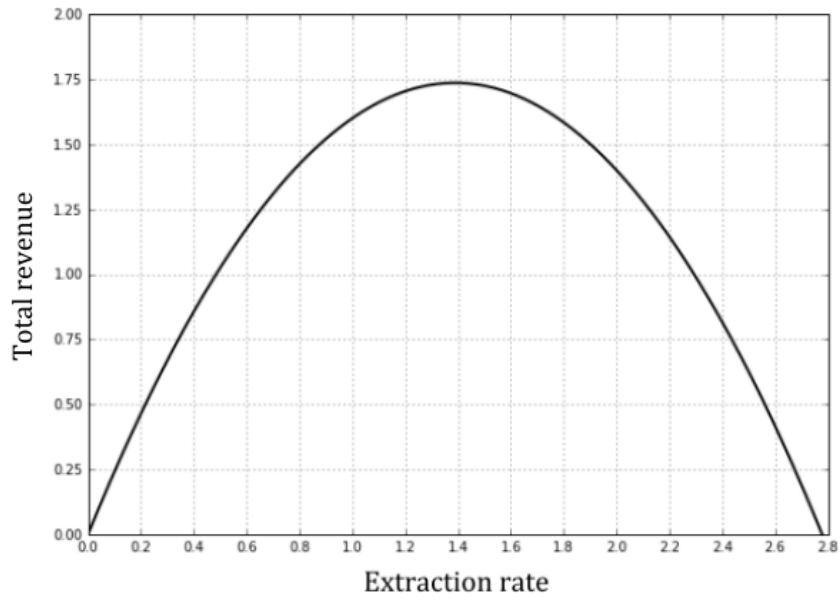


Figure B.2 – Unitary cost of extraction

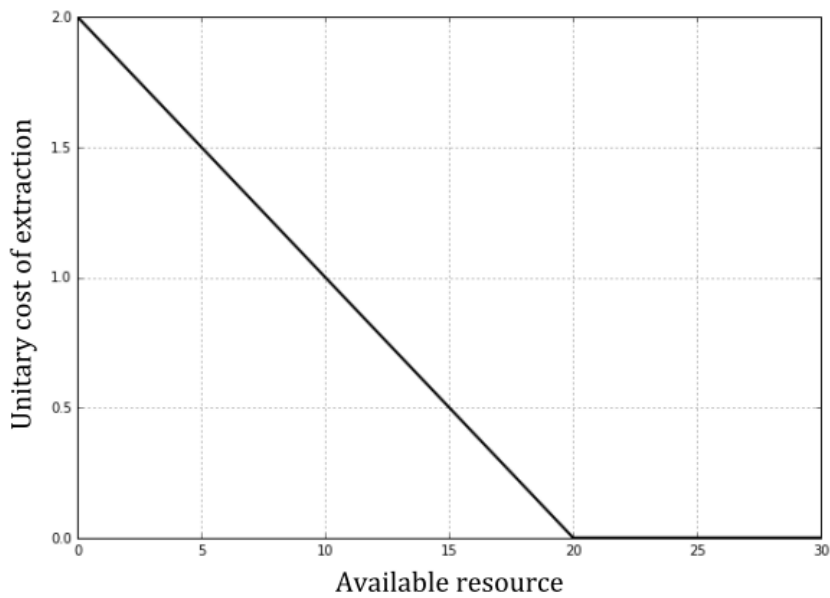
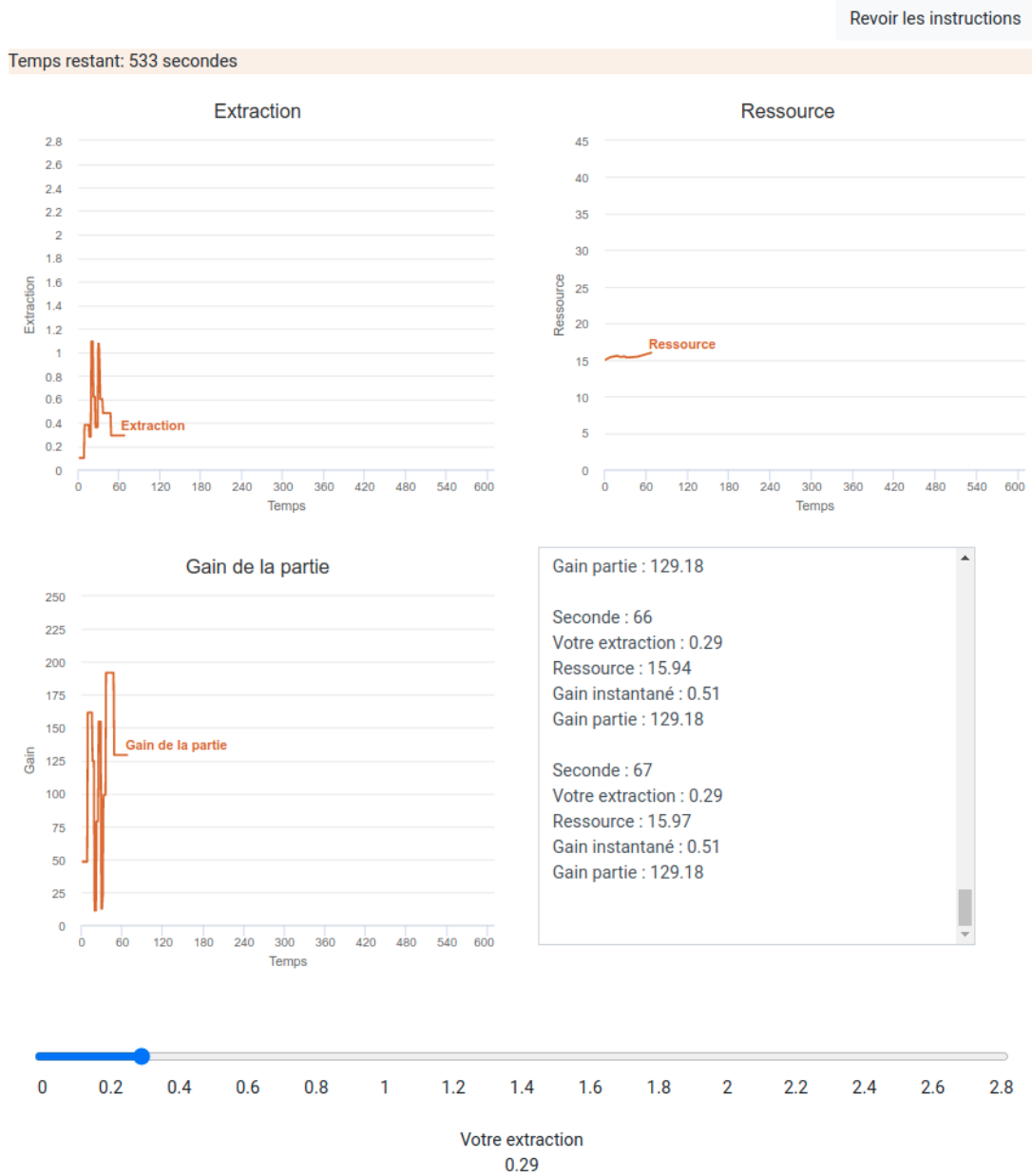


Figure B.3 – Decision-making screen shot. We follow a hypothetical subject who chooses his extraction rate at random



C.4 Additional Figures

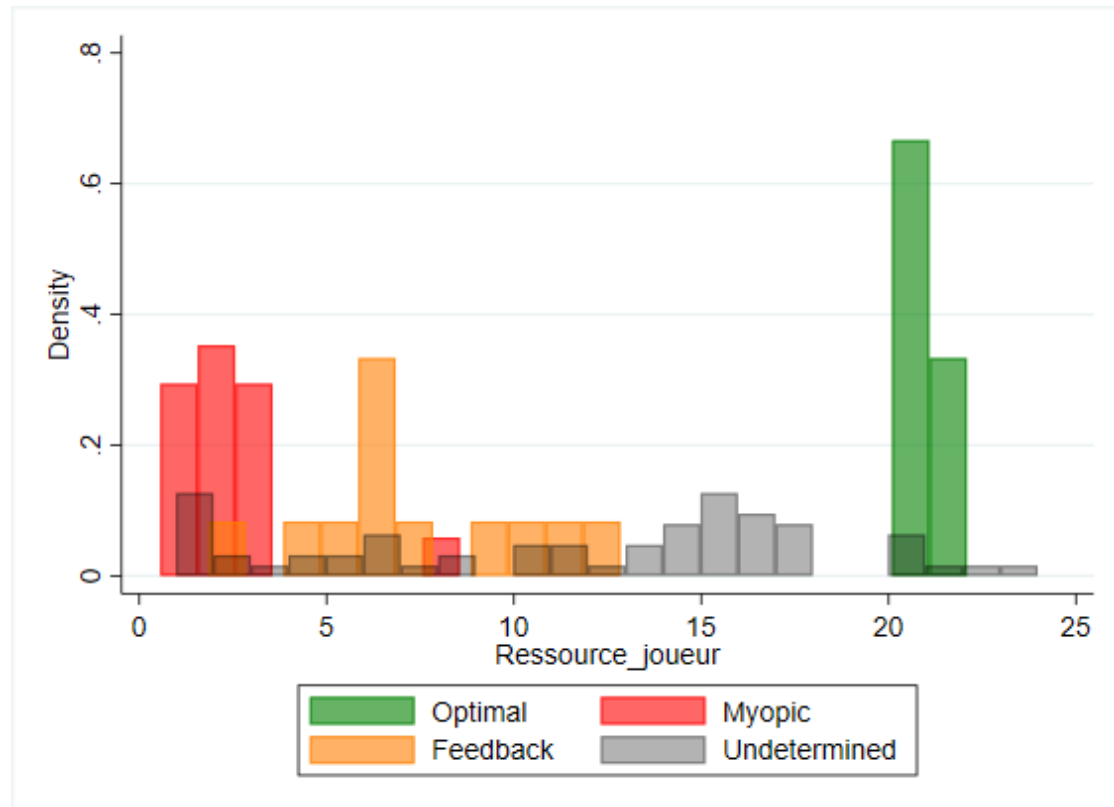


Figure B.4 – Resource level at the end of the game by categories (continuous and discrete time)

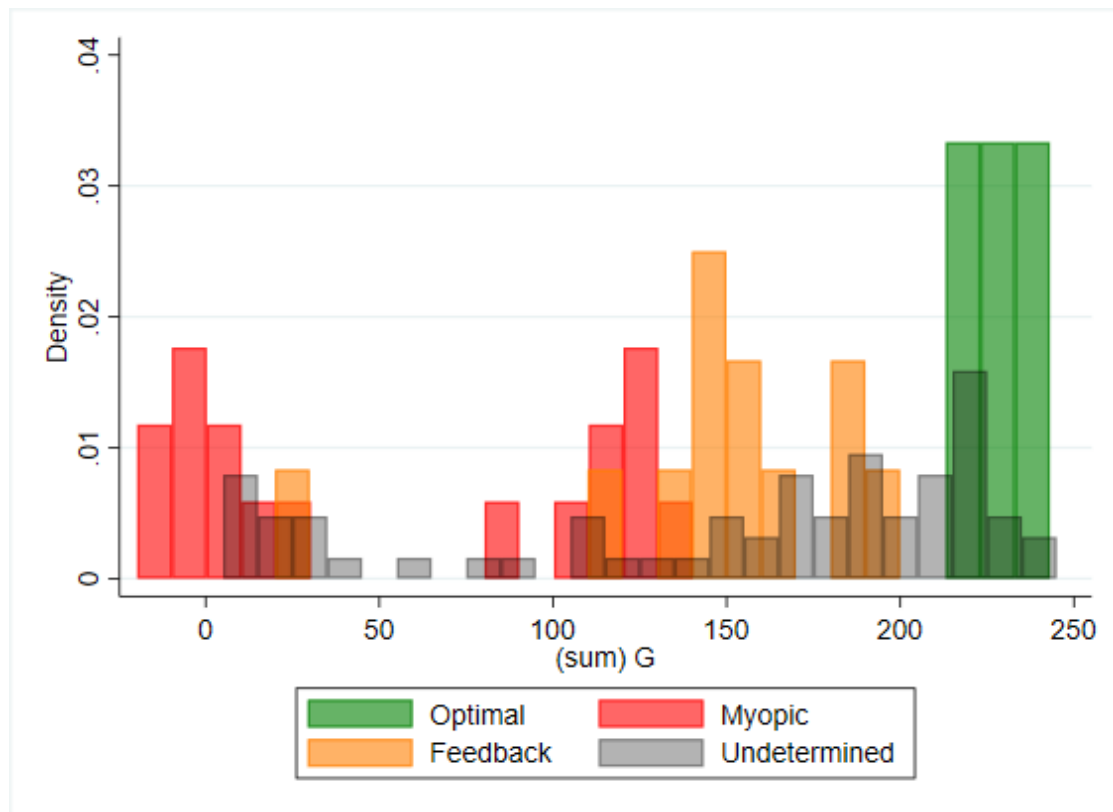


Figure B.5 – Total payoffs at the end of the game by categories (continuous and discrete time)

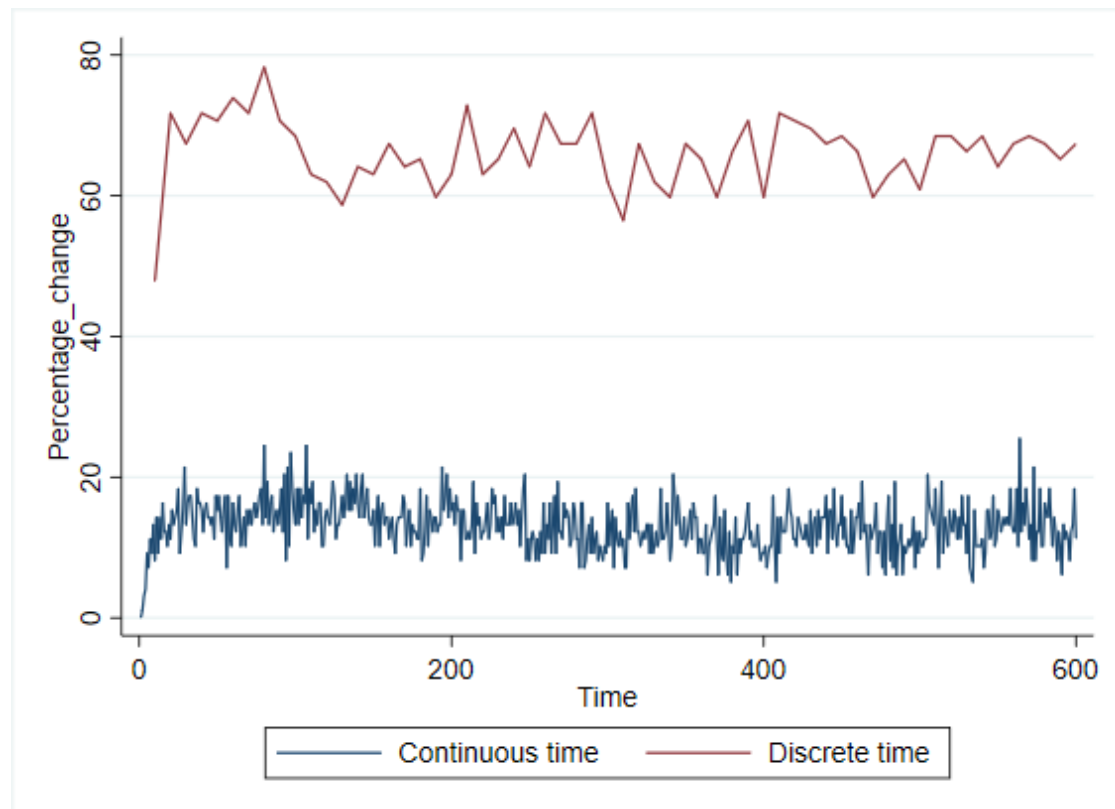


Figure B.6 – Proportion of subjects changing extraction levels at each period/instant

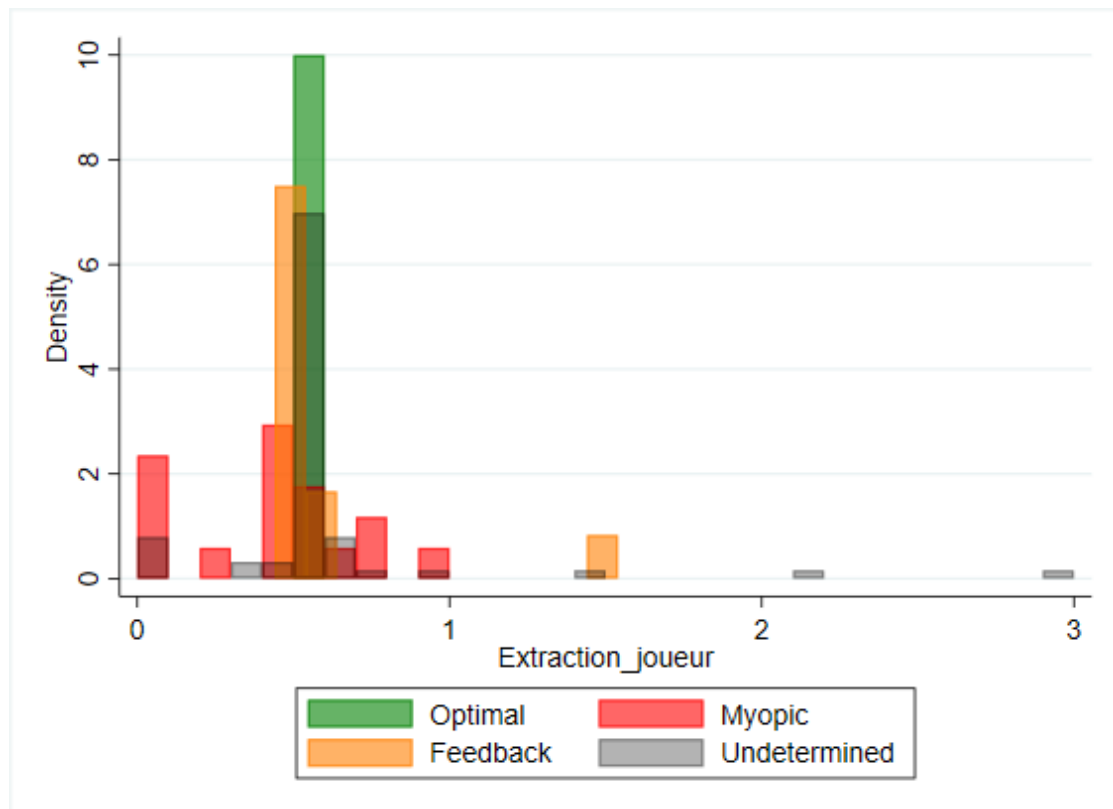


Figure B.7 – Extraction level at the end of the game by categories (continuous and discrete time)

Table C.1 – Groups with extraction levels at the end of the game greater or lower than the natural recharge ($R = 0.56$) by categories (continuous and discrete time)

	E<R		E>R	
	Continuous	Discrete	Continuous	Discrete
Optimal	1	2	0	0
Feedback	5	6	1	0
Myopic	1	11	2	3
Undetermined	32	17	7	7
Total	39	36	10	10

C.5 Instructions for the Optimal Control (Sole Agent)

Translated from French

C.5.1 Continuous Time Instructions

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

Earnings are in experimental currency units (ECU). The exchange rate of ECU to 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

You initially have 15 resource units. At any time, you can extract between 0 and 2.8 resource units with up to two-decimal points of precision. This means that you are free to choose the extraction rate you want, namely 0, 0.01, 0.02 ... 2.79, 2.8. You will move a slider similar to that depicted in Figure B.8 to make your choice. The value displayed below the slider when you release it is automatically taken into account and sent to the central computer which updates the information.

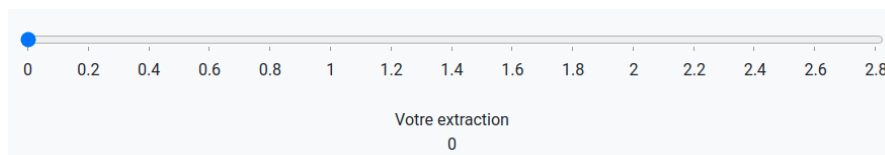


Figure B.8 – Slider for decision-making

Resource dynamics

The available resource continuously evolves. Its evolution depends on two elements: (i) your extraction rate at instant t denoted E_t and (ii) a fixed rate of 0.56 automatically added at each instant t .

Thus the resource evolves as follows:

- when your extraction rate is higher than the fixed rate, the resource decreases
- when your extraction rate is lower than the fixed rate, the resource grows
- when your extraction rate is equal to the fixed rate, the resource is stable

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

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

Payoff

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

Total revenue from extraction

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

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

Figure B.9 below shows the total revenue according to the extraction rate.

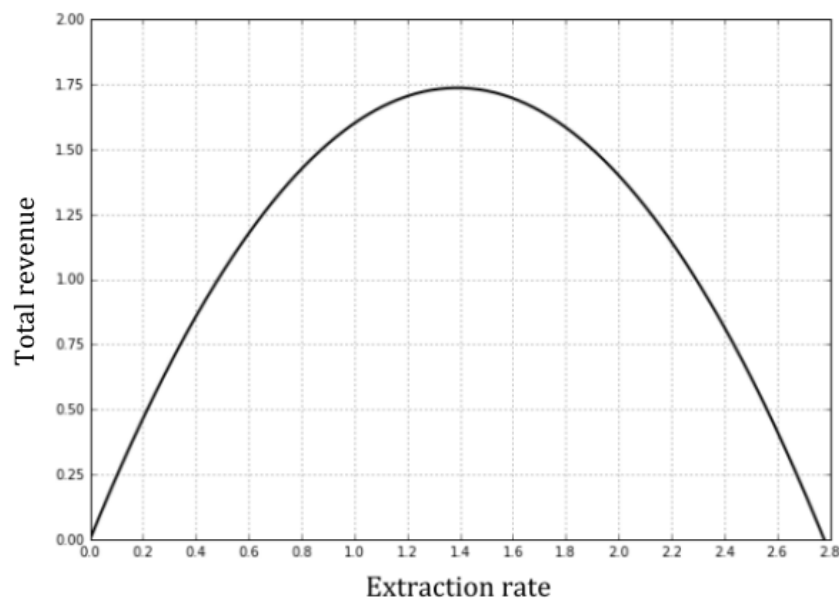


Figure B.9 – Total revenue from extraction

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 cost is null when the available resource is bigger than or equal to 20 units

Figure B.10 shows the unitary cost according to the available resource.

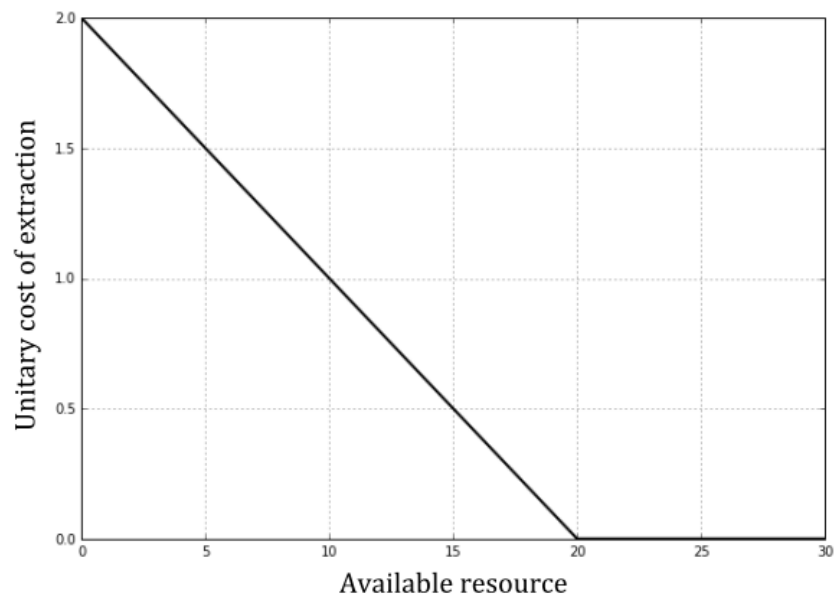


Figure B.10 – Unitary cost of extraction

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

$$C_t = E_t \times c_t.$$

Discounted instantaneous payoff

Each instant, 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 concretely means that the instant t payoff is multiplied by $e^{-0.005 \times t}$. Thus, a 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 first instants have greater impact on the payoff of the experiment than those of the last instants.

Payoff for the experiment

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

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

How the experiment works

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

The computer performs the calculations every second, and the data displayed on your screens is updated every second as well. A second corresponds to 0.1 instant in what 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. Figure B.11 on page 192 gives you a shot of the decision screen. Description of the areas is as follows:

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

Final details

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

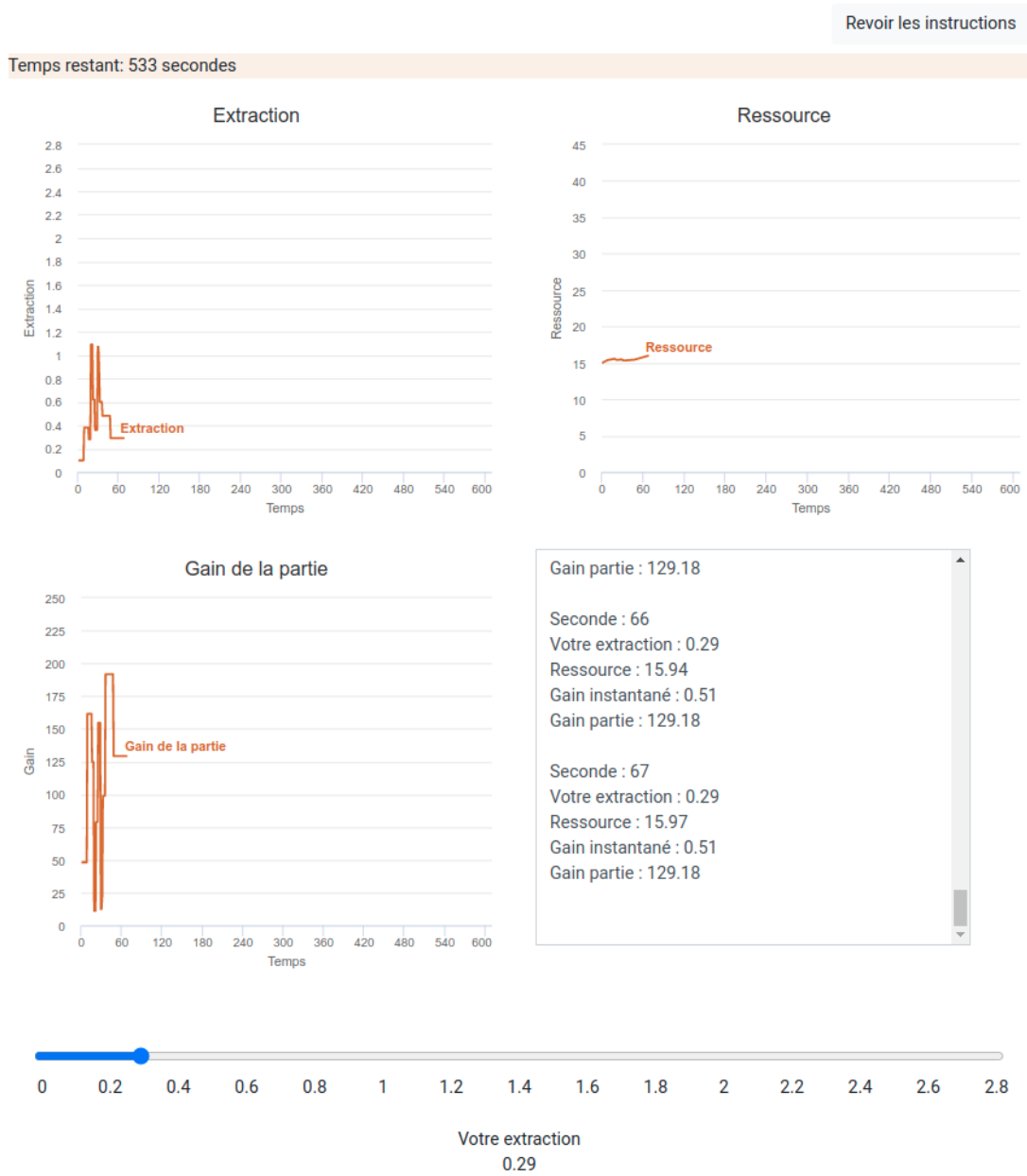


Figure B.11 – Decision-making screen shot. We follow a hypothetical subject who chooses his extraction rate at random

C.5.2 Discrete Time Instructions

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

Earnings are in experimental currency units (ECU). The exchange rate of ECU to 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

You initially have 15 resource units. Each period, you can extract an amount between 0 and 2.8 resource units with up to two decimal points of precision. This means that you are free to choose the amount you want to extract, namely 0, 0.01, 0.02 ... 2.79, 2.8. You will move a slider similar to that depicted in Figure B.12 to make your choice. You have 10 seconds to make your choice. At the end of these 10 seconds, the value below the slider is automatically taken into account, and is sent to the central computer which updates the information. Then the next period begins and you have again 10 seconds to change your extraction level.

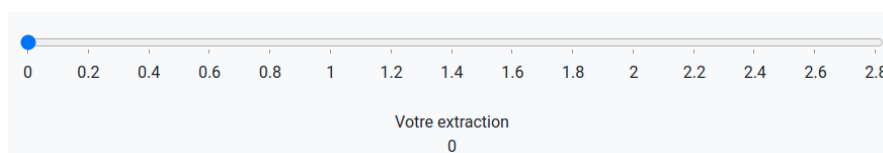


Figure B.12 – Slider for decision-making

Resource dynamics

The available amount of the resource evolves during each period. Its evolution depends on two elements: (i) the amount of resource you extract at each period n , denoted E_n , and (ii) a fixed amount of 0.56 automatically added at each period. By denoting R_n the amount of resource available at period n , the dynamics of the resource is as follows:

$$R_{n+1} = R_n - E_n + 0.56.$$

A graph on your screen will show you the resource's evolution at each period.

If at period n your action is such that it brings the resource to zero, your extraction level for this period will be set to zero by the computer.

Example

Suppose that at period n the amount of resource available is 15 units and that your extraction level is 0.30 units. At period $n + 1$ the amount of resource available will then be: $R_{n+1} = 15 - 0.30 + 0.56 = 15.26$ units.

Payoff

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

Total revenue from extraction

At period n , for an extracted amount E_n , the total revenue denoted REC_n is equal to:

$$REC_n = 2.5E_n - 0.9E_n^2.$$

Figure B.13 below shows the total revenue according to the extraction level.

Example

Let's assume that at a given period n your extraction level is 1.4, the total revenue will then be 1.736 units.

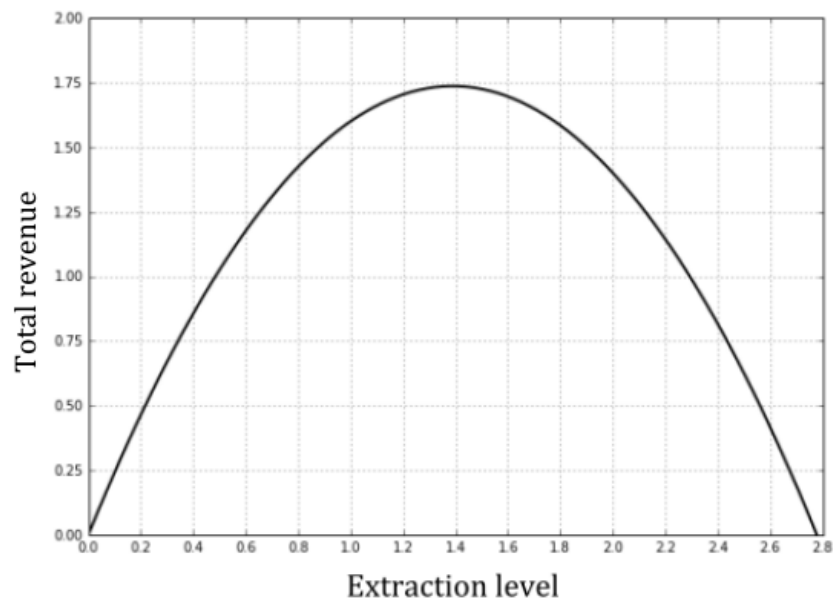


Figure B.13 – Total revenue from extraction

Cost of extraction

At period n for an available amount of resource R_n , the unitary cost c_n is equal to :

$$c_n = \begin{cases} (2 - 0.1R_n) & \text{if } 0 \leq R_n < 20, \\ 0 & \text{if } R_n \geq 20. \end{cases}$$

Thus,

- ✓ cost increases when the available amount of the resource decreases
- ✓ cost is positive when the available amount of the resource is strictly lower than 20 units and the cost is null when the available amount of the resource is greater than or equal to 20 units

Figure B.14 shows the unitary cost according to the available resource.

Total cost of extraction C_n , is equal to the amount extracted times the unitary cost, that is:

$$C_n = E_n \times c_n.$$

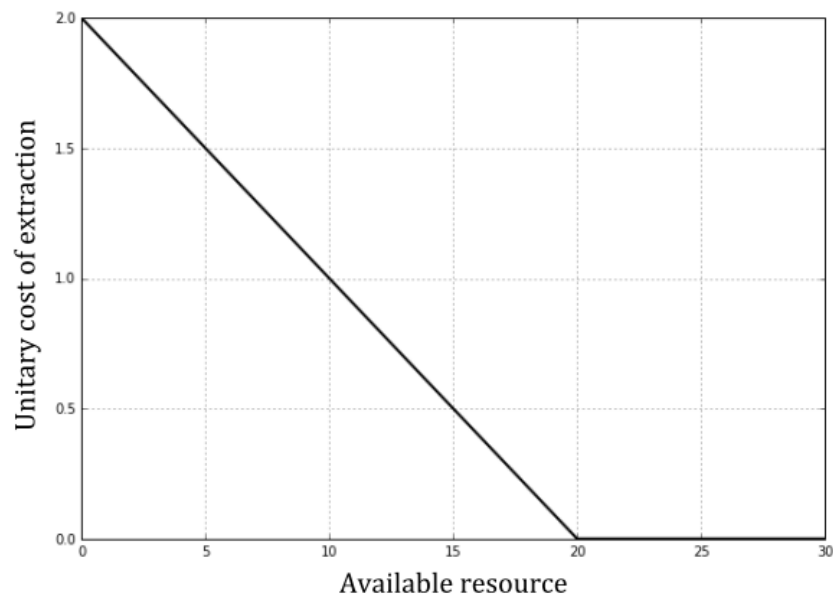


Figure B.14 – Unitary cost of extraction

Discounted period payoff

Each period, the payoff of the period (G_n), which is equal to the difference between total revenue and total cost ($G_n = REC_n - C_n$), is multiplied by a discount factor, allowing us to determine the present value of the payoff perceived in the future. The discount factor equals 0.995 and in concrete terms means that the payoff of period n is multiplied by 0.995^n . Thus, a same payoff at n has a different discounted value according to the period.

Example

Let's take a same payoff $G_n = 0.5$ at 4 different periods.

At period $n = 0$ the discounted payoff equals $0.5 \times 0.995^0 = 0.5$

At period $n = 1$ the discounted payoff equals $0.5 \times 0.995^1 = 0.4975$

At period $n = 10$ the discounted payoff equals $0.5 \times 0.995^{10} = 0.4755$

At period $n = 60$ the discounted payoff equals $0.5 \times 0.995^{60} = 0.3701$

What one should remember from this discounting principle is that the payoffs for the first period has a greater impact on the payoff of the experiment than those of the later periods.

Payoff for the experiment

Your payoff for the experiment includes two elements: (i) your cumulated payoff (the discounted sum of each period payoff) from the beginning of the experiment ($n = 0$) until the present period ($n = p$), and (ii) your "continuation payoff", which is your payoff if the experiment went on forever (from $n = p$ to $n = \infty$) with your extraction level being fixed to the present period.

Your remuneration for the experiment is your payoff for the last period of the experiment. This payoff corresponds to your cumulated payoff over all the periods of the experiment, plus the payoff computed as if the experiment continued indefinitely with your extraction level fixed at the level of the last period.

How the experiment works

Before the experiment starts you should decide upon an initial extraction level which will apply at the beginning of the experiment ($n = 0$). Then during each period you have 10 seconds to change this extracted amount by moving the slider on the window displayed on your screen. When you do not move the slider, the value considered in each period is the last one you set.

The decision screen includes four areas, in addition to the decision area with the slider. Three of these areas are graphic areas and the fourth is a text area. Figure [B.15](#) on page [199](#) gives you a shot of the decision screen. Description of the areas is as follows :

- ✓ graphic at the top left: your extraction level at each period
- ✓ graphic at the top right: the available resource at each period

- ✓ graphic at the bottom left: your payoff of the experiment, which, as explained previously, is composed of your cumulative payoff up to the present period, plus your payoff if your extraction is applied indefinitely
- ✓ text area at the bottom right: the same information as the curves but in text form, namely, for each period your extraction level, the available resource, your discounted period n payoff and your payoff for the experiment

Final details

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

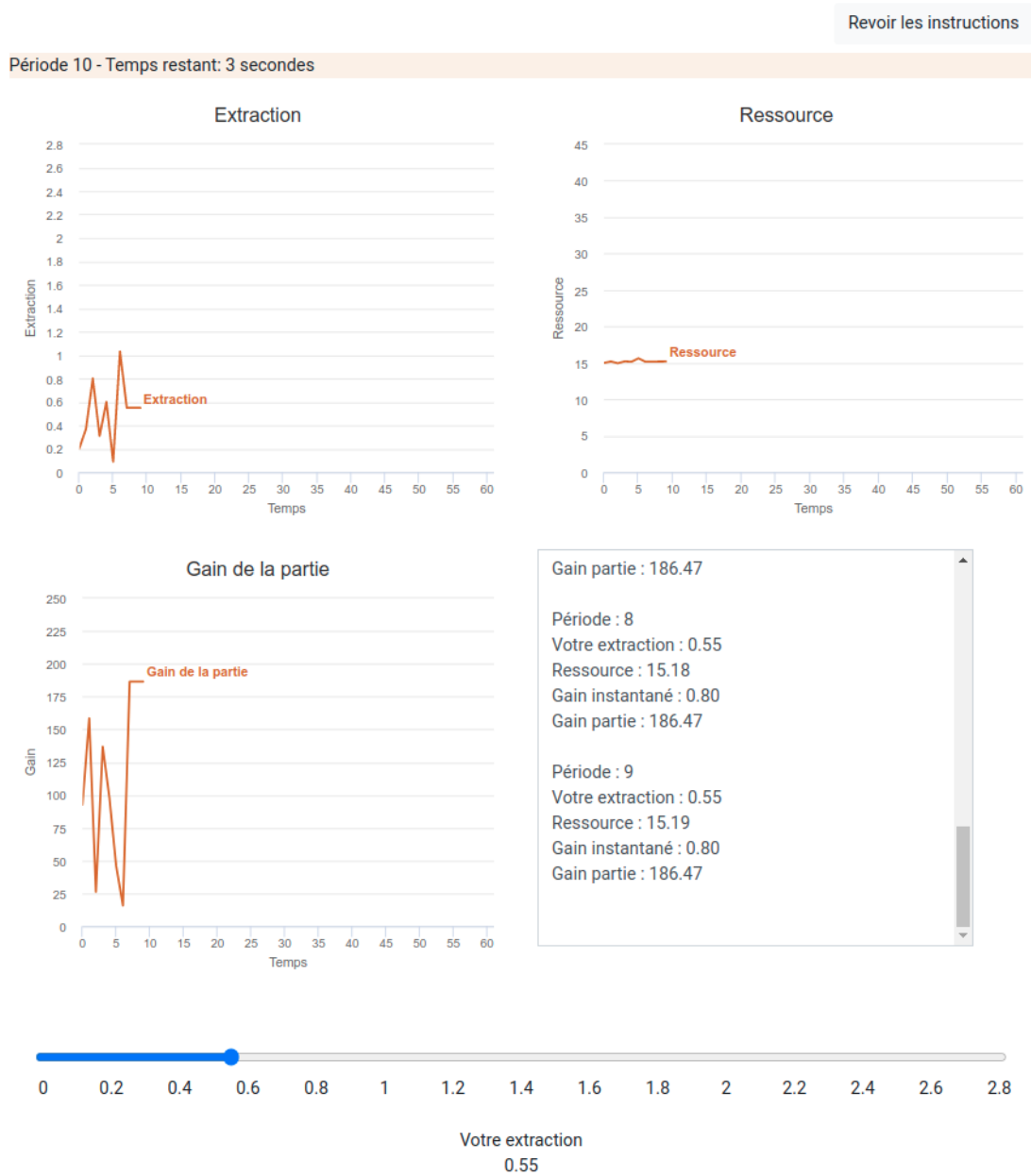


Figure B.15 – Decision-making screen shot. We follow a hypothetical subject who chooses his extraction rate at random

C.6 Instructions for the game (multiple agents)

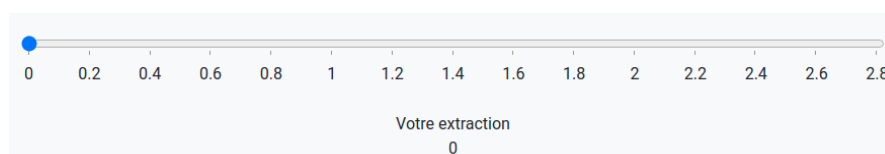
C.6.1 Continuous Time Instructions

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 these 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.

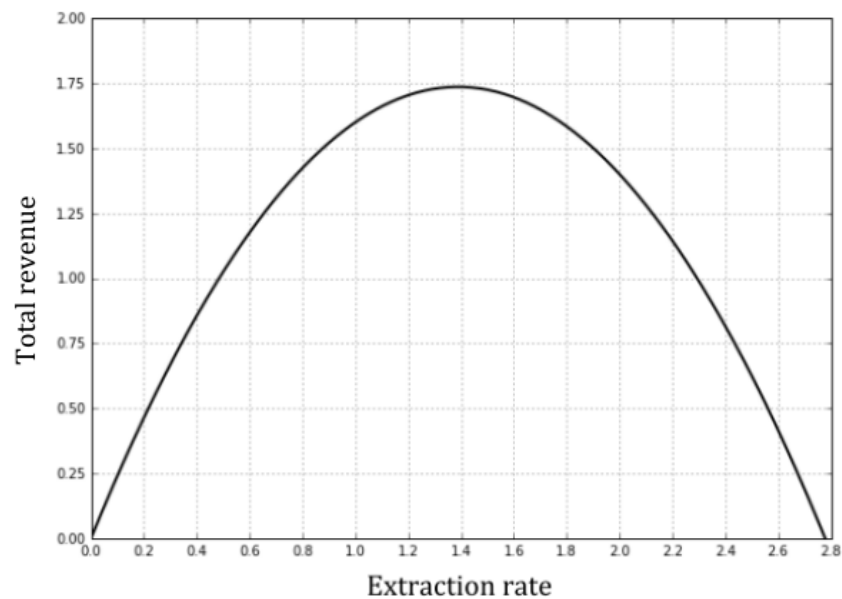
Total revenue from extraction

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

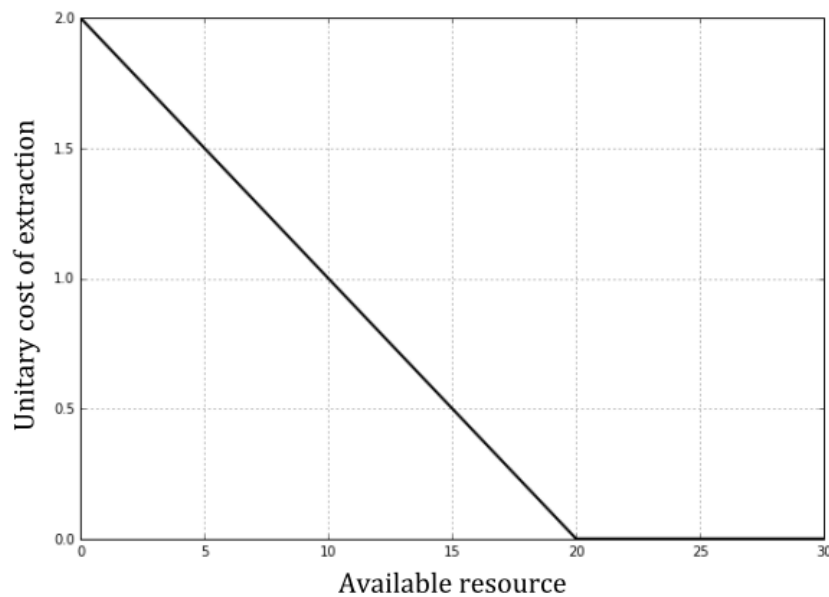
At the instant t for an available amount of resource R_t , the unitary cost c_t is equal to:

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

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

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€.

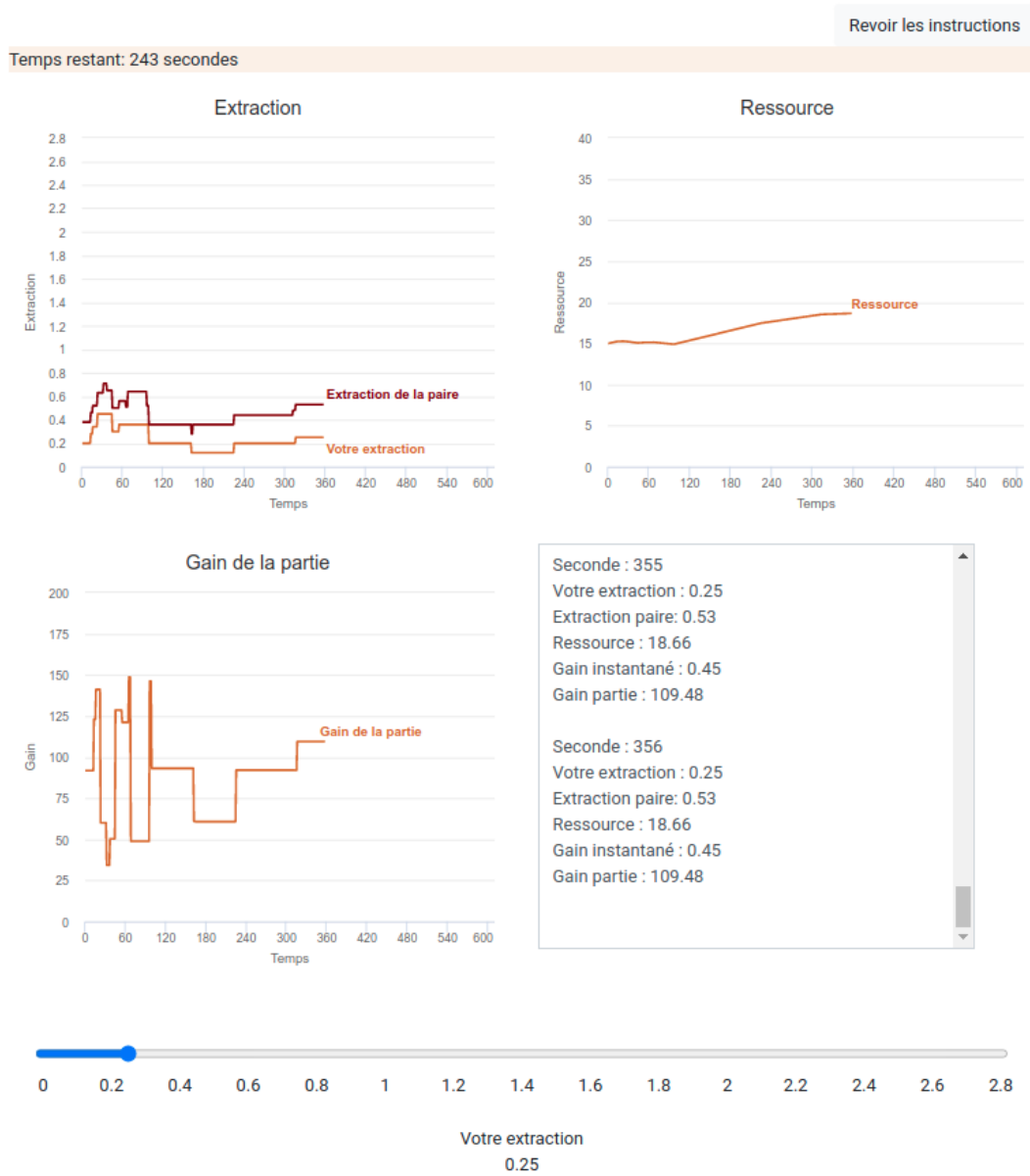


Figure B.16 – The game screen shot

C.6.2 Discrete Time Instructions

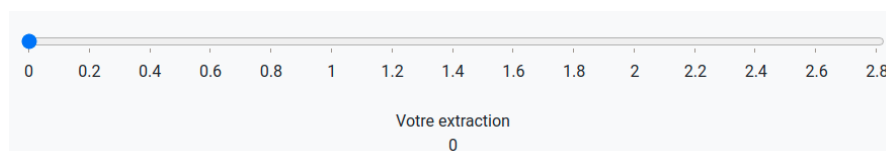
You are about to participate in a decision-making experiment. We ask you to carefully read the instructions in order to better understand the experiment. An experimenter

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 60-period training phase and a 60-period experimentation phase, each corresponding to 10 minutes. 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 each of the two players of the pair can extract an amount between 0 and 2.8 resource units with up to two decimal points of precision. You and the other player are free to choose how much you want to extract, 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.



You each have 10 seconds to make your choice. At the end of these 10 seconds the value below the slider is automatically taken into account, it is sent to the central computer which updates information. Then the next period begins and you, as well as the other player, have again 10 seconds to change your extraction level.

Resource dynamics

The available amount of resource evolves each period, and its evolution depends on two elements:

(i) the total amount of resource extracted by you and your partner at each period n , and

(ii) a fixed amount of 0.56 units automatically added at each period n . By denoting R_n the amount of resource available at period n , the dynamics of the resource is as follows:

$$R_{n+1} = R_n - (E_{1,n} + E_{2,n}) + 0.56,$$

where $E_{1,n}$ is the amount extracted by Player 1 and $E_{2,n}$ the amount extracted by Player 2.

Example

Suppose that at period n the amount of resource available is 15 units, that your extraction level is 0.30 units and that the extraction level of your partner is 0.22 units. The amount of resource available at period $n + 1$ will then be : $R_{n+1} = 15 - (0.30 + 0.22) + 0.56 = 15.04$ units.

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

If the total amount extracted by you and your partner is higher than the available resource, each layer's extraction is set to zero. You must choose another extraction compatible with the available resource.

Payoff

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

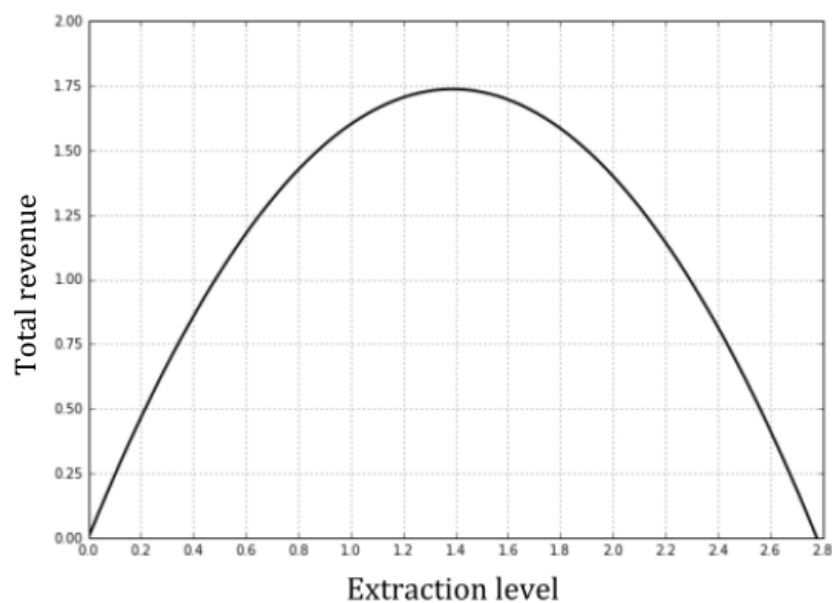
Total revenue from extraction

At period n , the total revenue denoted REC_n is equal to:

$$REC_n = 2.5E_n - 0.9E_n^2,$$

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

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

**Example**

Let's assume that at a given period n your extraction level is 1.4. The total revenue will then be 1.736 units.

Cost of extraction

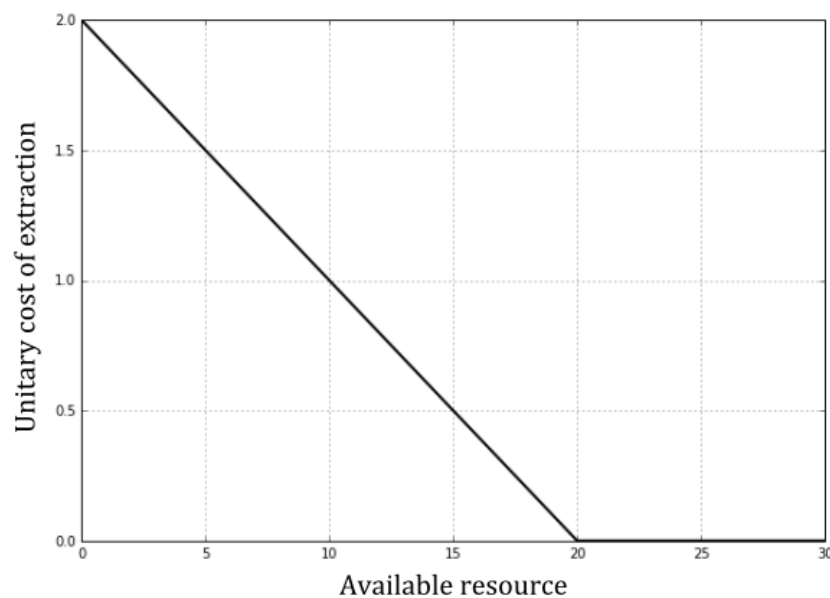
At period n , for an available amount of the resource R_n , the unitary cost c_n is equal to:

$$c_n = \begin{cases} (2 - 0.1R_n) & \text{if } 0 \leq R_n < 20, \\ 0 & \text{if } R_n \geq 20. \end{cases}$$

Thus,

- ✓ cost increases when the available resource decreases
- ✓ cost is positive when the available resource is strictly lower than 20 units and cost is null when the available resource is greater than or equal to 20 units
- ✓ **cost depends indirectly on the total extraction level of both players through the available resource**

The figure below shows the unitary cost according to the available resource.



Total cost of extraction C_n , is equal to the amount extracted times the unitary cost, that is:

$$C_n = E_n \times c_n.$$

Discounted instantaneous payoff

Each period, for each of the two players, the payoff of the period (G_n), which is equal to the difference between total revenue and total cost ($G_n = REC_n - C_n$), is multiplied by a discount factor, allowing us to determine the present value of the payoff perceived in the future. The discount factor equals 0.995 and concretely means that the payoff of period n is multiplied by 0.995^n . Thus, a same payoff at n has a different discounted value according to the period.

Example

Let's take a same payoff $G_n = 0.5$ at 4 different periods.

At period $n = 0$ the discounted payoff equals $0.5 \times 0.995^0 = 0.5$

At period $n = 1$ the discounted payoff equals $0.5 \times 0.995^1 = 0.4975$

At period $n = 10$ the discounted payoff equals $0.5 \times 0.995^{10} = 0.4755$

At period $n = 60$ the discounted payoff equals $0.5 \times 0.995^{60} = 0.3701$

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

Payoff for the experiment

Your payoff for the experiment, as well as that of the other player include two elements: (i) your cumulated payoff (the discounted sum of each period payoff) since the beginning of the experiment ($n = 0$) until the present period ($n = p$), and (ii) your "continuation payoff", which is your payoff if the experiment were to go on forever (from $n = p$ to period $n = \infty$) **with your extraction level and that of the other player** being fixed to the present period.

Your remuneration for this experiment is your payoff for the last period of the game. This payoff corresponds to your cumulated payoff over all the periods of the game, to which is added the payoff computed as if the game continued indefinitely with your extraction level and that of the other player of your pair fixed at that of the last period.

How the experiment works

Before the experiment starts you and the other player should each decide upon an initial extraction level, which will apply at the beginning of the experiment ($n = 0$). Then, at each period, each of you have 10 seconds to change this extracted amount by moving the slider on the window displayed on your screen. When you do not move the slider, the value that is considered at each period is the last one each of you set.

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

- ✓ graphic at the top left: your extraction level and the extraction level of your pair at each period
- ✓ graphic at the top right: the available resource at each period
- ✓ graphic at the bottom left: your payoff of the experiment, which is composed as explained previously of your cumulative payoff up to the present period, to which is added your payoff if your extraction and that of the other player of your pair is applied indefinitely
- ✓ text area at the bottom right: the same information as the curves but in the form of text, namely for each period, your extraction level, the total extraction level of your pair, the available resource, your discounted period n payoff and your payoff of the experiment.

Final details

This experiment includes a 60period training phase and a 60-period experimentation phase. It's your payoff for the experimentation that will be considered for your remuneration in euros. The exchange rate of ECUs to euros is as follows: 10 ECUs = 0.5€.

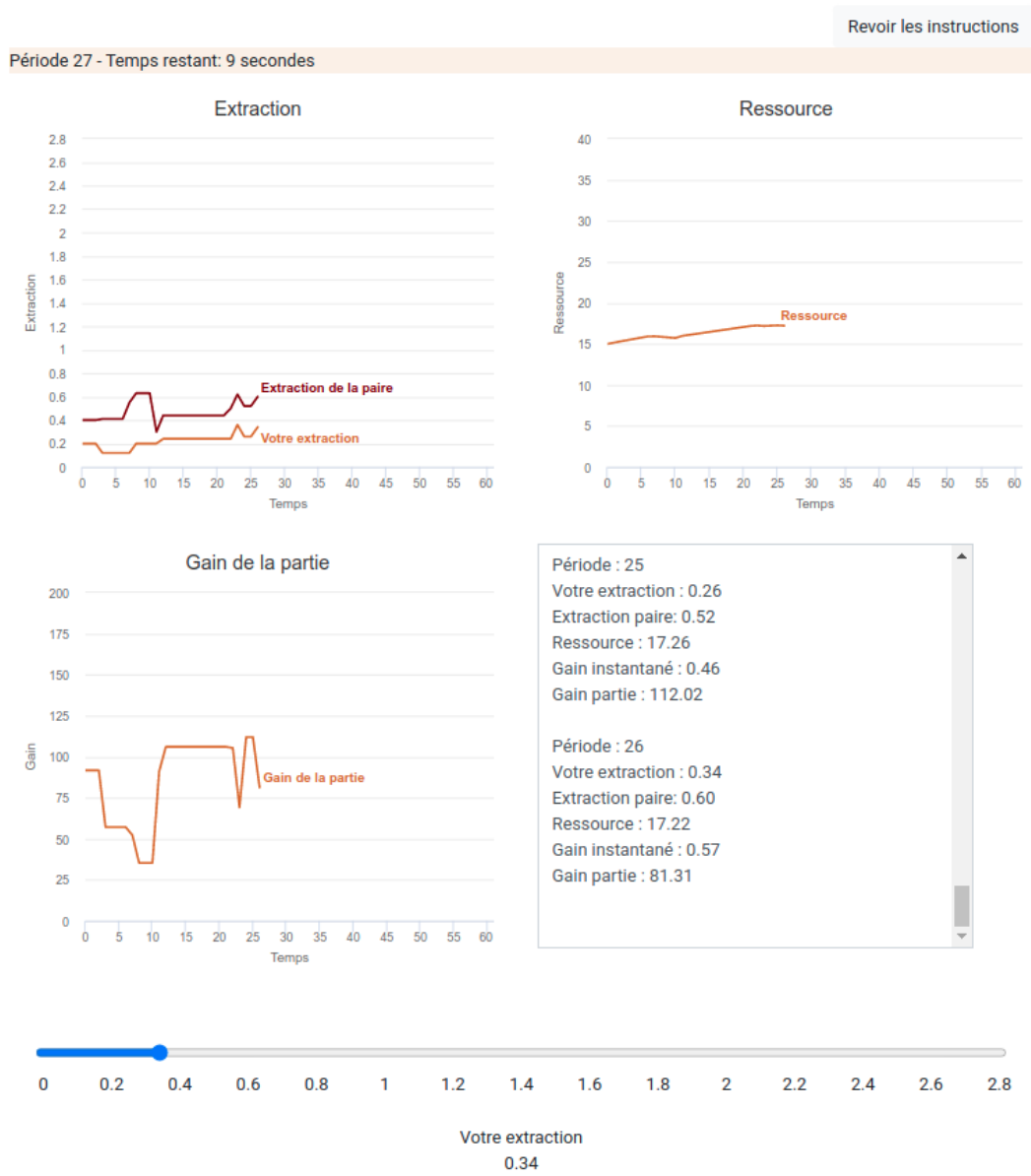


Figure B.17 – The game screen shot

C.7 Comprehension questionnaire for the optimal control (sole agent)

C.7.1 Continuous Time Comprehension Questionnaire

Question 5 – The amount of available resource is updated in real time :

true

false

Comment: The resource grows when the difference between the additional fixed rate and the extraction rate is positive, and decreases when the difference is negative.

Question 6 – 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 (see figure B.9 in the instructions), but the cost depends on the amount of available resource. Whether the unitary cost (also equivalent to the marginal cost) or the total cost (unitary cost \times extraction rate), the cost increases when the amount of the resource decreases but becomes equal to 0 when the amount of the available resource is greater than or equal to 20.

Question 7 – 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 therefore is one of the two elements used to compute the payoff of the experiment).

Question 8 – The payoff of 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 the extraction rate is that 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. First the discounted cumulated payoff from the initial instant $t = 0$ to the present instant. Second 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 no longer change your extraction rate. Your payoff for the experiment is the payoff you would earn at time $t = 600$ (10 minutes of play).

C.7.2 Discrete Time Comprehension Questionnaire

Question 9 – The amount of available resource is updated every period :

true

false

Comment: Every period, the resource decreases by the amount you extracted and increases by 0.56 units.

Question 10 – The payoff of period n depends on the amount of available resource :

true

false

Comment: The payoff of period n is the difference between the total revenue and the cost at this period. The total revenue only depends on the extraction level (see figure B.13 in the instructions), but the cost depends on the amount of available resource. Whether the unitary cost (also equivalent to the marginal cost) or the total cost (unitary cost \times extraction level), the cost increases when the amount of resource decreases but becomes equal to 0 when the amount of available resource is greater than or equal to 20.

Question 11 – The discounted payoff of period n is the one taken into account in the calculation of the cumulated payoff :

true

false

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

Question 12 – The payoff of the experiment at period x is composed of two elements: (i) the cumulated discounted payoff of each period between 0 and x , and (ii) the calculated payoff from period x to infinity, assuming that the extraction level is that of period x :

true

false

Comment: Each period the computer gives you the payoff of the experiment as if the experiment was to immediately end with the two elements mentioned above. First the discounted cumulated payoff from the initial period 0 to the present period. Second the payoff from the present period to infinity assuming that the dynamics of the resource evolves according to the defined rule, but also that you no longer change your extraction level. Your payoff for the experiment is the payoff you would earn at period 60 (10 minutes of play).

C.8 Comprehension questionnaire for the game (multiple agents)

C.8.1 Continuous Time Comprehension Questionnaire

Question 13 – 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 14 – 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 15 – 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 16 – 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 partner's 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).

C.8.2 Discrete Time Comprehension Questionnaire

Question 17 – The amount of available resource evolves at each period and depends on two elements: the amount extracted by you and your partner and a fixed amount of 0.56 :

true

false

Comment: The amount of available resource evolves at each period, depending on the amount extraction by you and your partner and a fixed amount of 0.56. Specifically, if the both players' extraction is greater than 0.56, the amount of the resource available decreases. If it is less than the fixed amount it increases, and if it is equal to the fixed amount, the amount of the resource available remains stable.

Question 18 – The payoff of period n depends on the amount of the available resource :

true

false

Comment: The payoff for period n is the difference between the total revenue and the cost during this period. The total revenue only depends on the extraction level, but the cost depends on the amount of the available resource. Whether the unitary cost or the total cost (unitary cost \times extraction level), 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 19 – The discounted payoff of period n is the amount taken into account in the calculation of the cumulated payoff :

true

false

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

Question 20 – The payoff of the experiment at period x is composed of two elements: (i) the cumulated discounted payoff of each period between 0 and x , and (ii) the calculated payoff from period x to infinity, assuming that your extraction level and that of the other player are those of period x :

true

false

Comment: During each period the computer gives you the payoff for the experiment as if the experiment was to immediately end with the two elements mentioned above: (i) the discounted cumulated payoff from the initial period 0 to the present period, (ii) the payoff from the present period to infinity, assuming that the dynamics of the resource evolve according to the defined rule, but also assuming that you and the other player no longer change your extraction level. Your payoff in euros for the experiment is your payoff at the last period of the game, namely at period 60 (10 minutes of play).

Appendix D

Appendices for Chapter 4

D.1 Instructions

Translated from French

D.1.1 The Baseline

For the baseline instructions, please refer to the continuous time instructions for the game, in Appendix [C.6.1](#) of Chapter 3.

D.1.2 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

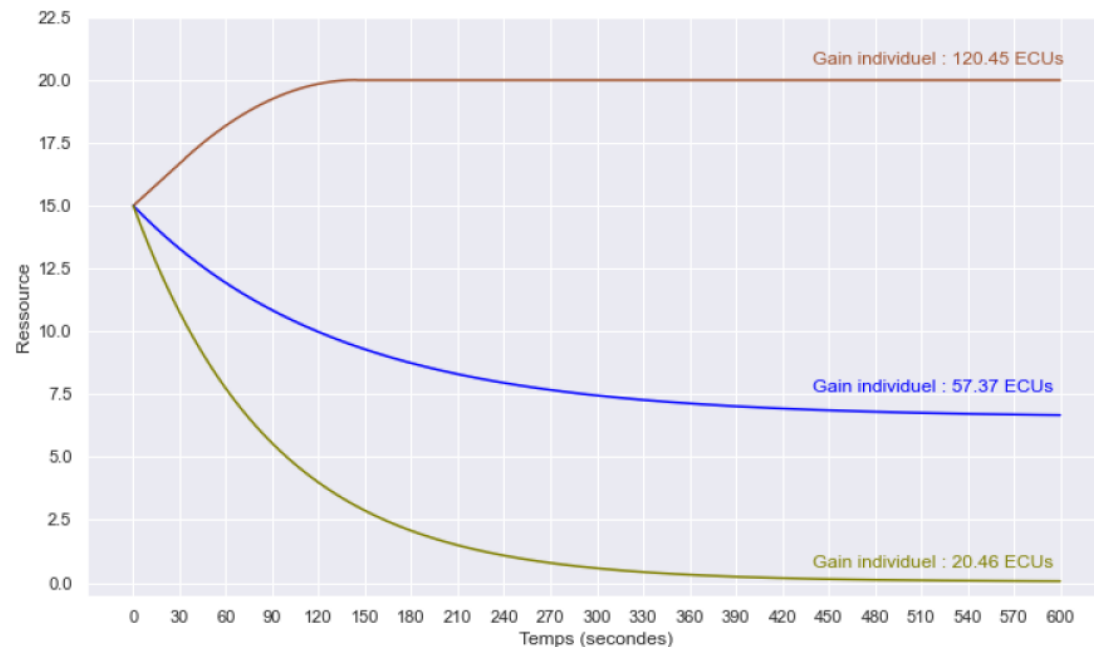


Figure B.1 – The injunctive norm

D.1.3 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

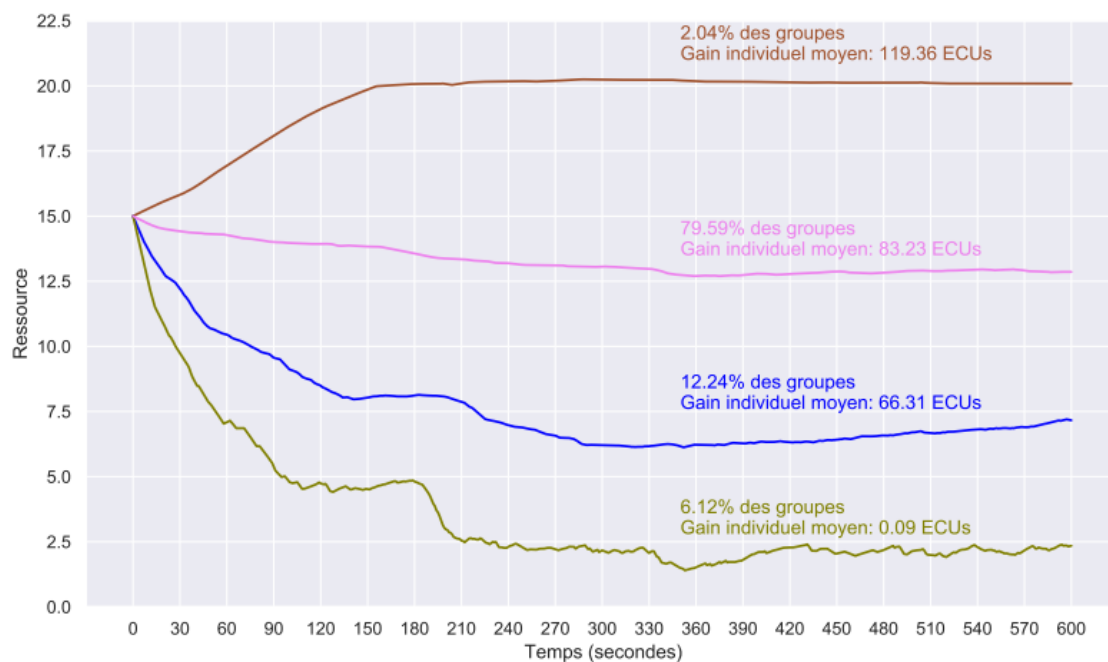


Figure B.2 – The descriptive norm

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.

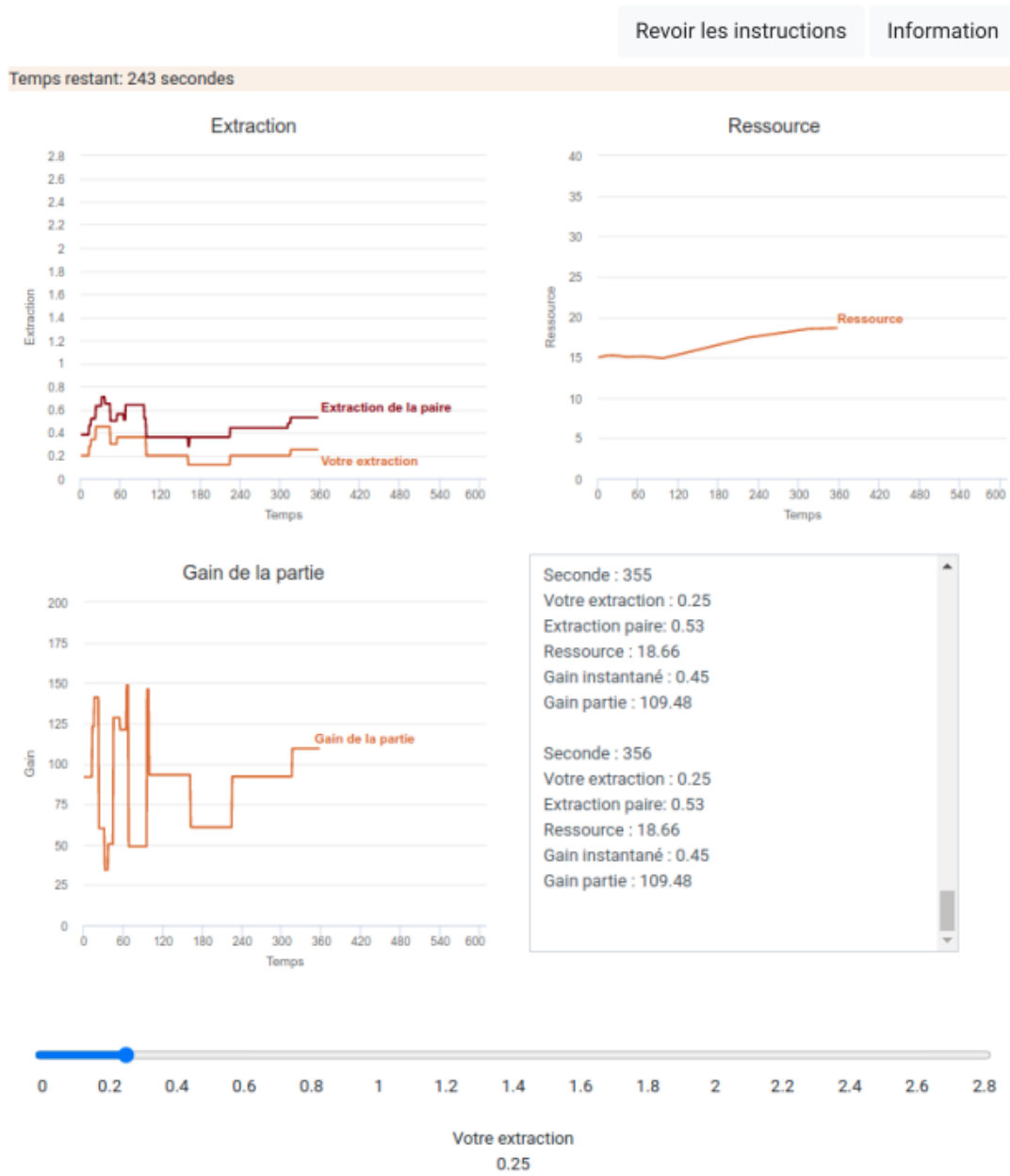


Figure B.3 – The game screen shot for nudge treatments

D.2 Comprehension Questionnaire

For the comprehension questionnaire used in the three treatments, please refer to the continuous time comprehension questionnaire for the game, in Appendix [C.8.1](#) of Chapter 3.

D.3 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.