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« Wealthy people do better? Experimental Evidence on Endogenous Time Preference Heterogeneity and the Effect of Wealth in Renewable Common-Pool Resources Exploitation »

Gaston A. GIORDANA

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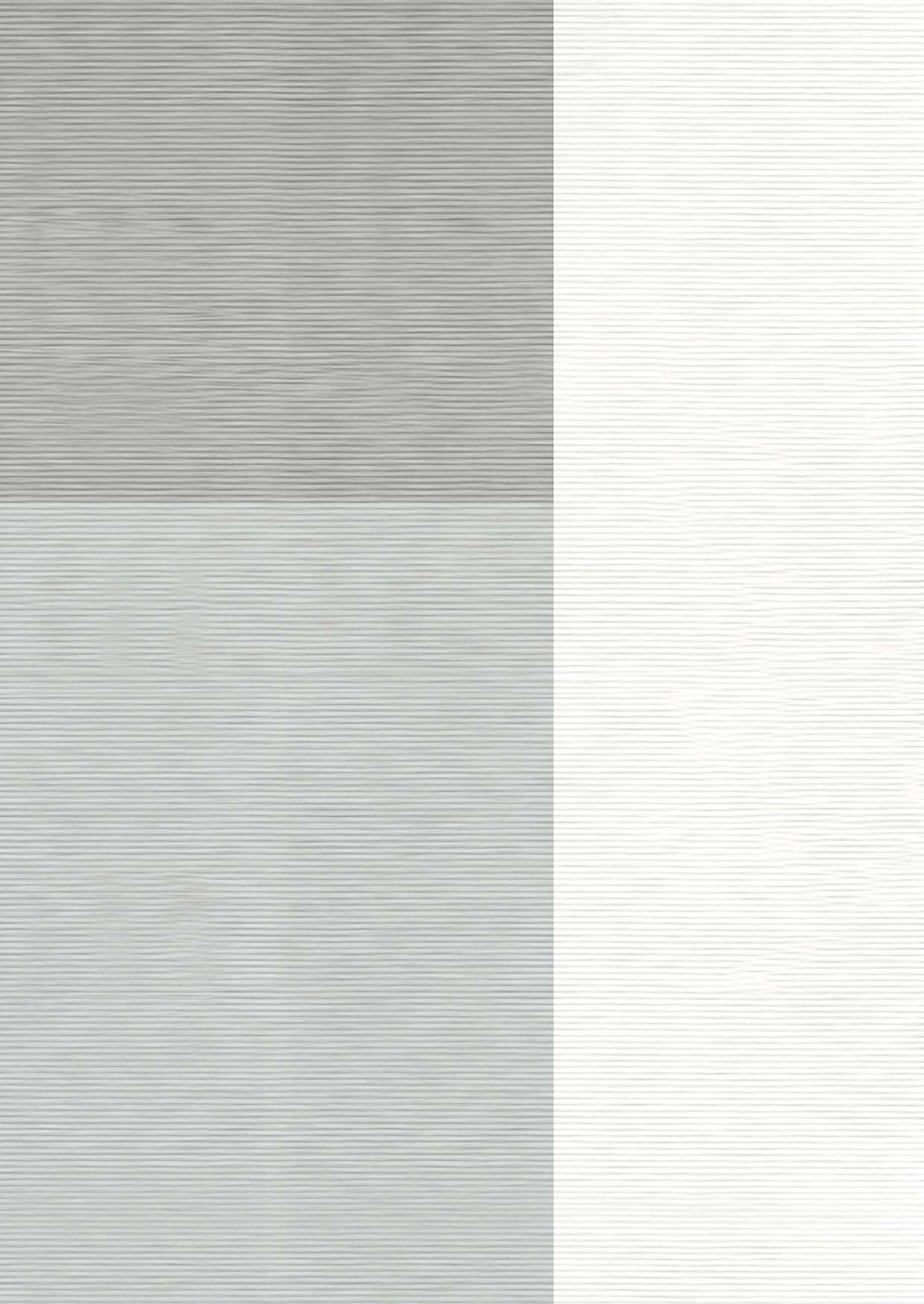
Faculté de Sciences Economiques - Espace Richter
Avenue de la Mer - Site de Richter C.S. 79606
34960 MONTPELLIER CEDEX 2
Tél: 33(0)467158495 Fax: 33(0)467158467
E-mail: lameta@lameta.univ-montp1.fr

UM1 Université Montpellier 1
agro Montpellier Ecole Nationale Supérieure Agronomique
CNRS Centre National de la Recherche Scientifique
INRA



Wealthy people do better?

Experimental Evidence on Endogenous Time Preference Heterogeneity and the Effect of Wealth in Renewable Common-Pool Resources Exploitation

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Gastón A. Giordana[♣]

Abstract

Aiming to better characterize the exploitation behavior of renewable common-pool resources, in this paper we explore alternative hypothesis about the valuation of the future by the agents and the possibility of heterogeneous behavior on this regard. To do this, we further analyze the experimental data of an *N*-person discrete-time deterministic dynamic game of *T* periods fixed duration. Firstly, we consider the homogeneous case where withdrawers' rate of time preference is symmetrically determined. Then, we calibrate the best fitting model assuming alternatively, exogenous and endogenous time preference. The exogenous time preference case is the traditional assumption in modeling intertemporal choices, i.e. every period, players discount future values at the same level. In the endogenous case, we statistically model the reduced form of the discount factor as a transformation of a second order polynomial on wealth. Secondly, we further explore the endogenous case looking forward to assess the extent of heterogeneity in the rate of time preference formation process. Dynamic problems resolution gives scope for the implementation of 'rules of thumb' as a consequence of its' intrinsic complexity. Then, in order to identify the different decisions rules and to classify appropriators within them, we implement a Bayesian classification algorithm based on Houser et al (2004) work. The application of this econometric procedure has allowed us to identify two types of appropriators: "Quasi Myopic" (QM) appropriators and "Disrupted Farsighted" (DF) appropriators. The algorithm has classified near 85% of the appropriators in our sample as QM, and 5% as DF; the lasting agents could not be identified. We used the fitted empirical model to perform simulations. Some results are: (i) initial wealth increase the average efficiency of exploitation; (ii) when initial wealth is high (low), a more equally (unequally) distribution of wealth between types results in higher efficiency in the exploitation of the resource.

Keywords: Bayesian classification, Common-Pool Resource, Endogenous Time preference, Experiments, Wealth distribution

JEL classification: C25, C35, C73, C92, D9, D62, H23, Q20, Q28.

♣ LAMETA, Faculté de Sciences Economiques, Avenue de la Mer - Site de Richter C.S. 79606, 34960 MONTPELLIER CEDEX 2, email: giordana@lameta.univ-montp1.fr

1. Introduction

Natural resources play a decisive role in the development of many economic regions. Many natural resources (e.g. fisheries, groundwater bodies, communal forests and grazing grounds) share the characteristics of common property goods; the market institution is indeed inefficient. Recent literature on the commons has mainly focused on the determination of factors that favor users' communities to achieve, without external intervention, successful collective action in order to efficiently use the common resource (Ostrom et al, 1994; Baland and Platteau, 1996). While the relationship between the population size and the ability to solve the commons dilemma is well understood, the consequences of wealth inequalities, as well as inequalities on other economic variables, just begin to be clearly formalized and empirically tested (*cf.* Olson, 1965; Baland and Platteau, 1997; Cardenas, 2003; Bardhan et al, 2007).

The theoretical and experimental work in the commons literature has mainly focalized in the rent dissipation problem that takes place within an exploitation period. However, the negative externalities resulting from the exploitation of fisheries, forests and groundwater bodies are principally of dynamic nature. It is important to explicitly consider in the analysis the dynamic aspects of natural resource exploitation for many reasons. First, the exploitation of the resource stock may not produce significant negative externalities within the exploitation period[1]. Rather, the overexploitation negative effects may be noticeable in the near or far future. For instance, the reduction of the water-table of a groundwater body may not have a huge economic impact in quite common contexts (Gisser and Sanchez, 1980; Koundouri, 2004). But, depending on characteristics of the aquifer, the cumulated reduction may lower the water-table enough to render the aquifer vulnerable to seawater intrusion in the case of coastal aquifers or, in other aquifer types, to be polluted by surface water or fossil groundwater. Secondly, when extraction activities do not result in current negative externalities, the willingness to engage in collective action may be sensible reduced as it depends on the *rate of time preference* of resource users (Ostrom, 1990). The rate of time preference refers to an index of the marginal rate of substitution between current and future consumption and payoffs (Fischer, 1930)[2]. While a resource user may be considered as a

[1] The duration in time of an exploitation period may differ depending on the natural resources.
[2] In the following we will interchangeably use the words "rate of time preference", "patience" and "discount factor". We will follow the convention of associating a "discount factor" with the inverse of the marginal rate of

cooperator in a static framework, she may result to be a free-rider when the externalities are dynamic if she has a low time preference. A user that shows a weak time preference will behave myopically as his discount factor is likely to be close to zero, ignoring the future consequences of his current decisions and free-riding on others conservation efforts. On the other hand, it can be expected that a user with a strong time preference engages himself more easily in collective action activities as she derives current utility from resource conservation. Thus, the heterogeneity on the rate of time preference within a population of resource users will affect the cooperative behavior as it leads to differential impatience among the users in making short-run sacrifices for resource conservation (Bardhan and Dayton, 2002). Moreover, time preference heterogeneity among the commons users may lead to the worst of the worlds (i.e. everybody behaving myopically) if the farsighted users behave as “conditional cooperators” conditioning their efforts towards conservation to the others’ efforts (Gächter et al, 2004).

Heterogeneity in the rate of time preference within a population of resource users is more likely if the later is endogenously determined. Since the discounted utility model of Samuelson (1937), the rate of time preferences are taken as exogenously given with little discussion of what determines their level. Yet, in the nineteen and early twenty century, intertemporal choices were interpreted as the joint product of many conflicting psychological motives (Frederick et al, 2002). Becker and Mulligan (1997) built up on these initial perceptions a model of endogenous time preference. Their point of departure consists in a particular definition of rationality that takes into account many kinds of human frailties. In their view, even rational people may excessively discount future utilities (i.e. the endowed discount level), but they assume that it is possible to partially or fully offset this “inherited weakness” by spending effort and goods to reduce the degree of over-discounting. In this framework, the heterogeneity in the rate of time preference may still be consequence of exogenous factors (e.g. intelligence, culture, religion) as the endowed discount level is exogenously fixed. But, the marginal cost and benefit of the effort to reduce the degree of over-discounting, as assumed by Becker and Mulligan (1997), is a function of individual economic variables (e.g wealth) that may be unequally distributed, resulting then in differences on the time preference between people.

substitution and a “rate of time preference” with a natural logarithm of the marginal rate of substitution. Thus, a patient person has a high discount factor and a low rate of time preference.

Aiming to better characterize the exploitation behavior of renewable common-pool resources, in this paper we explore alternative hypothesis about the valuation of the future by the agents and the possibility of heterogeneous behavior on this regard. To do this, we further analyze the experimental data of the unregulated treatment of Giordana and Willinger (2007). They implemented an experiment test of N-person discrete-time deterministic dynamic game of T periods fixed duration to assess the efficiency of second best incentive schemes in coping with stock externalities. Firstly, we consider the homogeneous case where withdrawers' rate of time preference is symmetrically determined. Then, we calibrate the best fitting model assuming alternatively, exogenous and endogenous time preference. The exogenous time preference case is the traditional assumption in modeling intertemporal choices, i.e. every period, players discount future values at the same level[3]. Thus, this assumption results in temporally consistent decisions. In the endogenous case, we follow Becker and Mulligan (1997) supposing that the rate of time preference that results in a particular value of the discount factor is not exogenously given by "a play of nature" at the beginning of the game. We think the process of time preference formation as an "unconscious" construction compounding various unpredictable forces (e.g. psychological, emotional, economics) along the lifetime of the agent. But, we do not explicitly model the decision of investment in over-discounting reducing effort. For simplicity seek, we rather statistically model the reduced form of the discount factor as a transformation of a second order polynomial on wealth.

One of our results points out that the endogenous rate of time preference assumption does as well as the exogenous one. Then, in a second part of this paper, we further explore the endogenous case looking forward to assess the extent of heterogeneity in the rate of time preference formation process. In such a complex decisional situation the information requirements are quite strong. So, it is likely that agents, when making a decision, use decision rules (i.e. rules of thumb) constructed on the basis of available information (Conlisk, 1996). As noted by Camerer (2003, p. 42), an optimal use of experimental data, resulting in a deeper description of the underlying behavior, requires the employ of adapted econometric techniques. Consequently, we adopt an exploratory approach: we adapt and apply to our experimental data the Bayesian classification algorithm developed by Houser et al (2004) (HKM algorithm). This statistical procedure allows us to make inferences about the number and the nature of the "decision rules" present in a population of subjects. The underlying idea

[3] All along the paper we will consider as synonymous the "rate of time preference" and the "discount factor".

is that, in complex environments, the rational choice is just one of the possible decision rules that can exist. The decision rules are approximated with flexible parametric functions (polynomials) on a set of relevant state variables. In our particular case we have specified the decision rules as functions of the unique observable state variables of the game: the stock of the resource and the individual accumulated wealth.

Our results support the possibility that discount factors result from an endogenous rate of time preference formation process. We found that in the homogenous population case, the estimated model with endogenous time preference accommodates the data as well as the model with exogenous one. Moreover, our results support some heterogeneity in the valuation of the future. The application of the HKM algorithm to the experimental data allowed us to identify two types of withdrawers with different rates of time preference. As the model implemented in the laboratory does not consider financial markets, neither the initial endowment nor the accumulation of wealth during the experiment should have an effect on behavior. Although, the accumulated wealth came-out as a pertinent state variable in explaining the extractions of the different types of withdrawers. Moreover, the effect of the accumulated wealth adjusts to the main predictions of the Becker and Mulligan (1997) model on endogenous time preferences, as well as some important implications of general models of CPR exploitation under wealth inequality (Bardhan et al, 2007; Baland and Platteau, 1996, 1997).

The paper is organized as follows. In section 2, we describe the theoretical model of a renewable Common-pool Resource exploitation under exogenous and endogenous time preference. Also, the experimental protocol of Giordana and Willinger (2007) is briefly depicted and the results of the econometrics treatments for the homogenous population case are exposed. In section 3 we describe the HKM classification algorithm and the way we specified it in order to adapt it to our data. In section 4, we expose the results of the application of HKM algorithm, as well as those that follow from the simulations of the resulting empirical model. Finally, section 6 we conclude and discuss some of the results.

2. An experiment on the exploitation of a renewable Common-pool resource

In this section we will briefly present the theoretical model and the experimental protocol implemented to test it which corresponds to the laissez-faire situation of Giordana and Willinger (2007) model. In order to solve the game, we will consider two alternative assumptions about the discount factor. First, the rate of time preference is assumed to be exogenously fixed. Secondly, following Becker and Mulligan (1997), we assumed that the rate of time preference is endogenously determined as a function of wealth. In both cases the rate of time preference is supposed homogenous among the whole population of withdrawers. Finally, we use experimental data of Giordana and Willinger (2007) to fit both models looking for a better description of the observed behavior in the laboratory.

2.1 A simple model of renewable common-pool resource exploitation

Let us consider 5 firms that extract units from a stock of a common resource. In each period $t = 1,\ldots,10$, firm i extracts y_i^t units. The evolution of the resource stock S^t is described by:

(1) $$S^{t+1} = S^t - \sum_{i=1}^{5} y_i^t + r\,,$$

where r (= 30) is a constant natural recharge known by all agents, and the stock in the initial period is $S^1 = 500$. Extracted units generate a profit equal to:

(2) $$w_i^t\left(y_i^t, S^t\right) = 5.3 \cdot y_i^t - 0.09 \cdot \left(y_i^t\right)^2 - y_i^t \cdot \left(7.6 - 0.01 \cdot S^t\right), \quad i = 1,\ldots,5.$$

As the profit function is the same for all agents we drop the subscript i. Past profits accumulate to constitute the wealth of each withdrawer i given by $W_i^t = W_i^0 + \sum_{s=1}^{t} w^s\left(y_i^s, S^s\right)$, where W_i^0 is the ith withdrawer wealth at the beginning of period 1.

As can be observed from equation (2), there is not within period externality: the t period profit of agent i is not affected by the current decisions of the other agents ($j \neq i$). The externality affecting firms in each period is dynamic because it is related to the evolution of the resource stock: current withdrawals reduce future stocks diminishing the future profits of every agent.

Every period each agent maximizes the sum of the discounted future profits:

(3) $$V^t\left(y_i^s, S^s\right) = w^t\left(y_i^s, S^s\right) + \sum_{s=t+1}^{T} \rho^{s-t} V\left(y_i^{s*}, S^s\right),$$

where t is the current period and ρ the discount factor and $y_i^{s*}\left(S^s\right)$ is the optimal feedback resulting from the solution of the subsequent subgames.

In the following we discuss different assumptions on the discount factor ρ to solve the dynamic game resulting from equation (1), (2) and (3). First, we consider a situation where rational agents' time preferences are exogenously given, secondly, the endogenous case is analyzed.

As a point of departure, let us model the reduced form of the discount factor $\rho_{i,t}$ of each agent i is a function $\phi\left(\Lambda_i^t\right)$ on a set Λ_i^t of economic variables. As Becker and Mulligan (1997) pointed out, some economic variables may affect the capacity and/or the cost, of each agent to perform effort to overcome their intrinsic myopia. For instance, let us consider that the unique element of Λ_i^t, is the wealth accumulated up to period t, W_i^t, of agent i. The function $\phi(\cdot)$ can be any that ensures that $\rho_{i,t} \in [0,1]$. Then, the discount factor is represented by:

(4) $$\rho_{i,t} = \phi\left(\alpha + \beta_1 \cdot W_i^t + \beta_2 \cdot \left(W_i^t\right)^2\right).$$

(i) Exogenous rate of time preference

In this subsection it is assumed that every individual in the population is exogenously endowed with the same rate of time preference. Then, $\beta_1 = \beta_2 = 0$, $\alpha \in [0,1]$ and the function $\phi(\cdot)$ is the identity; so, $\rho_{i,t} = \alpha \;\; \forall i,t$.

Two behavioral assumptions are considered to solve the dynamic game: selfish rational agents can be myopic or farsighted. In a farsighted population, appropriators are endowed with a future skewed time preference (i.e. $\rho_{i,t} = \alpha > 0 \;\; \forall i,t$); then, they internalize the impact of their current extractions on their own future profits. They define an optimal extraction plan, which is a best response to the other players' optimal extraction plans. This extraction plan is called feedback strategy if it is a function of the available stock S^t in each period *t*. In the myopic population case, agents are endowed with a present skewed time preference. Thus, under the assumption of myopic behavior the optimization horizon is restricted to one period (i.e. $\rho_{i,t} = \alpha = 0 \ \forall i, t$). Each period the myopic withdrawer calculates the profit maximizing extraction given the best responses of his rivals[4]. In each period of the game, except the last one, and given the resource stock available, myopic behavior leads to higher extractions compared to rational behavior.

The theoretical predictions under these behavioral assumptions are compared to the optimum extraction path which corresponds to maximizing the sum of discounted profits of all firms over the whole temporal horizon (i.e. the central planer solution). Figure 1 shows the extraction trajectories calculated with a closed-loop solution (agents observe S^t at the beginning of each period) and assuming that $\alpha = 1$ for farsighted and optimum solutions and $\alpha = 0$ for the myopic solution. The Figure 1 exposes the *unconditional predictions* which assume that all agents follow the theoretical prediction which results in a particular stock trajectory. But, if at least one player deviates, the stock trajectory will differ from the predicted one. Thus, the feedback functions outcome will be different from the unconditional predictions; we call *conditional predictions* the withdrawal trajectories calculated on the basis of the state variables trajectories observed in the laboratory.

As evidenced in Figure 1, the difference between the myopic and the farsighted trajectories reflects the differential degrees of patient of each type of withdrawer. Moreover, the differences with the optimum extraction trajectory highlight the inefficiency of the formers. Taking the optimum strategy as an efficiency benchmark[5], the myopic and farsighted strategies achieve, respectively, 74% and 52% of efficiency with respect to the benchmark.

[4] The analytical expressions for the farsighted and myopic solutions are available in Giordana and Willinger (2008) Appendix.

[5] Efficiency is defined as the wealth accumulated until the end of period *T* under a particular strategy with respect to the optimum strategy.

(ii) Endogenous rate of time preferences

In this subsection it is assumed that the rate of time preference of all the agents in the population follows a particular specification of equation (4). We assumed that $\beta_1, \beta_2, \alpha \in \Re - \{0\}$, and the function $\phi(\cdot)$ is any ensuring that $\rho_{i,t} \in [0,1]$. Note that β_1, β_2 and α are not *i*-indexed, then we still suppose homogeneous rate of time preference among withdrawers. The constant α represents the endowed rate of time preference and, the coefficients β measure the impact of wealth on the discount factor.

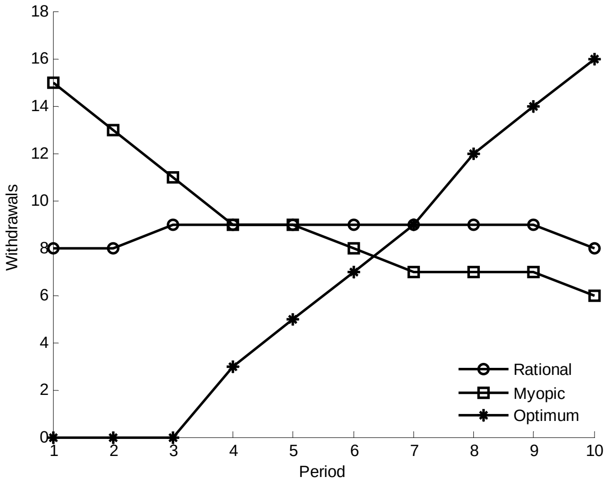


Figure 1: Exogenous time preference: unconditional predictions.

Under equation (4), an additional assumption is needed to guarantee the unicity of the symmetric solution of the game resulting of equations (1) to (3) and, to avoid the critic of "endogenizing preferences". The equation (4) is a statistical model of the reduced form of the discount factor resulting from a decision of investment in over-discounting reducing effort. But, the marginal cost and benefits of this effort respond to unconscious process that compound economical, emotional and psychological factors. Indeed, the practical assumption is that withdrawers "discover", at the beginning of each period and given their level of wealth, their specific rate of time preference on the basis of which they will discount the flow of future profits. Then, when agents accumulate wealth by using the resource at each period, they are not aware about the potential effects on their own discount rate.

In Figure 2 we plot the unconditional predictions for the exogenous and endogenous rate of time preference cases. The myopic ($\rho = 0$), the indifferent future-present farsighted withdrawer ($\rho = 1$) and the optimum behavior ($\rho = 1$) are plotted against some simulated trajectories for the endogenous model. In order to perform the simulated trajectories of the endogenous model we have specified equation (4) as:

(5) $$\rho_{i,t} = \ln\left[1 - \left(\alpha + 0.005 \cdot W_i^t + -0.0001 \cdot \left(W_i^t\right)^2\right)\right].$$

We have simulated the endogenous model for 4 different values of α. When α = 0 the trajectory almost perfectly mimics the myopic one. As the absolute value of α increases, the withdrawals in the initials periods are lower. But, as time passes the wealth accumulation increases the value of the future and enhances the discounting. As a consequence, the final withdrawals remain quite low with respect to the exogenous rate of time preference case.

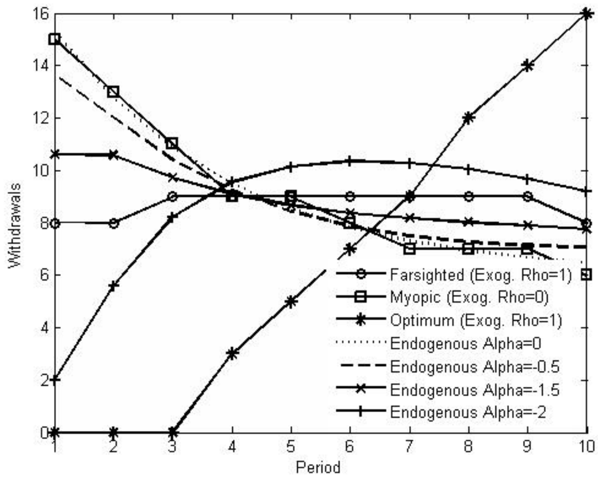


Figure 2: Endogenous versus exogenous time preference: unconditional predictions.

2.2 Experimental results

The experimental protocol was designed to capture the fundamental aspects of the game described above. In each period, subjects decide the amount of "units" to extract from an account. Given the parameterization (see equation (2)), in each period a subject earns experimental points depending on his/her unit order and on the available units in the account at the beginning of the decision period. All experimental sessions were conducted at the University of Montpellier 1 using the z-Tree computer program (Fischbacher, 2007) with subjects recruited from the pool of undergraduate students of LEEM[6]. More details about the design and implementation of the experiment are available in Giordana and Willinger (2007).

(i) Exogenous rate of time preference

With data from 6 groups of 5 subjects repeating 4 times the 10 periods dynamic game, Giordana and Willinger (2007) found that the myopic strategy is the best fitting one. The data of the Laissez-Faire treatment of Giordana and Willinger's experiment is used in Figure 3 which exposes the conditional predictions of the myopic, farsighted and optimum strategies, calculated on the basis of the observed stock trajectories. Also, the mean withdrawal trajectory (calculated over the 4 repetitions of the game) is plotted in Figure 3, as well as the limits of the bootstrap confidence intervals. As shown in Figure 3, the mean extraction path is close to the myopic conditional benchmark but significantly different from it (excepting the last three periods) as the limits of the confidence intervals do not overlap with the myopic conditional prediction. Also, the mean extraction path is significantly higher than the rational conditional benchmark excepting the last 3 periods, when the differences between all three strategies vanish.

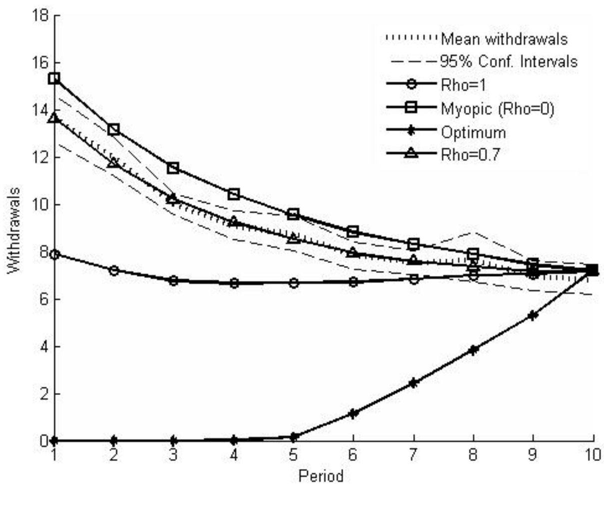


Figure 3: Conditional predictions versus the observed mean withdrawals trajectory.

In order to accommodate the observed trajectory, we have calculated the discount factor of the "mean withdrawer" that result in the best fitting withdrawal trajectory. To do so we have calculated for each agent 100 withdrawals trajectories, conditioned to the observed stock, for

[6] Laboratory of Experimental Economics of Montpellier.

values of the discount factor in the interval [0,1]. Then, we assigned to each agent the discount factor that minimizes the deviation between her extraction trajectory and the predicted one.

RESULT 2.1: In average, experimental withdrawers are farsighted with a rather high rate of time preference resulting in a discount factor equal to 0.7.

The comparison of individual observed withdrawal trajectories with conditional predictions for different levels of future discounting pointed out a discount factor equal to 0.7 as the one that, in average, minimizes deviations. The mean square deviation (MSD)[7] of the average extraction trajectory with respect to the conditional predictions of the myopic and the future-present indifferent withdrawers (i.e farsighted with ρ = 1) attained, respectively, 208.44 and 273.84. But, the conditional prediction of the farsighted withdrawers with ρ = 0.7 just attained 197.13. As is shown in Figure 3, this extraction trajectory almost perfectly reproduces the mean withdrawal trajectory.

(ii) Endogenous rate of time preferences

In this sub-section we will estimate the parameters of equation (5), β_1, β_2 and α. In order to perform this estimation, we used the individual discount factors estimated in the previous section as dependant variable to fit a generalized linear model. Our finding can be summarized in results 2.2 and 2.3.

RESULT 2.2: Wealthy withdrawers are more patient.

We estimated four models imposing different restrictions on the coefficients of equation (4). The preferred model is the first one. As can be observed in **Table 1**, model 1 achieves the best fitting (the lower log-pseudo likelihood) and the estimated coefficients are all significantly

[7] $MSD = \sum_t \sum_g \left(\bar{y}_g^t - \bar{y}^t\left(S^t, \theta\right)\right)^2 \Big/ N$, where $y^t\left(S^t, \theta\right)$ correspond to the mean conditional prediction for a population with a proportion θ of myopic agents, and for each group g $\bar{y}_g^t = \sum_{\forall i \in g} y_i^t \Big/ 5$.

different from zero at least at 9% of significance level. The estimated values of α and β_1 and β_2 indicates that the rate of time preference increases at a decreasing rate with wealth.

RESULT 2.3: The estimated model with endogenous rate of time preference accommodates better the observed mean withdrawals trajectory than the model with exogenous myopic (ρ = 0) rate of time preference.

The generalized linear models exposed in Table 1 have been calculated using a binomial distribution and the complementary-log link function. On the basis of the estimated discount factors predicted by model 1 (see equation (4)), we have calculated the corresponding withdrawals trajectories and compared them to the laboratory observations. As can be seen in Table 1, the mean square deviations of the preferred model with endogenous time preference is equal to 200.91 which is lower than the 208.44 resulting from the exogenous myopic rate of time preference model. Though, it is not significantly different of the exogenous time preference model, fitted in the previous section (*c.f.* Result 2.1), as the MSD is equal to 197.13.

Dependant Variable ρ	**Model 1**	Model 2 α =0	Model 3 β_2= 0	Model 4 α =β_2= 0
	Coefficient (p-value)			
Constant (α)	**-0.397207 (0.008)**	-	-0.4238201 (0.001)	-
W (β_1)	**0.0070587 (0.087)**	0.0007183 (0.731)	0.0002985 (0.859)	-0.0056137 (0.000)
W^2 (β_2)	**-0.0001017 (0.004)**	-0.000105 (0.000)	-	-
Log-pseudo Likelihood	**-738.878**	-753.837	-748.834	-767.083
Mean Square Deviation	**200.76**	200.98	203.1	201.01

Table 1: Fitted models of the discount factor on wealth.

Figure 4 plots the observed mean withdrawal trajectory and the conditional predictions for the exogenous rate of time preference model assuming myopic (ρ = 0), present-future indifferent farsighted (ρ = 1) withdrawers and the optimum behavior (ρ = 1), as well as the conditional predictions of the endogenous rate of time preference fitted model $\left(\rho = \phi\left(\Lambda_i^t\right)\right)$. The mean trajectory resulting from the preferred model, *i.e.* model 1, is exposed with diamond markers.

As can be observed this trajectory gets closer to the mean withdrawals observed in the laboratory than the myopic conditional prediction does. Moreover, there are not significant differences (at 5% confidence level) excepting period 3 extraction that lies outside the bootstrap confidence interval limits.

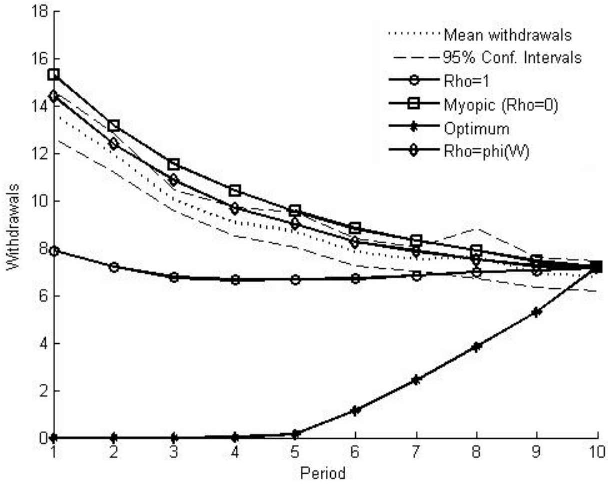


Figure 4: Conditional predictions versus mean withdrawals. Endogenous time preferences given by: $\rho_t = \log\left[1-\left(-0.397207+0.0070587\cdot W_t - 0.0001017\cdot W_t^{\,2}\right)\right]$

3. Heterogeneous and endogenous rate of time preference

Up to here it has been assumed that the rate of time preference, exogenously and endogenously determined, is homogeneous among the users of the common resource. This means that the users are supposed to discount future payoffs symmetrically. However, a more general formulation should consider the possibility for resource users with heterogeneous rate of time preference. Actually, if we look at Figures 3 and 4, it appears that the mean withdrawal trajectory may result from a linear combination of the myopic and the farsighted ones, when considering an exogenously given discount factor. In a complete information framework it can be shown straightforward that the homogeneous population cases depicted in Figure 2 (exogenous and endogenous cases) are just particular cases of the heterogeneous population composed at different proportions by rational selfish agents with divers discount factors[8]. On the other hand, while in imperfect information framework there may be a multiplicity of solutions to the game, there is not a solution in an incomplete information case. For instance, considering the agents' wealth as private information and assuming that the only

[8] For instance, Giordana (2007) study the two types case, i.e. Myopic and Farsighted withdrawers.

observable state variable is the resource stock that gives aggregate information about the others' extraction decisions, as it is the case of the experimental protocol in Giordana and Willinger (2007), just allow players to derive best response functions with respect to the "mean" rival. In this complex situations where multiplicity of equilibrium are common, it is pertinent to assume that rational agents may follow what some "rules of thumb" dictate, i.e. decision rules based on the available information that derivable at an affordable "reflective cost" (Conlinsk, 1996).

In the next section we adopt a more flexible methodology to explore the heterogeneity of behavior without imposing restrictive assumptions about the different types of behavior to be found. We will adapt the algorithm proposed by Houser et al (2004) to our experimental data in order to explore the number and nature of "decision rules" truly used by the players in the laboratory.

3.1 A Bayesian type classification algorithm: The HKM algorithm

The work of Houser et al (2004) proposed a Bayesian type classification algorithm (HKM algorithm) that allows drawing inferences about the number and the mathematical form of decision rules present in the population of players, as well as the probability with which each player uses each rule. The decision rules are modeled as a flexible parametric function conditional on an assumed set of relevant state variables. The number of decisions rules actually used in a population is determined using Bayesian decision theory (*cf.* Paap and Geweke, 2005).

Even if the HKM algorithm is applicable in a large number of cases, we will restrict ourselves to the baseline case: discrete choice Markov decision processes (in discrete time). The main reason to our choice is that all the extractions decisions observed in the laboratory are integers tough the choice set proposed to players was continuous. The baseline HKM algorithm was developed to classify individual decisions without interaction; we will then adapt it to individual decisions taken in the framework of a discrete-time deterministic dynamic game of T periods fixed duration.

3.1.1 The structural model

The optimal decision rule is obtained applying the Bellman's (1957) principle. In each period $t \ (\leq T)$ each subject $i \in N$ has to choose a level of withdrawal y_i^t in the set $\{1,...,J\}$. Subject i will choose the level of withdrawal $j*$ if and only if any other alternative achieves a higher latent value:

$$V_{ij*}^t\left(S^t, I_i^t\right) > V_{ij}^t\left(S^t, I_i^t\right) \quad \forall j \neq j*.$$

The value to subject i of choosing alternative j can be written as:

$$V_{ij}^t\left(S^t, I_i^t\right) = w_{ij}^t\left(S^t\right) + EV\left(S^{t+1}, I_i^{t+1} \middle| S^t, I_i^t, j, y_{-i}^t\right) \qquad t = 1,...,T \tag{6}$$

where $I_i^{t+1} = h\left(S^t, I_i^t, j, y_{-i}^t\right)$ and $S^{t+1} = g\left(S^t, y^t\right)$ are the (possible stochastic) Markovian law of motion for the state variables. In our case, the later law of motion is defined in equation (1) (page 5). We have distinguished the resource stock S^t, which is a common state variable to all the players, from the individual state denoted by I_i^{t+1}. While the resource stock impacts objectively on the value function of every subject, it may affect the individual state in a different manner. Actually, the individual state may include non pertinent information (Houser et al, 2004). The individual state represents the information set of subject i. It may include, for example, the decisions and payoff of previous periods, and any observable information about the other players' decisions. We assume that the individual state is given by the accumulated wealth of the agent: $I_i^t = W_i^t = W_i^0 + \sum_{s=1}^{t} w^s\left(y_i^s, S^s\right)$. The first term of equation (6) is the current payoff of subject i in period t resulting of choosing j is $w_{ij}^t\left(S^t\right)$. In our case there is not intra-period interaction between the players, then the payoff does not depend on y_{-i}^t, the period t decision vector of all subjects excepting i. The second term of equation (6) corresponds to the future component of the value function. It represents the expected value of the state variables (i.e. the resource stock and the individual state) given the current states and the subjects' decisions.

Houser et al (2004) generalized this framework by allowing for the possibility that subjects do not use the optimal decision rule based on the maximization of the expected value. And more important to the aim of this paper, Houser et al (2004) allowed for the possibility that there is heterogeneity in the decision rules that exist in a population of withdrawers. Therefore, they proposed to model the future component as a flexible function (i.e. polynomial) in the resource stock S^t and in the elements of the subject's information set I_i^t (the accumulated wealth in our case).

(7) $$EV\left(S^{t+1}, W_i^{t+1} \middle| S^t, I_i^t, j, y_{-i}^t\right) = F\left(S^t, W_i^t, j \middle| \pi_k\right) + \upsilon_{ij}^t \qquad k = 1,\dots,K$$

F(·) indicates the future component polynomial, π_k denotes a finite vector of parameters which are specific to the subject type *k*, and the random variable υ_{ij}^t accounts for idiosyncratic errors. The distribution of idiosyncratic errors may vary by type, so that optimization error may be more important for some types than others. The standard deviation of the optimization errors is represented by σ_k.

From equations (6) and (7), the value that the withdrawer *i* whose type is *k*, assigns to the extraction level *j* in period *t*, is

(8) $$V_{ij}^t\left(S^t, I_i^t \middle| k\right) = w_{ij}^t + F\left(S^t, I_i^t, j \middle| \pi_k\right) + \upsilon_{ij}^t$$

3.1.2 Statistical inference

The choice of subject *i* in each period *t* are observable by the econometrician, $\{\{\{y_i^t, \{w_{ij}^t\}_{j=1,\dots,J}\}_{t=1,\dots,T}\}_{i=1,\dots,N}\}$. The objective is to perform inferences about:

(i) The order of the *F* polynomial and the set of state variables that enter the polynomial.

(ii) The number of decision rule types *K* that are present in the population of withdrawers.

(iii) The vector of parameters π_k, σ_k for each type *k* = 1,…,*K*.

(iv) The population proportions of each type θ_k.

(v) The posterior probability $\tau_{i,k}$ that each subject is each type.

The inference problem is decomposed in two stages. The stage consists in drawing inferences about the parameters $\{\pi_k, \sigma_k, \theta_k\}$ for *k* = 1,…,*K*, given *K*, the order *G* of the *F* polynomial, the set of state variables considered and the distribution hypothesis of the optimization errors. The second stage of the inference problem consists in drawing inferences about the number of types K and the order of the F polynomial. The standard approach in Bayesian decision theory is to implement a range of models with different K and G, and use the marginal likelihood to choose among them. Recently developed simulation methods[9] have made this kind of complex inference problem quite tractable (*c.f.* chapter 3 in Paap and Geweke, 2005).

In the next section we will detail how this general framework is adapted to our experimental data.

3.2 Empirical specification

The HKM algorithm is based on the Gibbs sampling, a simulation method that allows the construction of sequences of the parameters drawn from the posterior probability function. In this section we will present the specification of the Gibbs sampler. We will also describe the likelihood function, the prior and posterior distributions of the model parameters.

3.2.1 The functional forms for the decision rules

In our specification, the future component polynomial integrates the resource stock, that is a state variable common to all the subjects, and the accumulated wealth up to period t W_i^t, that is part of each subject individual information set.

The Bayesian selection procedure pointed out as the preferred model a second order polynomial in the resource stock and the accumulated wealth. Thus, the future component F for the subjects of type k takes the form (without the subscript k):

(9) $$F\left(S^t, I_i^t, j \middle| \pi_k\right) = \pi_0 + \pi_1 \cdot S^t + \pi_2 \cdot \left(S^t\right)^2 + \pi_3 \cdot S^t \cdot W^t + \pi_4 \cdot W^t + \pi_5 \cdot \left(W^t\right)^2 .$$

[9] Markov Chain Monte Carlo (MCMC) methods.

As the choices made depend on the relative value of each alternative, the model is not identified in levels. The model is identified in the usual manner (Geweke et al., 1994) with a differenced system:

$$z_{ij}^{t}\left(S^{t},W_{i}^{t},j\middle|\pi_{k}\right)=\tilde{V}_{ij}^{t}\left(S^{t},W_{i}^{t},j\middle|\pi_{k}\right)-\tilde{V}_{i0}^{t}\left(S^{t},W_{i}^{t},0\middle|\pi_{k}\right)\qquad j\in\{1,\ldots,50\},$$

where $\tilde{V}_{ij}^{t}\left(S^{t},W_{i}^{t},j\middle|\pi_{k}\right)=V_{ij}^{t}\left(S^{t},W_{i}^{t},0\middle|\pi_{k}\right)\big/\left(\sigma_{k}(1,1)+\sigma_{k}(50,50)-\sigma_{k}(1,50)\right)^{1/2}$.

$$\begin{aligned}f\left(S^{t},W_{i}^{t},j\middle|\pi_{k}\right)&\equiv F\left(S^{t},W_{i}^{t},j\middle|\pi_{k}\right)-F\left(S^{t},W_{i}^{t},0\middle|\pi_{k}\right)\big/\left(\sigma_{k}(1,1)+\sigma_{k}(50,50)-\sigma_{k}(1,50)\right)^{1/2}\quad j=1,\ldots,50\\&=\pi_{0}^{*}+\pi_{1}^{*}\cdot S^{t}+\pi_{2}^{*}\cdot\left(S^{t}\right)^{2}+\pi_{3}^{*}\cdot S^{t}\cdot W^{t}+\pi_{4}^{*}\cdot W^{t}+\pi_{5}^{*}\cdot\left(W^{t}\right)^{2}\end{aligned}$$

The subject i's decision rule of type k in period t can be written:

$$z_{ij}^{t}\left(S^{t},W_{i}^{t}\middle|k\right)\equiv\tilde{V}_{ij}^{t}\left(S^{t},W_{i}^{t}\middle|k\right)-\tilde{V}_{i0}^{t}\left(S^{t},W_{i}^{t}\middle|k\right)=\tilde{w}_{ij}^{t}+f\left(S^{t},I_{i}^{t},j\middle|\pi_{k}\right)+\eta_{ij}^{t}>z_{il}^{t}\left(S^{t},W_{i}^{t}\middle|k\right)\ \forall l\neq j,$$

where $\eta_{ij}^{t}\equiv\upsilon_{ij}^{t}-\upsilon_{i0}^{t}$.

3.2.2 The likelihood function, Priors, and Joint Posterior Distribution of Parameters

The econometrician observes the choice trajectories of the subjects and the trajectory of the resource stock. Given the deterministic nature of the game, the accumulated wealth W_{i}^{t} can be calculated for each period. For each type k and given the values of the others parameters and variables, the latent values z are modeled with a *seemingly unrelated regressions model* (SUR). Then, for each type k it is assumed that $\eta_{i}^{t}\equiv iid\ N(0,\Sigma_{k})$. The probability function of the latent values z of type k is:

(10)

$$p\left(\left\{z_{ij}^{t}\right\}_{j=1,\ldots,50}\middle|\pi_{k}^{*}\right)\propto\prod_{n,t}\left|H_{k}\right|^{0.5}\exp\left\{-\frac{1}{2}\begin{pmatrix}\left\{z_{i1}^{t}-Q_{i1}^{t}{}'\pi_{k}^{*}\right\}\\\cdot\\\cdot\\\cdot\\\left\{z_{i50}^{t}-Q_{i50}^{t}{}'\pi_{k}^{*}\right\}\end{pmatrix}'H_{k}\begin{pmatrix}\left\{z_{i1}^{t}-Q_{i1}^{t}{}'\pi_{k}^{*}\right\}\\\cdot\\\cdot\\\cdot\\\left\{z_{i50}^{t}-Q_{i50}^{t}{}'\pi_{k}^{*}\right\}\end{pmatrix}\right\}\times I\left(\left\{z_{ij}^{t},d_{ij}^{t}\right\}_{j=1,\ldots,50}\right),$$

where, $H_k = \frac{1}{\Sigma_k}$ is the precision matrix, and $Q_{ij}^{t}\,'$ is the transposed vector of the polynomial terms (given the order *G*).

The indicator function *I* is the latent values *z* are not coherent with the observed choices:

(11) $$I\left(\left\{z_{ij}^{t}, d_{ij}^{t}\right\}_{j=1,\ldots,50}\right) = \begin{cases} 1 \text{ si } d_{ij}^{t} = 1 \,\&\, (z_{ij}^{t} > z_{il}^{t})(j \neq l) \\ \text{ou} \\ 1 \text{ si } (\forall j)(d_{ij}^{t} = 0 \,\&\, z_{ij}^{t} \leq 0) \\ \text{ou} \\ 0 \text{ dans un autre cas} \end{cases},$$ where $d_{i,j}^{t}$ is the choice indicator, $d_{ij}^{t} = \begin{pmatrix} 1 \text{ si j est choisit par i à la période t} \\ 0 \text{ dans les autres cas} \end{pmatrix}$.

Inference via the Gibbs sample starts with the specification of the complete data likelihood function. Then, given a particular *K* and *G*, this is:

(12)

$$L\left(\left\{z_{i}^{t}\right\}_{i=1,\ldots,N,t=1,\ldots,T}\left\{\tau_{n}\right\}_{n=1,N}\middle|\left\{\theta_{k}, \pi_{k}^{*}, \sigma_{k}^{-2}\right\}_{k=1,K}\right) \propto$$

$$\prod_{k=1,K}\prod_{n:\tau_n=k}\left[\theta_k \prod_{t=1,T}\left|H_k\right|^{0.5} \exp\left\{-\frac{1}{2}\begin{pmatrix}\left\{z_{i1}^{t} - Q_{i1}^{t}\,'\pi_k^{*}\right\} \\ . \\ . \\ . \\ \left\{z_{i50}^{t} - Q_{i50}^{t}\,'\pi_k^{*}\right\}\end{pmatrix}' H_k \begin{pmatrix}\left\{z_{i1}^{t} - Q_{i1}^{t}\,'\pi_k^{*}\right\} \\ . \\ . \\ . \\ \left\{z_{i50}^{t} - Q_{i50}^{t}\,'\pi_k^{*}\right\}\end{pmatrix}\right\} \times I\left(\left\{z_{ij}^{t}, d_{ij}^{t}\right\}_{j=1,\ldots,50}\right)\right]$$

We will present in the following paragraphs the prior distributions of the model parameters. The SUR model assumes that the parameters vector π follows a multivariate normal distribution: $\pi_k \sim N(0, \Lambda)$, where Λ is 6x6 diagonal matrix with all its' elements equal to 1^{e+20}. Additionally, the SUR model assumes that the precision matrix H_k follows a Whishart distribution: $H_k \sim Wi\left(A^{-1}, \underline{v}\right)$, where A^{-1} is positive defined matrix of scale parameters and $\underline{v} = (50-1)/2$ are the degrees of freedom.

The prior mean of the parameters vector π is null: the prior distribution is then centered on myopia. Though, the prior distribution is not very informative, there is a little prior weight on the myopic rule because the elements of the variance matrix Λ are very high. We have restricted the elements of the matrix to be equal. This may result in a drawback because it may impose too much prior weight on models for which the high-order terms of the polynomial dominate decisions.

3.2.3 The Gibbs sampling algorithm

On the basis of Houser et al (2004), in this sub-section we describe the application of the Gibbs sampler used to approximate the posterior parameters of the models. The Gibbs sampler is constituted of five blocs[10]:

(i) Draw of latent values *z*: given the parameters values the conditional posterior distribution of z_{ij}^t $j = 1,\ldots,50$ is given by:

$$p\left(\left\{z_{ij}^t\right\}_{j=1,\ldots,50}\middle|\pi_k^*\right)\propto\prod_{n,t}\left|H_k\right|^{0.5}\exp\left\{-\frac{1}{2}\begin{pmatrix}\left\{z_{i1}^t-Q_{i1}^t{}'\pi_k^*\right\}\\ \cdot\\ \cdot\\ \cdot\\ \left\{z_{i50}^t-Q_{i50}^t{}'\pi_k^*\right\}\end{pmatrix}' H_k\begin{pmatrix}\left\{z_{i1}^t-Q_{i1}^t{}'\pi_k^*\right\}\\ \cdot\\ \cdot\\ \cdot\\ \left\{z_{i50}^t-Q_{i50}^t{}'\pi_k^*\right\}\end{pmatrix}\right\}\times I\left(\left\{z_{ij}^t,d_{ij}^t\right\}_{j=1,\ldots,50}\right)$$

Following, Geweke (1991), the latent values *z* are drawn from a truncated multivariate Gaussian distribution.

(ii) Draw of the π_k^* ($k = 1,\ldots, K$) parameters. This and next blocs of the algorithm constitute the two blocs of the Gibbs sampler used to estimate the SUR model. It generates samples from the posterior distribution $\pi_k^*,H_k\left|z_k,Q_k\right.$ from the conditional posterior distribution π_k^* and H_k (see the next item):

$$\pi_k^*\left|H_k,z_k,Q_k\right.\sim N\left(\left\lfloor\underline{\Lambda}^{-1}+Q_k'\left(H_k\otimes I_T\right)z_k\right\rfloor\cdot\left\lfloor\underline{\Lambda}^{-1}\cdot\underline{\pi_k^*}+Q_k'\left(H_k\otimes I_T\right)z_k\right\rfloor\underline{\Lambda}+Q_k'\left(H_k\otimes I_T\right)z_k\right)$$

[10] The Matlab code developed largely use the BACC functions.

where, $\underline{\Lambda}$ and $\underline{\pi_k^*}$ are, respectively, the variance-covariance matrix and the parameters vector of the polynomial drawn in the previous iteration of the sampler.

(iii) Draw of the variance-covariance matrix of the optimization error H_k^{-1}, k = 1,…, K. Draws are done from the conditional posterior distribution given by:

$H_k \left| \pi_k^*, z_k, Q_k \sim Wi\left(\left[\underline{A} + \left(z_i^t - Q_k \pi_k^* \right)' \left(z_i^t - Q_k \pi_k^* \right) \right], \underline{v} + T \right) \right.$, where $\underline{A}$ is the matrix of scale parameters drawn in the previous iteration of the sampler. H_k is afterwards inversed to obtain Σ_k.

(iv) Draw of the population of proportion θ_k (k = 1,…, K). The conditional posterior distribution of θ_k is Di({2+N_k}k = 1,…,K). The drawing is made using standard procedures.

(v) Draw of the ith subject type, i = 1,…, N. The likelihood contribution for subject i given he/she uses decision rule k and with everything else known is represented by $L_k(i)$. Then, we draw from the following distribution:

$$\Pr(\tau_i = k') = \frac{L_{k'}(i)}{\sum_{k=1,K} L_k(i)}.$$

Finally, K (the number of types) and G (the polynomial order) have to be chosen. We estimate several models with different values of K and G, and then use Bayesian decision theory to choose among them. This requires construction of the marginal likelihood for each model. We have used the same procedure than Houser et al (2004) for constructing marginal likelihoods which is based on Lewis and Raftery (1997).

4. Results of applying the HKM algorithm

In this section we present the results of the HKM algorithm applied to our experimental data. We have fitted 12 models with different numbers of types K and polynomial orders G. But, we did not evaluate models with different state variables entering in the future component of the value function. The 12 considered models include in the polynomial two state variables:

the stock of the resource (*S*) and the accumulated wealth (*W*). The later state variable is not relevant for decision in the theoretical model studied[11].

We proceed with the selection of the preferred model and the evaluation of its' fit to the experimental data. After that we perform simulations of the preferred model to better characterize the estimated decision rules.

4.1 Model selection

In order to assess the convergence of the algorithm, we proceed at first by a visual evaluation of the sequences of the parameters π_k^* then, we practice several convergence tests[12] (*cf.* Appendix 1, page 43). Given the high dimension of the choice set, the algorithm is rather slow on a standard personal computer. Therefore, the inferences presented here are based on a fixed number of cycles (7500 cycles) of the algorithm. If the convergence tests reveal a problem, and as it is too time consuming to increase the number of cycles, we just give the precision level that has been reached with that number of iterations[13].

RESULT 4.1: The algorithm identified two types of agents: the "Quasi Myopic" (QM) and the "Disrupted Farsighted" (DF). The "Quasi Myopic" type regroups about 84% of the agents, but only 8% are "Disrupted Farsighted"; the remaining 8% could not be identified.

	Order of future component polynomial			
Number of types	G = 2	G = 3	G = 4	G = 5
2	**-3725**	-4180	-4085	-4274
3	-5649	-5580	-5592	-5248
4	-4681	-6381	-7726	-9116

Table 2: Marginal likelihood of the estimated models

[11] See Giordana and Willinger (2007) for the feedback functions of the homogenous population case with exogenous discount factors.

[12] Implemented by the "coda" function in Matlab; this function is available for free in the "Econometrics Toolbox" package of LeSage (1999).

[13] Aiming to reduce the size of the paper we did not introduce in Appendix 1 the convergence tests of the models other than the preferred one. However, they are available under request.

The comparison of the marginal likelihood indicates that the model with 2 types and G = 2 (order of the F polynomial) is the preferred model (Table 2). The estimated coefficients of the future component are exposed in Table 3. The interpretation of these coefficients is quite complex, we will pass then directly to the evaluation of the adjustment of the preferred model.

We attribute to every subject a type according to their posterior probability of being QM or DF. We obtain this probability, for every agent, by calculating the likelihood share on the basis of posterior parameters. Those subjects whose probability of being QM (or DF) was equal to 0.5 were considered as not identified.

	Prior Distribution		Type 1 : N = « Quasi Myopic »		Type 2 : N = « Disrupted Farsighted »	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
π_0 : Cte	0	1*e10	-149,71688	28,94230	-495,58605	23,11397
π_1 : St	0	1*e10	-0,10001	0,02218	-0,27049	0,01594
π_2 : St^2	0	1*e10	0,00006	0,00002	0,00009	0,00001
π_3 : St*W	0	1*e10	-0,87175	0,02171	-0,69733	0,01582
π_4 : W	0	1*e10	-0,00017	0,00005	-0,00015	0,00003
π_5 : W^2	0	1*e10	0,00011	0,00005	0,00009	0,00003
σ_η	-	-				
θ_k	0.5	-	0,8417		0.0833	

Table 3: Prior and posterior means and standard deviations of future component parameters

4.2 Evaluation of the fit

RESULT 4.2: The estimated decision rules adjust convincingly well to the observed extractions.

The Figure 5a traces the observed and the estimated average withdrawals of each type as well as those from the not identified individuals. The conditional theoretical predictions for the myopic and rational strategies are also exposed in Figure 5a. The QM decision rule slightly overvalues the individual withdrawals of the first four periods, but then it adjusts perfectly the behavior observed for almost all the remaining periods. The “Quasi Myopic” label of this decision rule is explained by the proximity of the withdrawals feigned under this rule and those resulting from the conditional theoretical prediction of the myopic strategy (under exogenous time preference). The mean extractions trajectory of the DF agents is also overvalued by the estimated decision rule between periods 2 and 5; in particular for periods 3 and 4, the differences are quite marked. We observe that DF average extractions present a non-stationary pattern: from period 7 until period 9, the mean extractions of the DF subjects are underestimated because they get clearly closer to the QM trajectories (observed and estimated). However, the Figure 5a clearly shows that the main aspects of the observed behavior of the DF subjects are captured by estimated decision rule. This means that the withdrawals are lower than those of the QM subjects for almost the whole temporal horizon (justifying the “farsighted” label). The too weak extraction level during the last period justifies the “disrupted” character of these agents: they persist in valuing the future while there is not any more. The predictive capacity of DF rule seems reasonable, though Figure 5a points out that could be insightful to consider additional state variables into the future component polynomial to better capture the non-stationary pattern. The average withdrawals of the not identified agents do not show any particular tendency. They are very variable with relatively distant peaks. Thus, the incapacity to identify this behavior does not reveal a defect in the performance of the algorithm.

We observe in the Figure 5b a very good adjustment of the estimated rules to the mean extraction trajectory (the not identified subjects are not considered in the calculation of this trajectory).

(a) (b)

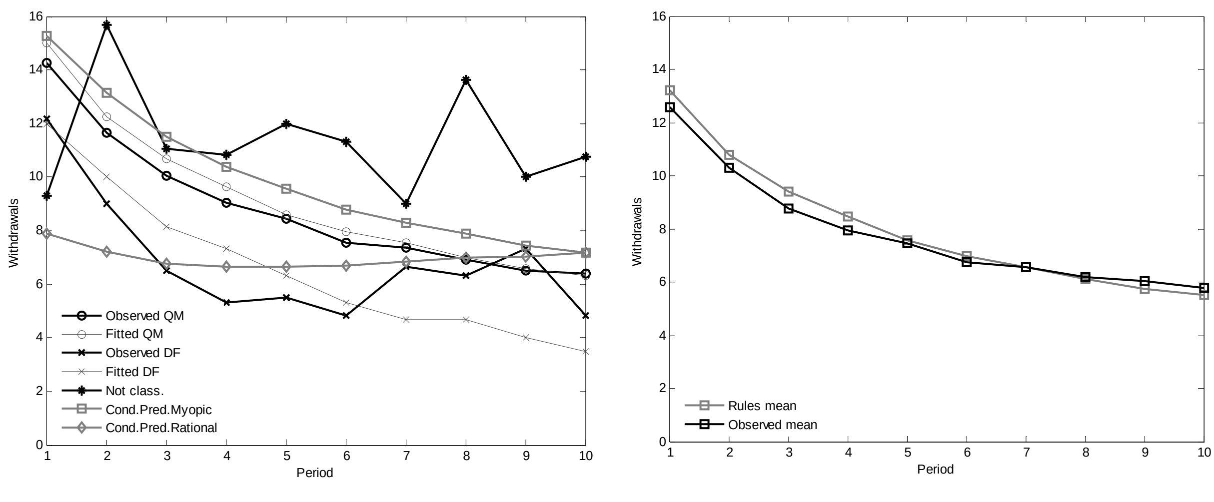


Figure 5: Observed and estimated mean withdrawals

RESULT 4.3: The comparison of the observed individual extractions of each withdrawer type with the conditional predictions reveals that the QM and the DF estimated rules give the best fitting predictions.

The Table 4 exposes the square deviation of the average extractions of each type of agent (the not identified subjects are not considered) with respect to each prediction (i.e. myopic conditional prediction, farsighted with exogenous and endogenous discount factor, QM and DF predictions). As can be seen in Table 5, the best predictors of each type mean withdrawals are the corresponding estimated rules: the QM rule square deviation with respect to the QM subjects is 1.92 and the DF rule square deviation with respect to the DF subjects reaches 28. It should be noted that the model with a population of farsighted withdrawers, each with exogenous discount factors equal to 0.7, predicts the mean extraction of the QM subjects as well as the QM rule. However, this model is not a good predictor of the DF subjects' mean withdrawals, as the DF rule's square deviation is significantly lower.

Predictions \ Type	Quasi Myopic	Disrupted Farsighted
QM	**1.92**	78
DF	51	**28**
Myopic	13	119
Farsighted (ρ = 0.7)	1.98	62
Farsighted $\left(\rho = \phi\left(\Lambda_i^t\right)\right)$	8	107.7

Table 4: Square deviation of prediction for each type's mean withdrawals.

The results exposed in this sub-section certainly confirm the good performance of the statistical procedure. On the one hand, the estimated decisions rules adjust very well the observed extractions and, on the other hand, the classification algorithm seems to have done a very good work.

4.3 Decision rules characterization

In order to fully describe the characteristics of the extraction trajectories of the identified types, we perform simulations using different sets of parameters. A first series of simulations are carried out with the same set of parameters used in the experimental design of Giordana and Willinger (2007) (*c.f.* equation (2), page 5). Secondly, aiming to further stand out the effects of wealth distribution on withdrawals trajectories of each estimated type and on the exploitation efficiency, we performed a second series of simulations using another set of parameters (Table 5).

4.3.1 First series of simulations: QM and DF populations

Aiming to characterize the trajectories depicted under the estimated decision rules, in this series of simulations it is assumed that the entire population of withdrawers is of the same type, i.e. QM or DF. We first simulate one-shot withdrawals of QM and DF populations for different levels of the state variables. Then, we compare the exploitation efficiency according to the whole population of withdrawers behaves as one of the estimated types or as one of the three theoretical strategies considered (i.e. myopic, rational and optimum). Though, the resulting extraction trajectories are not completely comparable because they result in different paths of the state variables (i.e. the resource's stock and the accumulated wealth). Consequently, we also compare trajectories conditioned to the paths of the state variables generated under the estimated decision rules (i.e. Quasi Myopic and Disrupted Farsighted).

RESULT 4.4: The Stock of the resource and the Accumulated Wealth are complements in determining the level of extractions.

In both estimated decision rules, the state variables affect the individual withdrawals in opposite directions: the state variable Stock (Accumulated Wealth) is directly (indirectly) related with the withdrawal level. Similarly to the myopic and rational theoretical strategies, the individual withdrawals of each type relates directly to the stock level. The cumulated wealth is not relevant in the theoretical model considered, though it impacts negatively on the level of extraction of each type. Figure 6 plots the individual extraction level of a QM agent for different combinations of the state variables. As can be noted from this figure, the QM rule (and the DF also[14]) results in well behaving concave extraction level curves: to leave the

[14] The surface resulting for the DF rule has a similar form.

extraction level unchanged, an increment of the resource stock must be compensated by an increment in wealth.

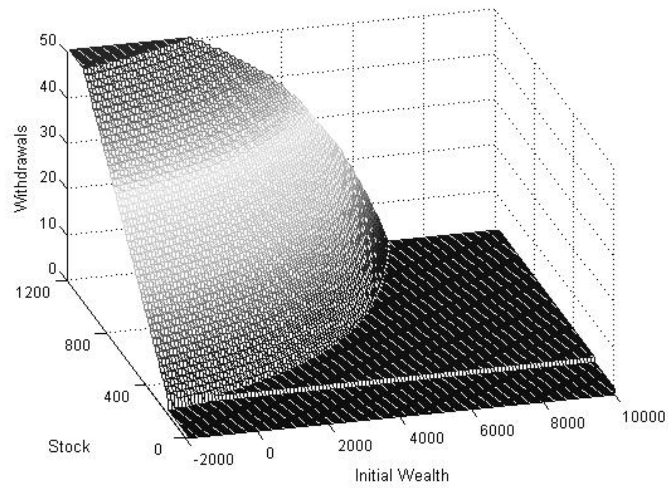


Figure 6: Individual Quasi Myopic extractions for different combinations of Stock and Wealth levels.

RESULT 4.5: The estimated decision rules result in more efficient withdrawal trajectories that the myopic strategy.

Figure 7 shows that the trajectory of individual extractions in a QM population is similar to the myopic trajectory: they start and finish at the same level, but we observe differences of just a unit in the periods 2, 3, 5 and 9. In consequence, the myopic strategy engenders a withdrawal trajectory that is slightly less efficient than the QM trajectory: 52% of efficiency versus 56%, respectively. Figure 7 also shows that the trajectory of individual extractions in a DF population (hereafter trajectory DF) lies below the myopic and QM trajectories (excepting periods 7 and 10 of the QM trajectory), when three trajectories coincide. The efficiency of the DF trajectory is 67%, which is sharply superior with respect to the QM rule and the myopic strategy, but it is still lower than the predicted efficiency for the rational strategy (74% of efficiency).

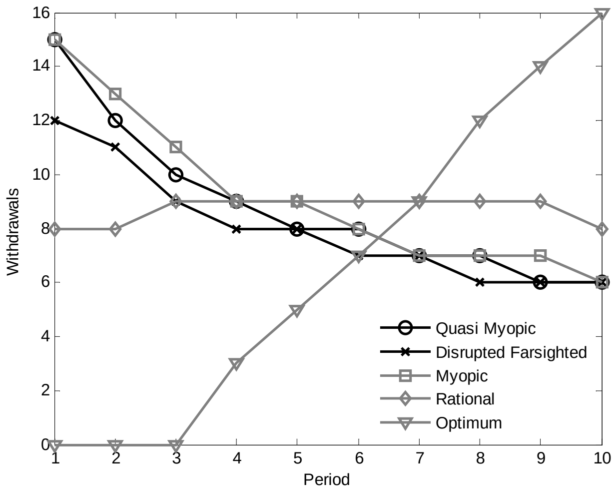


Figure 7: Simulated individual extractions under the estimated decision rules and the theoretical strategies.

RESULT 4.6: The wealth effect in the QM and DF decision rules results in withdrawal trajectories that converges faster to a level of total extraction that, given the natural recharge of the resource, ensures henceforth a constant Stock.

The Figure 8a plots the extraction trajectories under the QM decision rule. It also plots, conditioned to the path of the state variables Stock and Wealth generated under the QM rule, the extraction trajectories resulting from the DF rule and the three theoretical hypotheses of behavior. Whereas the conditional theoretical predictions converge to the same level of extraction in the final period, the estimated rules of decision, in Figure 8a, predict lower withdrawals during the temporal horizon and particularly in the last period. This evidences for the negative "wealth effect" stated before. The myopic and QM extractions are identical in the initial period but, as the wealth accumulates, the QM extractions move away from the myopic conditional prediction. The DF rule (conditional to the QM state variables paths) results in an extraction trajectory that is parallel and lower with respect to the QM trajectory. It worth be noted that the QM trajectory converges (in period 9), to an equalitarian distribution of the natural recharge (30/5 = 6); that is, the QM rule leads to a "pseudo stationary state" where the stock of the resource neither increases nor decreases. Nevertheless, the accumulated wealth continues to increase. Then, we cannot pronounce us on the characteristics of this state.

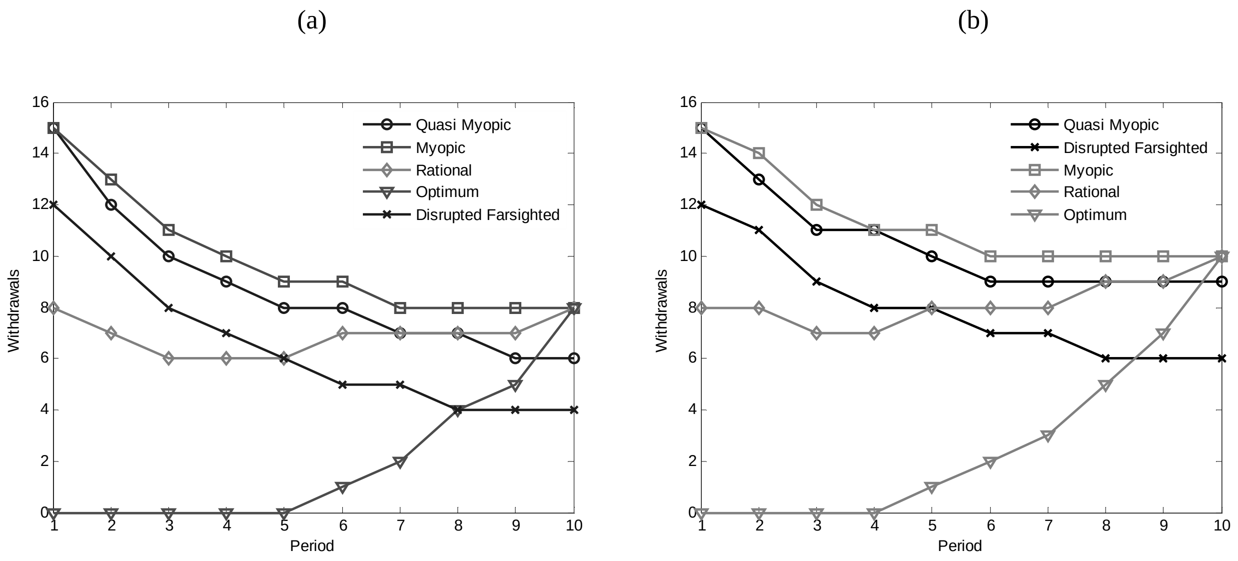


Figure 8: Individual simulated withdrawals and conditional predictions for the theoretical strategies (Myopic, Rational and Optimum). (a) Quasi Myopic rule; (b) Disrupted Farsighted rule.

The Figure 8b is similar to Figure 8a but the calculations are done on the basis of the state variable paths generated under the DF decision rule. The DF withdrawals trajectory is below the QM one in every period. The resulting path of the state variable Stock is thus superior in every period with respect to the path resulting from a population following the QM rule. So, Figure 8b shows that the extraction trajectory converges more quickly to a “pseudo stationary state” with a higher stock level than the QM rule case. As a consequence, the wealth also evolves in a different way according to the type of the population: whereas the DF rule predicts relatively poor agents at the beginning of the temporal horizon and rich agents at the end, under the QM rule, the prediction is reversed.

RESULT 4.7: The stock effect on the QM and DF extraction trajectories crowds out the wealth effect.

The comparison of the QM trajectories in the Figure 8a and b allows us to characterize better the effect of the state variables interaction. In the Figure 8a the QM trajectory is even closer to the myopic conditional prediction with respect to the Figure 8b. This is because under the DF rule the withdrawers are relatively poor during the first periods of the temporal horizon weakening the wealth effect strength. The difference between the myopic and the QM withdrawals, as can be seen in Figure 8a, amplifies during the last two periods. On the contrary, in the Figure 8b, this difference remains constant from period 5 till the end. It appears that the effect of a high stock of the resource, resulting from the DF rule, absorbs the wealth effect observed in the Figure 8a.

Similarly to the QM rule case, the stock effect on the extraction trajectory crowds out the wealth effect in the DF rule case. The comparison of Figure 8a and b lets see that the DF trajectory in the former figure, when conditioning to the state variables evolution generated by a QM population, lies below the DF trajectory plotted in the later. In the first half of the temporal horizon the differences are limited to one unit. In the last five periods the difference increases to two units even that wealth is higher with regard to the rule QM case. However, the stock is also higher with respect to the QM rule case inducing higher extractions.

The empirical model resulting from the estimated types gives a consistent description of the observed behavior. Then, it can be used to evaluate the impact, on the CPR exploitation behavior, of modifications in the context (i.e. natural recharge of the resource, initial wealth and its distribution between types). In the next section we perform a second series of simulations of the empirical model to assess the impact of wealth inequality.

4.3.2 Second series of simulations: the effect of wealth inequality

The results exposed in the previous sections render interesting the evaluation of the consequences, on the withdrawal trajectories and the efficiency of the exploitation, of the agents' wealth and its distribution. We shall study the effect on the trajectories of individual withdrawals of: (*i*) the amount of initial wealth, and (*ii*) the distribution of the initial wealth between types of withdrawers.

The parameter setting used in all the simulations performed is exposed in the Table 5. Most of the parameters values remained unchanged with regard to those used for the experiments in the laboratory (Giordana and Willinger, 2007). However, we lengthened the temporal horizon from 10 to 15 periods, the number of withdrawers from 5 to 10 individuals and we modified the characteristics of the resource: the initial stock of the resource was incremented from 500 to 1000 units and the natural recharge was also incremented to 60 units by period. We implement these changes in the parameter set mainly because, as stated in the previous subsection, the effect of wealth is stronger at the end of the temporal horizon. We look forward to modify the accumulated wealth path to better assess its' impact. We are aware that the validity of these simulations follows from the assumption that the implementation of the experimental treatment with the parameter setting exposed in Table 5 would have allowed us to estimate the same decision rules.

Population size (N)	Composition of the population	Profit function	Cost function	Resource's Stock	Choice set
10	50% of "Quasi Myopic" 50% of "Disrupted Farsighted"	a = 5,3 b = 0,09	p = 7,55 f = 0,01 z = 0,001	$S(0)$ = 1000 r = 60	{0,50}

Table 5: Parameters' values common to every one of the performed simulations.

Before we analyze how the distribution of wealth between the types impacts on the efficiency of the exploitation, we describe the withdrawal trajectories simulated for various levels of initial wealth. We have calculated 51 withdrawal trajectories for each type of withdrawer in the mixed population considering that the initial wealth of each individual varies from 0 to 5000 points. These trajectories are presented in the Figure 10. The nuance of the grey color indicates the intensity of the withdrawals in excess/shortage with respect to the level that guarantees a constant resource stock.

RESULT 4.8: As the initial wealth increases: *(i)* the extraction trajectories of both types converge progressively to an equalitarian distribution of the recharge between types; *(ii)* beyond a particular level of wealth, an unequal distribution of the recharge between the types comes out again.

The Figure 9 (a) and (b) show that the initial extractions are strongly reduced by an increase of the initial wealth, even up to result in constant or increasing trajectories when the wealth is very high. These figures also show that the extractions at the end of the temporal horizon are less affected. The phenomenon of convergence towards a pseudo stationary state is not altered. Nevertheless, we observe that according to the raise of the initial wealth, the distribution of the recharge becomes more and more equalitarian. Firstly, the QM extractions (Figure 9a) converge to a higher amount than DF extractions (Figure 9b). Beyond a particular level of wealth, the PP final extractions become higher than the QM ones, but the convergence is less clear because trajectories show some variability.

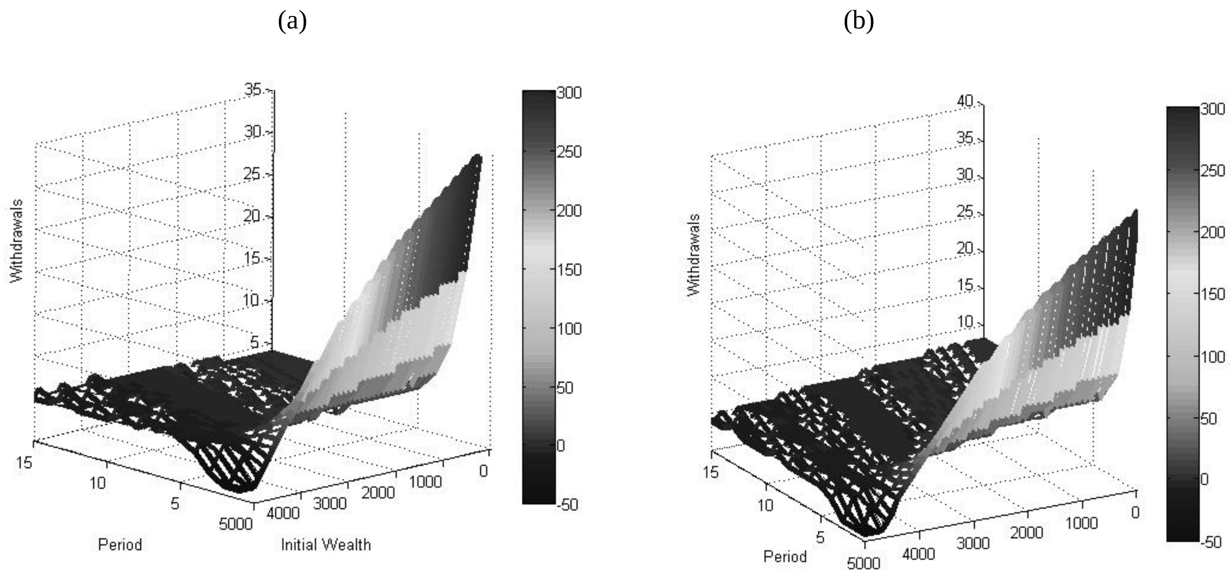


Figure 9: Individual withdrawal trajectories for different amounts of initial wealth: (a) Quasi Myopic, (b) Disrupted Farsighted.

RESULT 4.9: Richer populations do better, though up to a certain level of wealth.

The efficiency of the resource exploitation by a mixed population of QM and DF withdrawers increases, at a decreasing rate, with the initial wealth of agents. As can be seen in Figure 10 the mean efficiency achieves its' maximum when the initial wealth of each agent is equal to 4100 points. During the increasing segment of the mean efficiency, the QM trajectories are more efficient as a consequence of the relatively low DF extractions. But, the opposite is observed during the decreasing segment. This can be resumed in the following result:

RESULT 4.9bis: As initial wealth increases, final wealth distribution between withdrawers types first degrades, then beyond a certain level of wealth it gets ameliorated to finish achieving equality in the final wealth distribution when wealth reaches the level $\hat{W}$.

As can be seen in Figure 10, the vertical distance between the efficiency achieved by the trajectories of each type of withdrawer is maximal when the initial wealth is between 2000 and 2500 points. Beyond this level, efficiency distances get reduce and achieve equality when $\hat{\omega}$. The analysis of the extraction trajectories shapes, exposed in Result 4.8, clarifies the statements of Result 4.9.

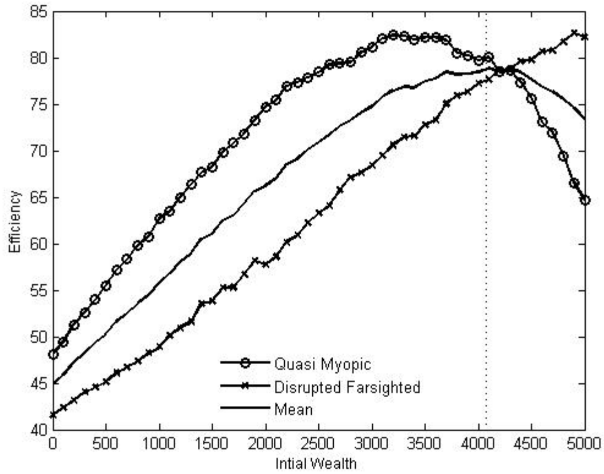


Figure 10: Efficiency of the resource exploitation by a mixed population of QM and DF agents for different amounts of initial wealth.

Let us suppose that at the beginning of the temporal horizon, an amount $\overline{W}$ of wealth is distributed between types of withdrawers in an equal or unequal manner. But, inside the group of withdrawers of the same type, the wealth is equally distributed.

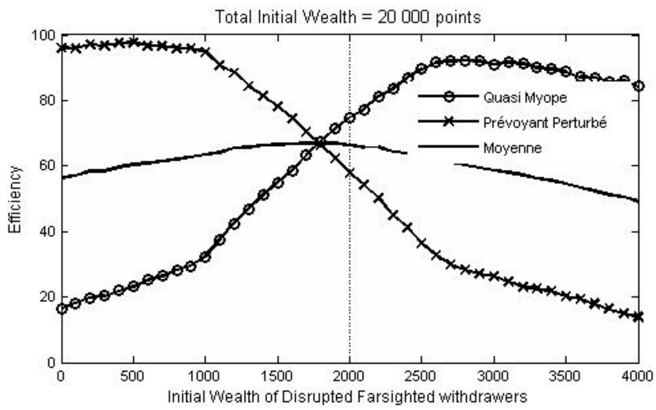
RESULT 4.10: In terms of the resource exploitation efficiency, equality in wealth distribution is better in rich populations of withdrawers, but some extent of inequality does better in poorer populations.

The distribution of wealth that maximizes the exploitation efficiency is less unequal as long as the initial wealth gets higher. Nevertheless, the distributions resulting in relatively poor DF withdrawers dominate those where they are relatively richer. Figure 11 lets see the previous result's statements. It shows the efficiency of the withdrawal trajectories for each type, as well as the mean efficiency, calculated for different distributions of three distinct levels of initial wealth. The comparison of the 3 windows in Figure 11 shows that the wealth distribution between types that maximizes the mean efficiency is progressively less unequal as long as the initial wealth goes from 20 000 until 41 000 points. The window (c) in the Figure 11 exposes alternative distributions of the initial wealth amount that, when equally distributed, attains the maximum efficiency, as has been shown in Figure 10 (i.e. $\overline{W} = N \cdot \hat{\omega}$). As can be seen in window (c), the equal distribution of the initial wealth maximizes de mean efficiency. This is coherent with the Figure 10.

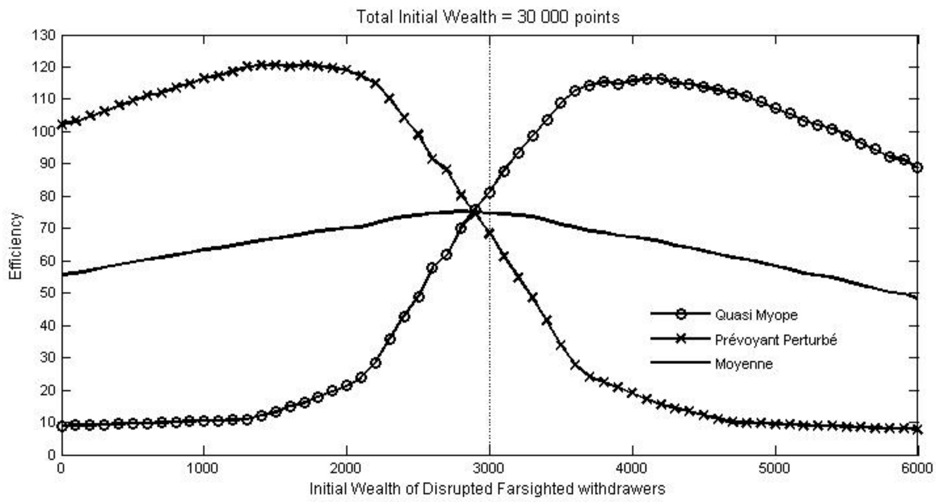
Additionally, it can be seen, in all three windows of Figure 11, that for the same level of wealth distribution inequality, the distributions resulting in poorer DF agents attain a higher mean efficiency, and that the maximum mean efficiency is attained when final wealth distribution is egalitarian. This can be resumed in the following results:

RESULT 4.10bis: Independently of both, the amount of initial wealth and its initial distribution: (i) maximal efficiency is reached when final wealth is equally distributed between types; (ii) initial wealth distribution that favors QM agents are superior in terms of mean efficiency.

(a)



(b)



(c)

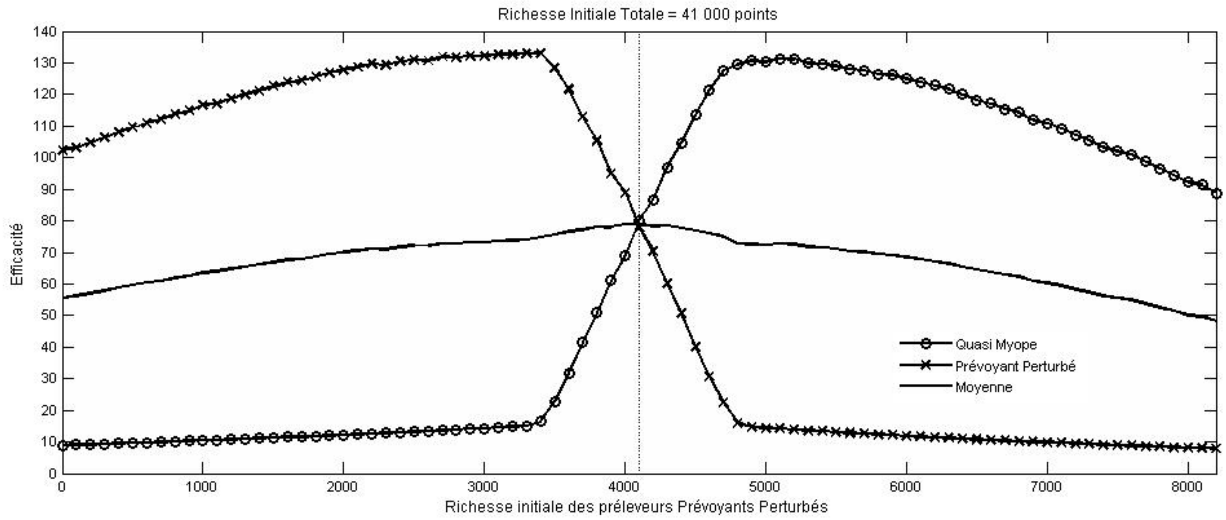


Figure 11: Efficiency of the extraction trajectories of a mixed population of QM and DF agents. The trajectories correspond to different distributions of an initial wealth of (a) 20 000, (b) 30 000 and (c) 41 000 points.

6. Conclusion and discussion

Aiming to better characterize the exploitation behavior of renewable common-pool resources, in this paper we explore alternative hypothesis about the valuation of future by the agents and the possibility of heterogeneous behavior on this regard. To do this, we adopt an exploratory approach then, we further analyze the data collected by Giordana and Willinger (2007) in their experimental test of an *N*-person discrete-time deterministic dynamic game of *T* periods fixed duration. Firstly, assuming that the rate of time preference is symmetrically determined among withdrawers (homogeneous case), we estimated models of exogenous and endogenous discounting. In the exogenous time preference case, players discount future values in every decision period at the same level. In the endogenous case, we statistically modeled the discount factor reduced form as a complementary log transformation of a second order polynomial on cumulated wealth. Afterwards, we further explore the endogenous case looking forward to assess the extent of heterogeneity in the subjects' appraisal of the resource's future value. Consequently, we adapt and apply to our experimental data the Bayesian classification algorithm developed by Houser et al (2004) (HKM algorithm). This statistical procedure allows us to make inferences about the number and nature of the decision rules present in a population of subjects as well as about the probability with which each subject uses each rule. The future component of each rule (i.e. the future value of the resource) is modeled as a polynomial on relevant state variables; we have considered: the stock of the resource and the accumulated wealth. Our results can be summarized as follows:

(i) *Time preference heterogeneity.* The model with heterogeneous time preference among withdrawers gives the best fitting of the observed withdrawals trajectories.

(ii) *Classification.* The preferred model identifies two types of decision rules (modeled as second order polynomials): "Quasi Myopic" (QM) and "Disrupted Farsighted" (DF). The algorithm classifies about 84% of the agents as QM, but only 5% as DF; the remaining 11% could not be identified.

(iii) *Decision rules' withdrawals trajectories characterization*. In both estimated decision rules, the state variables affect the individual withdrawals in opposite directions. While the state variable Stock is directly related with the withdrawal level, the Accumulated Wealth is indirectly related. The "stock effect" direction corresponds to the theoretical predictions, and the "wealth effect" coincides with the estimated endogenous time preference model in the homogenous population case. Moreover, the complementarity between the stock and the wealth avoids that the wealth effect excessively reduces extractions in the final periods when the resource has little future value.

(iv) *Efficiency*. Assuming that the whole population of withdrawers behaves alternatively as one of the estimated decision rules, the resulting trajectory are more efficient than the exogenous myopic discounting trajectory (ρ = 0), but they are still less efficient than the time indifferent farsighted trajectory (ρ = 1).

(v) *Wealth & Efficiency.* Assuming equality in wealth distribution at the departure point:

   a. Richer populations do better, though up to a certain level of wealth, $\hat{W}$.
   b. As initial wealth increases, final wealth distribution between withdrawers types first degrades, then beyond a certain level of wealth it gets ameliorated to finish achieving equality when wealth reaches the level $\hat{W}$.

(vi) *Wealth Distribution & Efficiency.* Assuming a fixed amount of wealth unequally distributed between the types of withdrawers but equally distributed within withdrawers of the same type:

   a. Equality in initial wealth distribution is better in rich populations of withdrawers, but some extent of inequality in initial wealth does better in poorer populations.

b. Independently of both, the amount of initial wealth and its distribution, maximal efficiency is reached when final wealth is equally distributed between types.

These results corroborate to some extent the implications of theoretical models recently developed on time preference formation (Becker and Mulligan, 1994, 1997) (B&M 94, 97) and on the effects of wealth inequality in the exploitation of common-pool resources (Baland and Platteau, 1997, 1998; Bardhan et al, 2007). However, attention must be paid when doing comparisons as the theoretical frameworks are quite distinct. While Becker and Mulligan formalize the time preference formation process of agents taking individual intertemporal decisions, our experimental data results from an interaction situation, i.e. exploitation of common resource. On the other hand, the analysis of Baland and Platteau (1997) and of Bardhan et al. (2007) about the effect of wealth inequality on the efficiency in the commons, focus on the rent dissipation problem within an exploitation period, leaving the dynamic externalities untreated.

One of the main implications of the B&M97's model is that "…*there is a complementarity between future utilities and weighting the future more heavily. Consequently, anything that raises future utilities without raising the marginal utility of current consumption will tend to lower the equilibrium discount on the future*" (page 739). Our results agree with this assertion. On the one hand, a raise in the stock of the resource enhance future and current payoffs, hence in accordance with this assertion, it results in increased current extractions for both decision rules (depending on the level of the stock and the wealth of the agent). An increment in current extractions implies a relative low future value of the resource, which means high discounting (i.e. low discount factors). On the other hand, a raise in the level of wealth does not modify the level of payoffs but enhances the future final reward of the experiment; therefore, agreeing with the assertion, current extractions diminish, reflecting a higher future value of the resource hence low discounting (i.e. high discount factors). To this to be true we must think experimental subjects as consumers looking forward to maximize their reward at the end of the session. Assuming that the utility of consumption is a concave function and that they will exhaust the budget constraint, the reduced form of the utility can be written in terms of the accumulated wealth. At the beginning of the game the accumulated wealth is low so the marginal utility of current payoffs is very high, then they heavily discount future. As a consequence of wealth accumulation the marginal utility of consumption decreases then, the willingness to perform over-discounting reducing efforts increases. Within the framework of section 2's model, it can be shown straightforward under which conditions these comparative static hold.

The implications of the B&M97's model about the effects of wealth on future discounting should not be applied straightforwardly to a strategic interaction framework in theoretical grounds. In the baseline situation, assuming that the cost of the discount reducing effort is independent of wealth and income, they show that wealthy consumers will be more patient and then, inequalities will be deepened (Becker and Mulligan, 1997; page 745). While our results also show that wealth enhances patient, the impact on the final wealth distribution are not so clear-cut. This B&M97's second implication, results from the fact that time preference implies increased future consumption and then more utility. However, in a common resource game, time preference may imply lower future payoffs depending on the degree of patient of the other common users affecting their willingness to engage in short-term sacrifices aimed to ensure future conservation (this phenomenon is known as the "race for the water" in the groundwater exploitation literature (Burt and Provencher, 1993)). This is why we show that some extent of inequality is better in terms exploitation efficiency: all the unequal distributions of initial wealth that favors Quasi Myopic withdrawers (i.e. impatient users) are better if the initial wealth is inferior to $\overline{W} = \hat{\omega} \cdot N$. On the other hand, it comes out from our empirical results that there is, for each level of initial wealth, an optimal unequal distribution and, unless the initial wealth distribution is close to it, the final wealth distribution strongly degrades.

The advanced argument about the effect of wealth on future consumption of the experimental subjects helps explain why ours results on the effects of the initial wealth level and its' distribution on the efficiency of the resource appropriation do not totally agree with the firsts two theoretical propositions of Baland and Platteau (1997) (B&P97). The B&P97's first proposition asserts that "*in the appropriation game the more unequal the distribution of wealth, the more efficient the use of the CPR*" (page 456), and the second one that "*a disequalizing change in the distribution of access rights, e.g. through credit constraints, may increase the welfare of all users*" (page 457). Our results do not support the first proposition and just partially the second one. The simulations of the empirical model showed that there are "equalizing" changes that increase the welfare of all users and, depending on the richness of the population there may be disequalizing changes that improve total efficiency but they are not Pareto improvements. While this is disappointing, some factors explain these discrepancies as both analysis are not frankly comparable. First, while B&P97 study homogeneous agents, we work with two types of withdrawers with distinct time preferences. We did not evaluate wealth distribution among homogenous withdrawers but just between groups of the same type. Secondly and may be more important, in their analysis the distribution of wealth is related to the distribution of external constraints that limit the amount of exploitation effort which some users can exert and then it may reduce the extent of overexploitation by altering the distribution of access rights. In our case, wealth does not restrict the ability to use the resource. On the contrary, following the argument advanced in a previous paragraph, it increases the interest of resource conservation. Then, it may be more adapted to consider our framework as a public good (i.e. resource conservation) game where the wealth increases the interest of contributing on it.

Baland and Platteau (1997) continue their analysis of wealth inequality studying the case of the private provision of a common good. They assume that the interest on the common good of each agent depends on her wealth[15]. Then, different wealth distributions result in different equilibrium behaviour of agents which can be characterised as constrained cooperators, potential cooperators and defectors. Changes in the distribution of wealth may generate shifts in the equilibrium types of agents: potential cooperators may be seen themselfs converted in defectors or constrained cooperators, following a particular modification of the wealth distribution. This implies that "*the poorer the economy the higher must be the proportion of defectors with no wealth in the population. If the economy is rich enough, however, wealth distribution may be perfectly egalitarian*", (Proposition 7, page 467). Our results fully corroborate these theoretical propositions. In our empirical model, the equilibrium types of the agents are given and independent of the wealth level: they are all constrained cooperators as we have shown that wealth increases patient (i.e. contributions to the common good). This is the raison why the optimal distribution is, for relatively poorer populations (or economies), almost egalitarian and fully egalitarian when the population is rich enough. The inequalities when the population are poor are thus explained by the time preference type of withdrawers (i.e. Quasi Myopic or Disrupted Farsighted). Therefore, when the economy is poor is better, in average, to give more wealth to those which the impact of wealth on patient is lower (i.e. Quasi Myopic) than to those which are intrinsically more patient (i.e. Disrupted Farsighted).

[15] This is the critical assumption that allows avoiding the neutrality of wealth in the private provision of public goods as predicted by Bergstrom et al (1986) in the case of pure public goods.

To conclude we would like to stand out the robustness of our results to the common critic of artificiality regarding the experimental methodology. Some scholars accuse the experimental methodology to generate assertions that are not validated in the “real” world but in the “lab” world as the saliency of choices or the limitations of the choice sets “artificially” bring subjects to make particular decisions (Bardsley, 2005). Let us assume that this critic could be valid for some experimental protocols. Unlikely, our observations do not come-out from a factorial experimental design trying to identifies the impact of wealth and its’ distribution on the CPR exploitation efficiency. Rather, we econometrically modelled observed behaviour on the basis of pertinent state variables aiming to assess the effect of wealth and its’ significance.

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APPENDIX 1: Convergence tests of the preferred model

Model 1: 2 order polynomial – 2 types

The tests exposed in Table A.9 indicate that the coefficients π_k of the polynomial did not converge after 14.300 cycles of the Gibbs sampler. The autocorrelation coefficients are too high, the Raftery-Lewis (RL) diagnostic demands 172.106 cycles and to thin the sample by two; the I-stat is also too high (I-stat>5 evidences convergence problems) and all the RNE are too low. The RL diagnostic proposes to leave the first 1220 cycles. Looking up Figure A.21 and A.13 we decided to leave the first 2500 cycles. Then, after reducing the precision of the estimation (q=0.0125, r=0.015), the RL diagnostic indicates a convergence (Table A.6) tough it is not perfect.

The convergence diagnostics applied to the others parameters σ_k and θ_k, show that there is convergence.

Given convergence diagnostics results exposed in Table A.6, the calculation of the posteriors is done from the shortened (of the first 2500 cycles) and thinned sample (by 5).

Raftery-Lewis Diagnostics for each parameter chain (q=0.0125, r=0.01500, s=0.950000). Based on sample size = 11800					
TYPE	Thin	Burn	Total(N)	(Nmin)	Istat
1	3	98	6290	211	29.8
2	5	157	9667	211	45.8

Table A.6: Raftery-Lewis's convergence diagnostic of the π_k sequence of the shortened sample; model 1.

Raftery-Lewis Diagnostics for each parameter chain (q=0.025, r=0.01, s=0.95). Based on sample size = 4100											
Type 1						Type 2					
Variable	Thin	Burn	Total(N)	(Nmin)	I-stat	Variable	Thin	Burn	Total(N)	(Nmin)	I-stat
variable 1	1	2	951	937	1.015	variable 1	1	2	951	937	1.015
.	.	.	.	.	.	.	.	.	.	.	.
variable 50	1	2	951	937	1.015	variable 50	1	2	951	937	1.015

Table A.7: Raftery-Lewis's convergence diagnostic of the σ_k sequence of the shortened and thinned sample; model 1.

Raftery-Lewis Diagnostics for each parameter chain (q=0.025, r=0.01, s=0.95). Based on sample size = 4100											
Type 1						Type 2					
Variable	Thin	Burn	Total(N)	(Nmin)	I-stat	Variable	Thin	Burn	Total(N)	(Nmin)	I-stat
theta1	1	2	970	937	1.035	theta2	1	2	914	937	0.975

Table A.8: Raftery-Lewis's convergence diagnostic of the θ_k sequence of the shortened and thinned sample; model 1.

MCMC CONVERGENCE diagnostics
Based on sample size = 14300

Model 1: 2° order – 2 types

TYPE 1

Autocorrelations within each parameter chain

Variable	Lag 1	Lag 5	Lag 10	Lag 50
Cte	0.997	0.985	0.970	0.870
St	0.877	0.691	0.659	0.568
St^2	0.657	0.093	0.105	0.024
W	0.963	0.904	0.896	0.799
W*St	0.684	0.329	0.287	0.171
W^2	0.572	0.137	0.069	0.046

Raftery-Lewis Diagnostics for each parameter chain
(q=0.0250, r=0.010000, s=0.950000)

Variable	Thin	Burn	Total(N)	(Nmin)	I-stat
Cte	2	1220	172106	937	183.678
St	2	1220	172106	937	183.678
St^2	2	1220	172106	937	183.678
W	2	1220	172106	937	183.678
W*St	2	1220	172106	937	183.678
W^2	2	1220	172106	937	183.678

Geweke Diagnostics for each parameter chain

Variable	Mean	std dev	NSE iid	RNE iid
Cte	-181.109471	129.259556	1.080923	1.000000
St	-0.111639	0.059410	0.000497	1.000000
St^2	0.000061	0.000048	0.000000	1.000000
W	-0.856031	0.066610	0.000557	1.000000
W*St	-0.000171	0.000071	0.000001	1.000000
W^2	0.000108	0.000055	0.000000	1.000000

Variable	NSE 4%	RNE 4%	NSE 8%	RNE 8%	NSE 15%	RNE 15%
Cte	20.240169	0.002852	23.940014	0.002039	26.956126	0.001608
St	0.007200	0.004761	0.008682	0.003274	0.009887	0.002525
St^2	0.000002	0.040371	0.000002	0.030301	0.000003	0.023825
W	0.010045	0.003075	0.011847	0.002211	0.013378	0.001734
W*St	0.000004	0.023465	0.000004	0.023023	0.000004	0.025659
W^2	0.000001	0.094775	0.000002	0.084645	0.000002	0.083480

Geweke Chi-squared test for each parameter chain
First 20% versus Last 50% of the sample
Variable Cte

TYPE 2

Variable	Lag 1	Lag 5	Lag 10	Lag 50
Cte	0.996	0.978	0.956	0.797
St	0.993	0.954	0.914	0.729
St^2	0.845	0.438	0.339	0.438
W	0.995	0.980	0.967	0.827
W*St	0.846	0.542	0.428	0.375
W^2	0.678	0.110	-0.026	0.430

Variable	Thin	Burn	Total(N)	(Nmin)	I-stat
Cte	2	1220	172106	937	183.678
St	2	1220	172106	937	183.678
St^2	2	1220	172106	937	183.678
W	2	1220	172106	937	183.678
W*St	2	1220	172106	937	183.678
W^2	2	1220	172106	937	183.678

Variable	Mean	std dev	NSE iid	RNE iid
Cte	-530.486212	180.811408	1.512021	1.000000
St	-0.284996	0.077292	0.000646	1.000000
St^2	0.000094	0.000025	0.000000	1.000000
W	-0.680510	0.084792	0.000709	1.000000
W*St	-0.000144	0.000043	0.000000	1.000000
W^2	0.000086	0.000027	0.000000	1.000000

Variable	NSE 4%	RNE 4%	NSE 8%	RNE 8%	NSE 15%	RNE 15%
Cte	26.363849	0.003289	30.075825	0.002527	32.245549	0.002199
St	0.010626	0.003700	0.012343	0.002742	0.013347	0.002345
St^2	0.000002	0.008496	0.000003	0.006360	0.000003	0.005494
W	0.012566	0.003184	0.014431	0.002414	0.015513	0.002089
W*St	0.000003	0.011520	0.000004	0.009568	0.000004	0.008505
W^2	0.000001	0.027329	0.000001	0.022637	0.000002	0.019788

Variable Cte

NSE estimate	Mean	N.S.E.	Chi-sq Prob	NSE estimate	Mean	N.S.E.	Chi-sq Prob
i.i.d.	-144.373029	0.331570	0.000000	i.i.d.	-506.923889	0.236538	0.000000
4% taper	-145.198575	4.676970	0.000320	4% taper	-507.141692	3.415591	0.016731
8% taper	-144.884369	5.633327	0.006977	8% taper	-507.103752	4.247440	0.067016
15% taper	-144.618897	6.223391	0.028121	15% taper	-507.058945	4.838084	0.131943
Variable	St			Variable	St		
NSE estimate	Mean	N.S.E.	Chi-sq Prob	NSE estimate	Mean	N.S.E.	Chi-sq Prob
i.i.d.	-0.097298	0.000258	0.000000	i.i.d.	-0.276264	0.000179	0.000000
4% taper	-0.097695	0.002403	0.000134	4% taper	-0.276290	0.001737	0.013706
8% taper	-0.097422	0.002740	0.002781	8% taper	-0.276259	0.002129	0.058425
15% taper	-0.097195	0.002883	0.011680	15% taper	-0.276219	0.002369	0.120543
Variable	St^2			Variable	St^2		
NSE estimate	Mean	N.S.E.	Chi-sq Prob	NSE estimate	Mean	N.S.E.	Chi-sq Prob
i.i.d.	0.000057	0.000000	0.000000	i.i.d.	0.000093	0.000000	0.000000
4% taper	0.000058	0.000001	0.000704	4% taper	0.000092	0.000000	0.015011
8% taper	0.000058	0.000001	0.005839	8% taper	0.000092	0.000000	0.058940
15% taper	0.000057	0.000001	0.017423	15% taper	0.000092	0.000000	0.121312
Variable	W			Variable	W		
NSE estimate	Mean	N.S.E.	Chi-sq Prob	NSE estimate	Mean	N.S.E.	Chi-sq Prob
i.i.d.	-0.874869	0.000252	0.000000	i.i.d.	-0.691394	0.000174	0.000000
4% taper	-0.874706	0.002648	0.000199	4% taper	-0.691368	0.001828	0.014323
8% taper	-0.875029	0.003008	0.005388	8% taper	-0.691401	0.002237	0.062009
15% taper	-0.875266	0.003140	0.024081	15% taper	-0.691438	0.002493	0.126730
Variable	W*St			Variable	W*St		
NSE estimate	Mean	N.S.E.	Chi-sq Prob	NSE estimate	Mean	N.S.E.	Chi-sq Prob
i.i.d.	-0.000172	0.000001	0.000000	i.i.d.	-0.000147	0.000000	0.000000
4% taper	-0.000173	0.000002	0.287405	4% taper	-0.000147	0.000001	0.035961
8% taper	-0.000173	0.000002	0.362994	8% taper	-0.000147	0.000001	0.078470
15% taper	-0.000173	0.000001	0.386389	15% taper	-0.000148	0.000001	0.129007
Variable	W^2			Variable	W^2		
NSE estimate	Mean	N.S.E.	Chi-sq Prob	NSE estimate	Mean	N.S.E.	Chi-sq Prob
i.i.d.	0.000107	0.000001	0.000014	i.i.d.	0.000086	0.000000	0.000000
4% taper	0.000108	0.000002	0.079681	4% taper	0.000087	0.000001	0.006544
8% taper	0.000107	0.000002	0.078051	8% taper	0.000088	0.000001	0.035210
15% taper	0.000107	0.000001	0.101609	15% taper	0.000088	0.000000	0.084125

Table A.9: Convergence evaluation of $\pi_{k\cdot}$; model 1

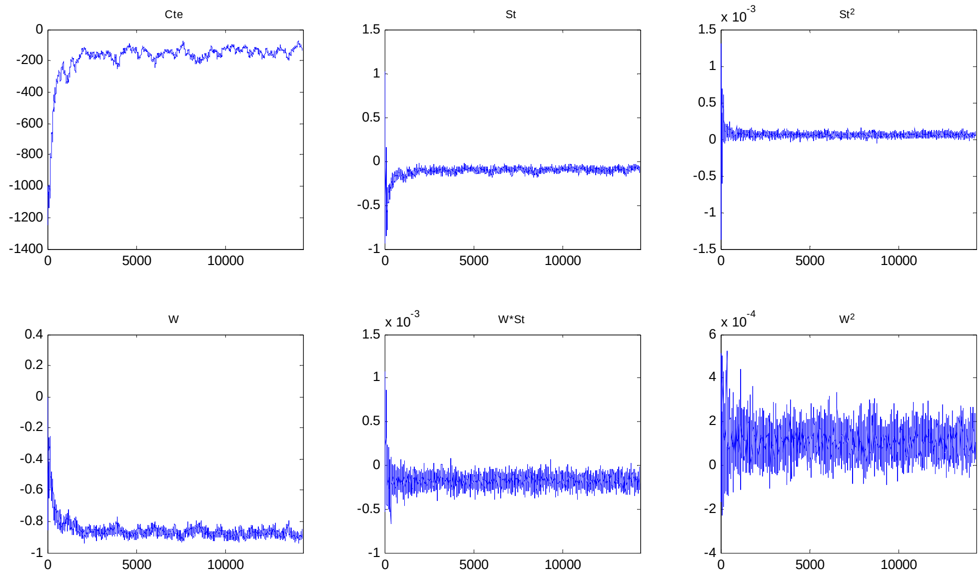

Figure A.12 : Sequences of the polynomial's coefficients of Model 1; type 1

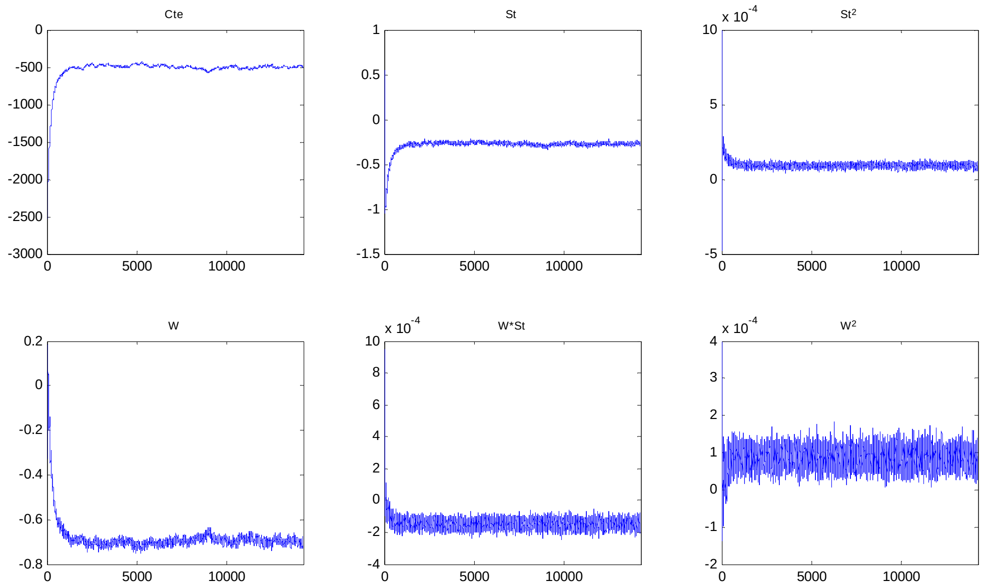

Figure A.13 : Sequences of the polynomial's coefficients of Model 1; type 2

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Contact :

Stéphane MUSSARD : mussard@lameta.univ-montp1.fr