Do Static Externalities Offset Dynamic Externalities? An Experimental Study of the Exploitation of Substitutable Common-Pool Resources

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Overexploitation of coastal aquifers may lead to seawater intrusion, which irreversibly degrades groundwater. The seawater intrusion process may imply that its consequences would not be perceptible until after decades of accumulated overexploitation. In such a dynamic setting, static externalities may enhance the users' awareness about the resource's common nature, inducing more conservative individual behaviors. Aiming to evaluate this hypothesis, we experimentally test predictions from a dynamic game of substitutable common-pool resource (CPR) exploitation. The players have to decide whether to use a free private good or to extract from one of two costly CPRs. Our findings do not give substantial support to the initial conjecture. Nevertheless, the presence of static externalities does induce some kind of payoff reassurance strategies in the resource choice decisions, but these strategies do not correspond to the optimum benchmark.

Key Words: common-pool resources, substitutable goods, dynamic externalities, survival data, proportional hazard, experiment

In many coastal zones, rich groundwater reservoirs have often been generated after thousands of years of deposit sedimentation, producing multiple closed layers with high quality water. For end-users, each such layer represents an imperfect substitute toward other water resources, like surface water or a shallow aquifer. Today, most of these coastal reservoirs are overexploited due to the increasing

concentration of human settlements—50 percent of the world population lives within 60 km of a shoreline—agricultural development, and economic activities. Overexploitation increases the risk of natural seawater intrusion into the aquifer because excessive pumping lowers the water table, facilitating seawater invasion into the fresh groundwater reservoir. This process, which renders groundwater useless for irrigation and human consumption, is accelerated by the tendency of sea levels to rise due to climate change.

In many areas, groundwater is exploited under common property regimes, which induces insufficient incentives toward conservation of the resource, leading to a "tragedy of the commons" (Hardin 1968). However, the empirical literature on "commons" provides many examples of local communities that have succeeded in setting up self-enforcing rules to avoid such an undesirable collective issue (Ostrom, Gardner, and Walker 1994).[1] But the threat of seawater intrusion in the

[1] Research on the commons has focused mainly on the identification of the factors that favor collective action in order to efficiently use the

case of coastal aquifers is hardly perceived by local communities who exploit them, mainly because in most cases the possible damages are delayed by several decades, and often affect only future generations. Consequently, unless future consequences of current exploitation are correctly assessed, the slowness of the groundwater's quality degradation progression supports a process of delay and inertia in implementing regulation policies or in setting up formal property rights to prevent inefficient use (Libecap 2008, Giordana and Montginoul 2006). This particularity of coastal aquifers raises the issue of the sustainable exploitation of such types of resources.[2]

As the common-pool resource becomes relatively scarce, two types of negative externalities affect its users: a static externality and a dynamic externality. In a given period, a static externality arises whenever current withdrawals reduce current exploitation profits,[3] because users compete with each other for the available units. A dynamic externality arises if such static competition among users also affects the available units of the resource in future periods. For instance, if the current withdrawals are larger than the natural recharge, then, assuming that the population of users and their needs are constant over time, a dynamic externality may arise. In such a situation, the current extraction decision of any given agent affects not only the future profits of his rivals, but his own future profits as well. In many natural settings, dynamic externalities overlap with static externalities.

Our research hypothesis is that users who experience both a static and a dynamic externality are more likely to follow a sustainable path of exploitation than users who experience only dynamic externalities. The reason is that users who have to face both types of externalities have a stronger awareness of the external link that ties them together. Because of such awareness they are also more likely to adopt withdrawal strategies that lead them to a collective exploitation path closer to a sustainable exploitation. Even if there is no arena where the community of appropriators can build up self-enforcing social norms for the exploitation of the common property resource, appropriators will individually adjust their initially selfishly oriented behavior toward more socially beneficial actions.[4]

In order to evaluate the above behavioral hypothesis, we designed an experiment on the exploitation of common-pool resources (CPRs) generating both static and dynamic externalities. Besides our focus on the behavioral issue, the experiment is also designed to give some insights about exploitation strategies with respect to substitutable resources. Therefore, the experiment captures some of the complexity of the field study that motivated our initial research question: the exploitation of a multi-layer groundwater coastal aquifer. In some cases, the various layers are closed reservoirs that contain high quality water, which represents an imperfect substitute for other water resources (e.g., surface water) available to end-users. From a technical point of view, the exploitation of a particular reservoir can be considered as a choice between imperfectly substitutable resources. Appropriators may prefer to exploit a CPR because they are unsatisfied with the exploitation of an outside option due to low water quality or quantity rationing. We capture this dimension in our experiment by allowing participants to withdraw units from different accounts, which corresponds in the field to pumping water in different reservoirs.[5]

In order to assess the possible effects of static externalities on exploitation efficiency of a set of resources, we implement two experimental treatments. In treatment A, the exploitation of the

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common resource. The experimental work in the commons literature has mainly focalized in the rent dissipation problem that takes place within an exploitation period [for a good survey, see Ostrom, Gardner, and Walker (1994), Ostrom (1999)]. Few papers analyze the exploitation of CPR in a dynamic setting: see Herr, Gardner, and Walker (1997), Moxnes (1998), Osés-Eraso, Udina, and Viladrich-Grau (2008), and Giordana and Willinger (2009).

[2] Experimental research has shown that human subjects do not have a good perception of future consequences of their current actions (Herr, Gardner, and Walker 1997, Moxnes 1998, Giordana 2008). One can therefore expect that in situations involving dynamic externalities, the outcome of individual decisions will be very inefficient.

[3] For example, pumping generates an immediate decrease of the water table around the extraction point, which increases the energy cost of extraction groundwater for every borehole sufficiently close to it (Brozovic, Sunding, and Zilberman 2006).

[4] We are not arguing that in solving the static externality the community solves at the same time the dynamic one.

[5] Actually, many experimental studies dealing with an *N*-person time-independent prisoner's dilemma consider the allocation of an endowment between two different investments: a private investment and a group investment. The private investment does not suffer from externalities: the returns are independent of the group's decisions. The group investment has the same status as a CPR. Some references are: Walker and Gardner (1992), Ostrom, Gardner, and Walker (1994), Mason and Phillips (1997), Apesteguia (2006), and Cardenas, Stranlund, and Willis (2002).

CPRs generates only a dynamic externality, while in treatment B it generates both a static and a dynamic externality. The exploitation game has a finite horizon. In each period participants have to make two decisions: (i) from which account to withdraw units (out of three), and (ii) the quantity to extract from the chosen account. Depending on the behavioral assumption, we derive three extraction paths that are taken as benchmarks for analyzing our data: rational behavior, myopic behavior, and cooperative behavior. Rational behavior leads to a subgame-perfect equilibrium, myopic behavior to static optimization, and cooperative behavior to the joint profit maximization outcome. Although different behavioral assumptions generate different extraction paths, these are exactly the same under both treatments: in other words, the presence or absence of a static externality does not affect the predicted extraction paths. Our main analysis is based on a comparison of the observed extraction paths to the predicted paths, in order to identify the best-fitting behavioral assumption. Using survival data analysis, we also evaluate the determinants of the resource choice path by estimating a conditional-competing risk set Cox proportional hazard model (Prentice, Williams, and Peterson 1981).

Our findings do not support the hypothesis about the positive effect of static externalities in dynamic CPR dilemmas. The observed extraction paths are similar in both treatments and follow mainly the myopic prediction. However, the introduction of static externalities does induce, in the resource choice decision, some kind of individual payoff reassurance strategies, although the resource choice strategies do not correspond to the optimum benchmark and result in users avoiding using the same resource as their rivals.

In this article, we first introduce the dynamic game of substitute CPR exploitation and the three benchmark predictions: subgame perfection, myopia, and joint profit maximization. Second, we present the experimental design and participants' decision task. Third, we summarize our main experimental findings, before concluding.

A Dynamic Game of Substitute Common-Pool Resource Exploitation

Our experiment is based on a discrete finite time dynamic game of substitute CPR exploitation. We first introduce the model before discussing possible solutions depending on alternative behavioral assumptions. We present the model in terms of substitute water resources.

Assume that N identical appropriators (here, irrigators), indexed by i, extract water in each period from one of three available water resources. Resource 1 is surface water, available without restrictions at a fixed market unitary price but with a lower quality than the other (groundwater) resources. Resources 2 and 3 are CPRs, characterized at each period t by a stock of available units. This simplified description corresponds to the simplest multilayer aquifer typically encountered in many coastal zones. Appropriator i extracts a quantity $y_{i,j}^t$ from the jth resource ($j = 1, 2, 3$) in period t. The evolution of groundwater stocks is described by equation (1):

$$(1) \qquad S_j^{t+1} = S_j^t - Y_j^t + r_j, \qquad j = 2, 3$$

$$S_2^0 < S_3^0 \text{ and } r_3 < r_2,$$

where S_j^t is the stock of available units of the jth groundwater resource in period t, r_j is the natural recharge per period of the jth groundwater resource stock, and

$$Y_j^t = \sum_{\forall i} y_{i,j}^t$$

is the total extraction from the jth groundwater resource in period t.

To simplify the derivation of the optimal extraction path, we assume that each appropriator can extract water only from one resource at a time. However, appropriators may switch from one resource to another at any time. We assume that, depending on the resource, switching will be more or less costly. Switching costs might be incurred by the need to build wells or to install pumping equipment. We assume that such costs have to be paid only once, i.e., at the first instance the resource is mobilized. After that, free access to the resource is warranted. We model the switching cost assumption as follows: access to resources 2 and 3 requires a constant and one-time sunk investment, $c_j (j = 2, 3)$, while resource 1 is access-fee free. Furthermore, we assume that $c_2 \leq W_i^0 < c_3$ (where W_i^0 denotes the initial wealth), i.e., the initial budget constraint does not allow extrac-

tion from resource 3 in the initial period. Note that resource 2, which represents the shallow groundwater resource, requires a lower sunk cost than resource 3, the deeper layer. Equation (1) captures the empirical regularity (Barrocu 2003, Dörfliger 2003, Günay 2003) that the shallow groundwater resource has a larger recharge. The budget constraint implies that appropriators can rely only on their private wealth to access groundwater resources[6] (borrowing is not feasible).

The per-unit extraction cost is assumed to be constant for resource 1 (p_1) and, for resources 2 and 3, linearly decreasing in the available stock and linearly increasing in total extraction of the period:

$$(2) \quad AC(S_j^t, Y_j^t) = p_j + z \times Y_j^t - f \times S_j^t, \quad j = 2, 3,$$

where $0 < p_1 < p_3 < p_2$, $S_2^0 < S_3^0$, $z, f \geq 0$. In equation (2), z captures the static externality and f the dynamic externality on the current extraction cost. The inequality $p_3 < p_2$ is justified by the better water quality of the deeper layer, which, we assume, reduces the maintenance cost of the irrigation network. Note that the externalities, both static and dynamic, are assumed identical for both underground layers. The inequality $p_1 < p_3$ reflects a common practice in the pricing of irrigated systems: the price does not consider the infrastructure cost.

Given our assumptions, resource 3 is more attractive than resource 2 in period 1, but requires a larger sunk cost to be exploited, which is not feasible in period 1 due to the initial budget constraint. Access to resource 3 is possible only if additional earnings have been accumulated in subsequent periods.

Let us now define the profit function. According to equation (1), groundwater stocks grow naturally with recharge and decrease with extractions. Extracted water generates a gross return to appropriator i in period t, given by

$$(3) \quad u_i(y_{i,j}^t) = a \times y_{i,j}^t - b \times (y_{i,j}^t)^2, \quad j = 1, 2, 3,$$

where $a, b > 0$. The quadratic (gross) return reflects decreasing marginal revenue from the resource exploitation. Given gross returns, the net profit for period t for withdrawer i depends on her extraction decision and her investment decision:

$$(4) \quad U_i(y_{i,j}^t) = u_i(y_{i,j}^t) - AC_j^t \times y_{i,j}^t - I_j^t \times c_j,$$

where I_j^t ($j = 2, 3$) is a binary variable, which equals 1 if the appropriator has ever extracted from the jth resource before period t, and zero otherwise. We assume that appropriator i's objective function is to maximize the sum of her discounted profits, i.e.,

$$\sum_{s=1}^{T} \rho^{s-1} \times U_i^s,$$

where ρ is the discount factor. Let W_i^t be the ith appropriator's accumulated wealth in period t:

$$(5) \quad W_i^t = W^0 + \sum_{s=1}^{t} U_i^s \quad \forall i.$$

In each period, each appropriator has to make two decisions: (i) from which resource to extract, and (ii) the volume of extraction. The problem is solved backwards: first, she calculates the return-maximizing amount of extraction for each resource (proceeding backwards also), and second, she chooses the resource that generates the largest profit. At the individual level, the solution of this choice problem is a two-dimensional vector, specifying for each period the choice of the resource ($j = 1, 2, 3$) and the level of extraction from the chosen resource. The equilibrium profile depends on the assumption about the withdrawer's behavior. We consider three types of behavior, assuming behavioral homogeneity within the extractor's population: perfect rationality, myopic behavior, and cooperative behavior. Each of these behaviors corresponds to a particular prediction which we take as benchmark solutions. They will be labeled *rational*, *myopic*, and *optimum* outcomes, respectively.[7]

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[6] In the literature, investment decision is treated as a strategic variable that enables an appropriator to accommodate or deter entry (Barham, Chavas, and Coomes 1998, Aggarwal and Narayan 2004).

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[7] The rational and optimum benchmarks are calculated assuming a discount factor equal to 1. This is an extreme case, which means that future profits are not discounted, where the future has the same weight as the current period.

Rational appropriators 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 plan. To do this, rational appropriators first calculate, for each groundwater resource, optimal feedback functions that depend on the available stock in t and on the remaining periods until $\hat{t}_i(j, y)$ (i.e., the transition period when appropriator i switches from resource j to resource y). The optimal feedbacks allow computation of water extraction paths, taking transition periods as given. Rational appropriators are supposed to be able to compare the payoff of all possible alternatives (i.e., varying the transition periods of their own and those of their rivals) and choose the better one. The computation of the subgame perfect equilibrium is a very time-demanding task. For instance, in the first period of a 10-period game with 5 players, each player has to compare $2^{5 \times 2} \times 3^{5 \times 8}$ possibilities (approximately $1.25e^{22}$ in scientific notation), approximately $3.89e^{20}$ in the second period, and so on. Moreover, the solution relies on a particular information structure: appropriators must observe perfectly the available stock of each resource at the beginning of each period (Basar and Olsder 1999). This allows adapting extractions and resource choices to every period's conditions; thus, there is no commitment on extraction decisions.[8]

Under myopic behavior, the optimization horizon is restricted to one period. Appropriators calculate the profit-maximizing extraction for each resource, and then choose the most profitable available option under their budget constraint, given the decisions of their rivals. Hence, the calculus burden is sensibly lower: assuming that all the appropriators in the population are myopic, in each period they need to compare 243 strategies if there are both static and dynamic externalities, but only 3 strategies if there are only dynamic externalities. In the latter case the strategic dimension collapses to an individual choice problem. Given the resource stock, myopic behavior leads to higher extraction levels than the subgame perfect extraction path. The difference is due to the fact that rational appropriators take into account

the impact of their current decision on the future periods' available stocks. Furthermore, they anticipate the future natural recharge. The larger the natural recharge, the larger the difference between rational and myopic extractions' trajectories.

The optimum extraction path requires that the discounted aggregate profit of all appropriators is maximized over the whole horizon. This corresponds to an outcome that would be achieved if all appropriators decided to cooperate and maximize their joint profit. The optimum extraction path follows an extraction trajectory with a slightly positive slope, which vanishes for a null natural recharge.

Experimental Design

The experiment was designed to capture fundamental aspects of the game described by equations (1) through (5). In order to reduce the complexity of the decision environment, some simplifications had to be made. The experimental game was presented without any particular context: in each period, each subject had to decide from which of the three available "accounts" he or she wanted to extract his or her desired amount of "units." Given the parameterization (see Table 1), a subject earns experimental points depending on his or her unit order and on the available units in the chosen account in that period. To facilitate subjects' decision task, we decided to make no distinction between benefits and costs of extractions. Instead, the outcomes of decisions were directly given in profit units.

The experiment compares the extraction decisions in two treatments. In treatment A, only dynamic externalities affect accounts 2 and 3 ($z = 0$). In treatment B, both static and dynamic externalities affect accounts 2 and 3 ($z = 0.001$). Parameter values were calculated to guarantee that predictions and efficiency of myopic and rational strategies are equal for both treatments.

Table 2 shows the trajectory of individual unit orders[9] for each benchmark strategy. All benchmarks start with orders from account 2, but with differing units: orders of myopic players are larger than orders of rational players, and both are above the optimum order. By the fourth period,

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[8] See Levhari and Mirman (1980), Levhari, Michener, and Mirman (1981), and Reinganum and Stokey (1985) for examples of this strategy applied in models of fisheries exploitation.

[9] Subjects can order units from only one account per period. The dashes in Table 2 mean zero unit order.

Table 1. Parameterization

	Parameters	
	Treatment A	Treatment B
Group size (N)	5	
Benefit function	$a = 5.35$ $b = 0.09$	$a = 5.35$ $b = 0.087$
Cost function	$z = 0$ $p_1 = 3.88$ $p_2 = 7.55$ $p_3 = 7.4$ $f = 0.01$	$z = 0.001$ $p_1 = 3.9$ $p_2 = 7.55$ $p_3 = 7.4$ $f = 0.01$
Account evolution	$S_2^0 = 500$ $r_2 = 5$ $S_3^0 = 750$ $r_3 = 2$	
Access fee	$c_2 = 15$ $c_3 = 40$	
Available range of unit orders	$[0,50]$	
Initial wealth (W^0)	15 experimental points	

rational and optimum players switch to account 3, while myopic players order from account 1 before switching to account 3 from period 5 to period 9, and switching back again to account 1 in the final period. Rational players switch to account 2 in period 9 and to account 1 in the last period. In contrast to other strategies, the optimum strategy involves a single switch (in period 4) from account 2 to account 3 and with a slight increase of demand over time. The reason is that on the optimum path fewer units are withdrawn from account 2 in early periods to allow accumulation of wealth in order to access account 3 in period 4 and withdraw from that account for all remaining periods. In contrast to myopic and rational strategies, the optimum strategy depletes resource 3 at a weaker pace, preventing the need to switch back to account 1.

Experimental Implementation

All experimental sessions were conducted at the University of Montpellier I, in Montpellier, France. The experiment was run on Z-Tree (Fischbacher 2007) software. Subjects were recruited from the

pool of undergraduate students of LEEM,[10] most majoring in economics or management. No subject had participated in a similar experiment before. Recruitment was mainly done by e-mail: subjects were invited to participate in an experimental game lasting approximately one hour and a half, and were told that they would receive a payment based on their decision and the decisions of the group (in addition to a show-up fee).

At least two groups participated in each session. Subjects were assigned to separate boxes on a random basis. No communication was allowed. At the beginning of each session, subjects started reading individually written instructions, which were read again aloud to implement common knowledge. Subjects' understanding was checked individually by means of a questionnaire. Subjects' eventual clarification questions were answered privately.

Each subject participated in four repetitions of a 10-period dynamic game, which will be referred to as series 1, 2, 3, and 4. Subjects were given a show-up fee, calculated to cover eventual losses. Prior to series 1, each subject was randomly and anonymously assigned to a fixed group of five subjects, for the duration of the session.

Decision Setting

In each period, subjects had to choose independently and simultaneously the account from which to order units. Individual unit orders were restricted to integer values in the range [0,50]. Three payoff tables were provided, one for each account. Each table indicated the payoff for each possible combination of available units in the account and unit order.[11] For treatment B, subjects had to deduct from the payoffs for accounts 2 and 3 a percentage of the total unit orders on the account that corresponded to the intra-period externality of the period. Profits were expressed in "experimental points," and subjects knew the point/euro conversion rate.

The group size and the profit function were common knowledge. At the beginning of each period, subjects were informed about their accumulated wealth since the beginning of the series and

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[10] Laboratory of Experimental Economics of Montpellier.

[11] For practical reasons the complete table for all possible values of S_j could not be provided. In its place, subjects were given a partial table as well as the formulas that were used to calculate profits.

Table 2. Predicted Extraction Trajectories from Each Account

	Rational ($\rho = 1$)			Myopic ($\rho = 0$)			Optimum ($\rho = 1$)					
	Treatments A and B			Treatments A and B			Treatment A			Treatment B		
Period	Accounts			Accounts			Accounts			Accounts		
	1	2	3	1	2	3	1	2	3	1	2	3
1	--	14	--	--	16	--	--	10	--	--	10	--
2	--	11	--	--	12	--	--	10	--	--	10	--
3	--	9	--	--	9	--	--	11	--	--	10	--
4	--	--	26	8	--	--	--	--	11	--	--	11
5	--	--	21	--	--	31	--	--	11	--	--	11
6	--	--	16	--	--	22	--	--	11	--	--	11
7	--	--	13	--	--	16	--	--	12	--	--	12
8	--	--	10	--	--	12	--	--	12	--	--	12
9	--	8	--	--	--	9	--	--	12	--	--	12
10	8	--	--	8	--	--	--	--	12	--	--	12
Efficiency	84 %			78 %			100 %			100 %		

Note: Dashes indicate zero unit order.

about the available units in accounts 2 and 3. They were also informed about their profit for the current period. Furthermore, the "history record" was available, summarizing the data of each of the past periods: profits, unit orders (for each account), available units in accounts 2 and 3, and accumulated wealth.

Experimental Results

The benchmark strategy predictions reported in Table 2 are unconditional benchmarks: they are based on the assumption that subjects do not deviate from predictions. If deviations from benchmark outcomes occur, new outcomes conditional on the history of play should be calculated. For the sake of tractability, we restrict our data analysis to comparisons to the unconditional benchmarks.

We ran four sessions, which involved the participation of 55 subjects. Data from a total of 44 series (at the group level) were collected. Since our experiment was designed to capture some of the complex interactions that arise in the field, our data analysis will focus primarily on those

aspects that are most relevant for the field issue. First, we start with a measure of the global fit of our experimental data with respect to our three unconditional benchmarks. We rely therefore on a mean score measure that combines the two key dimensions of our multiple common pools problem: the account choice and the volume extracted. Second, we analyze separately unit orders and account choices. The analysis of mean unit orders will provide a first insight into the nature of deviations from benchmark predictions. Further insights will be provided by individual account choice decisions.

Global Fit

Let $y_{i,j}^{t\,e}$ be the predicted unit order for player i in period t from account j, and let $y_{i,j}^{t}$ be the observed decision of subject i. A simple but biased measure of deviation between these two values is given by

$$D_{i,t} = \sum_{j=1}^{3} \left| y_{i,j}^{t} - y_{i,j}^{t\,e} \right|$$

for agent i. The corresponding aggregate measure is

$$D = \left. \sum_{i=1}^{N} \sum_{t=1}^{T} \sum_{j=1}^{3} \left| y_{i,j}^{t} - y_{i,j}^{t}{}^{e} \right| \middle/ NT \right. .$$

Deviations can occur because of a wrong account choice with respect to the prediction, and/or because unit orders differ from the predicted amounts. The measure D overestimates the deviation, because it double-counts unit-order deviations.[12] Furthermore, D is also biased in the sense that it may favor some of the benchmarks while penalizing other ones.[13] Consequently, in order to compare individual unit-order data to benchmarks and minimize possible scale and double-counting biases due to "wrong" account choices, we use the following corrected mean score measure (MSM):

$$(6) \quad MSM = \left. \sum_{t} \sum_{i} \sum_{j=1}^{3} \left(\frac{I_{j}^{t}}{1 + \left| y_{i,j}^{t} - y_{i,j}^{t}{}^{e} \right|} \right) \middle/ N \times T \right. ,$$

where $y_{i,j}^{t}{}^{e}$ is the predicted unit order from account j at period t, and I_{j}^{t} is a binary variable equal to 1 if positive orders are predicted from account j in period t and 0 otherwise. The MSM of individual unit orders is not affected by double-counting and scale biases, as only orders from the predicted account are considered in the calculation of the score. However, it accounts for the intensity of the deviation, as large deviations with respect to benchmarks result in lower scores. In Tables 3 and 4 we depict the MSM for each series of treatments, A and B, respectively. The following observations result:

OBSERVATION 1. For both treatments A and B, the myopic strategy is the best-fitting one.

The last rows of Tables 3 and 4 report the average MSM for each of the three benchmarks. The

Table 3. Mean Score Measure (Treatment A)

Benchmark	Rational	Myopic	Optimum
Series 1	72.4 (8.3)	79.7 (10.1)	72.3 (3.8)
Series 2	73.8 (6.3)	81.8 (7.2)	73.7 (2.6)
Series 3	75.4 (9.3)	83.4 (11.3)	74.4 (1.7)
Series 4	75.7 (8.4)	84.6 (6.5)	74.6 (5.9)
Global mean	74.3 (9.4)	82.4 (14.3)	73.7 (7.7)

Note: Standard deviations are in parentheses.

Table 4. Mean Score Measure (Treatment B)

Benchmark	Rational	Myopic	Optimum
Series 1	71 (6.8)	77.5 (0.9)	72.4 (2.8)
Series 2	72.7 (7.9)	79.4 (6.7)	73.1 (5)
Series 3	73.6 (5.3)	80.6 (7.6)	73.4 (5.2)
Series 4	73.1 (3.4)	79.9 (5.8)	73.2 (9)
Global mean	72.6 (7.5)	79.4 (11.3)	73 (11.2)

Note: Standard deviations are in parentheses.

myopic benchmark has the maximum score, followed by the rational benchmark in treatment A (Table 3) and by the optimum benchmark in treatment B (Table 4). The MSM for the myopic benchmark is significantly larger for both treatments compared to the two other benchmarks [two-way ANOVA test (Friedman's test),[14] p-values < 0.001 for the four performed tests]. However, the MSM is not significantly different between the rational and the optimum benchmark.[15]

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[12] For example, consider the fourth-period myopic benchmark: ordering x units from account 2 generates a deviation, in absolute terms, of $x + 8 = |(0 - x)| + |(8 - 0)|$, while ordering from account 1 would produce a deviation of $|8 - x| = |(8 - x)| + |(0 - 0)| < 8 + x$.

[13] For instance, while all the fifth-period benchmarks predict to extract from the third account, ordering x units from account 2 generates a deviation of $x + 21 = |(0 - 0)| + |(0 - x)| + |(21 - 0)|$ for the rational benchmark, a deviation of $x + 30 = |(0 - 0)| + |(0 - x)| + |(30 - 0)|$ for the myopic benchmark, and a deviation of $x + 11 = |(0 - 0)| + |(0 - x)| + |(11 - 0)|$ for the optimum benchmark. Thus, the error in account choice favors, in terms of this deviation measure, the optimum strategy as being $x + 11 < x + 21 < x + 30$.

[14] Friedmans's ANOVA test is aimed to test for column effects (benchmarks) after row effects (repetition of the game) are removed. The null hypothesis of the test is that there are no column effects (all three benchmarks result in the same score).

[15] Additionally, we have calculated decision efficiency. We defined "efficiency" as the ratio between the observed profit and the theoretical optimal profits. Beside the fact that this efficiency measure suffers from flaws similar to those of the deviation measures discussed previously, it shows that decisions are, on average, far away from the optimum benchmark in both treatments (mean efficiency equals 54 percent and 55 percent in treatments A and B, respectively).

This result is robust to subjects' learning that might have occurred by repeating the dynamic game.[16] The myopic strategy achieves also the highest mean score in every repetition of the game (Tables 3 and 4).

OBSERVATION 2. The myopic and rational strategies fit the data better when exploitation generates only dynamic externalities (treatment A) than when both static and dynamic externalities are generated (treatment B).

In treatment B, the MSMs are lower than in treatment A for every benchmark. These differences are significant for the rational and myopic predictions (Friedman's test p-value < 0.007 and 0.01, respectively). However, the difference is not significant for the optimum benchmark (Friedman's test p-value < 0.1745). Thus, the statistical evidence does not totally support the assertion that treatment B decisions are closer to the optimum benchmark as measured by the MSM.

Tables 3 and 4 show that the MSMs are quite high for all three benchmarks, suggesting that there are also substantial deviations from the myopic prediction. In order to get a first insight on the origin of these deviations, we analyze in the following subsection the individual unit orders.

Individual Unit Orders

As unit orders are conditioned by the account choice, we estimate the mean trajectories for each account by focusing only on the data of subjects who order from that account. This allows us to analyze the extraction decisions for each account separately and independently from the other subjects. Additionally, it provides preliminary insights about deviations in the account choice with respect to the benchmarks.

OBSERVATION 3. The shape of mean unit-order trajectories reveals that:

(i) Account 2 unit orders are better fitted by the myopic benchmark in treatment A, but are hard to classify in treatment B;

(ii) In both treatments, account 3 unit orders follow closely the rational and myopic benchmarks.

Figure 1 displays mean unit orders in each of the three accounts, together with the limits of 95 percent confidence intervals[17] and the unconditional benchmarks. In treatment A, we observe that, excepting period 3, the mean unit orders from account 2 coincide with the myopic benchmark. Conversely, in treatment B, mean unit orders from account 2 coincide with the rational, myopic, and optimum benchmarks (excepting period 1, where there are significant differences with the myopic and optimum benchmarks). Then, in periods 1 and 2, mean unit orders are significantly lower in treatment B.

Between periods 4 through 8, the three theoretical benchmarks coincide with the zero unit-order prediction from account 2. Mean unit orders from account 2 are significantly higher than predictions in both treatments, as the bootstrap interval does not include the zero.

In accordance with the predictions, and as a consequence of the budget constraint, mean unit orders from account 3 are null for periods 1 through 3 in both treatments. In subsequent periods, the mean unit-order trajectories in both treatments follow closer the myopic and rational benchmarks than the optimum benchmark.

The previous observations do not support in a substantial way our initial intuition about the effect of static externalities. While Observation 2 suggests that myopic and rational strategies fit better when there are only dynamic externalities being generated, Observation 3 shows that accounts are overexploited with respect to social optimum in both treatments. Moreover, Observation 3 shows that there is no treatment effect on individual unit orders. Then, the differences in the mean score measure raised in Observation 2 must be explained by the choice of accounts. Additionally, Figure 1 evidences substantial deviations in the account choices in both treatments. We turn now to the analysis of account choice decisions.

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[16] Excepting the last repetition of treatment B, the MSM of each benchmark increases as the game is repeated. This indicates that a learning process is ongoing where each subject learns how to better implement the strategy of his or her choice.

[17] The confidence intervals are non-parametric. The limits have been calculated using a bootstrap procedure (Efron et al. 2001). Every point lying within the limits of the interval is not significantly different from the mean unit orders.
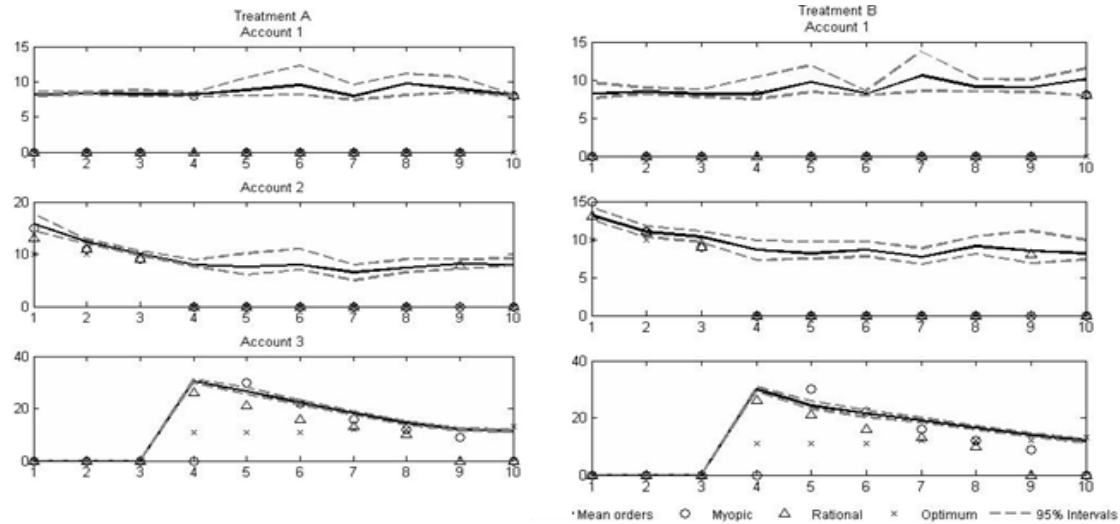
Figure 1. Treatment A and B Mean Orders

Notes: The full lines with square icons indicate observed unit mean orders. Dashed lines represent limits of the bootstrap 95 percent confidence intervals. Markers indicate unconditional benchmarks.

Account Choices and Transitions

In this subsection we explain and characterize deviations in the account choice decisions. We first compare the observed pattern of account use with the theoretical benchmarks. Second, we analyze the genesis of the account use pattern by studying transitions between accounts.[18] Finally, in order to understand the determinants of transitions, we formulate a survival data econometric model of competing risks with ordered events (Lancaster 1990). In contrast to discrete choice models, the survival data model allows us to take into consideration the account choice history of each subject in a more explicit way.

Account Choices

OBSERVATION 4. The observed pattern of account use indicates that:

(i) in both treatments, account 1 is excessively demanded with respect to benchmarks;

(ii) in treatment A decisions are close to the myopic benchmark;

_____

[18] A transition corresponds to a switching from one resource to another between two consecutive periods (t and $t + 1$).

(ii) in treatment B, subjects are split among the available accounts.

Figure 2 presents the mean proportion of subjects using each of the possible accounts (over all groups and all repetitions of the game), and Table 5 exposes the p-values of the non-parametric two-way ANOVA test comparing the proportion of account users between treatments. As we can see from Table 2, account 1 is relatively rarely used. The data shows, however, for both treatments, that the proportion of account 1 users is significantly different from zero in every period. There is not significant difference in the use of account 1 between treatments, except in periods 2 and 6, where the proportion of users in treatment B is larger. The peaks in periods 4 and 10 for treatment A indicate that a fraction of the subjects follow the myopic strategy. Treatment A is also closer to the theoretical predictions regarding the use of accounts 2 and 3. All the theoretical benchmarks predict that after period 3, account 2 will no longer be used (except in period 9 for the rational benchmark). Instead, account 3 is the most frequently exploited. Figure 2 shows that, after period 3, the proportion of users of account 2 in treatment A is smaller than in treatment B (excepting period 10), and Table 5 indicates that these
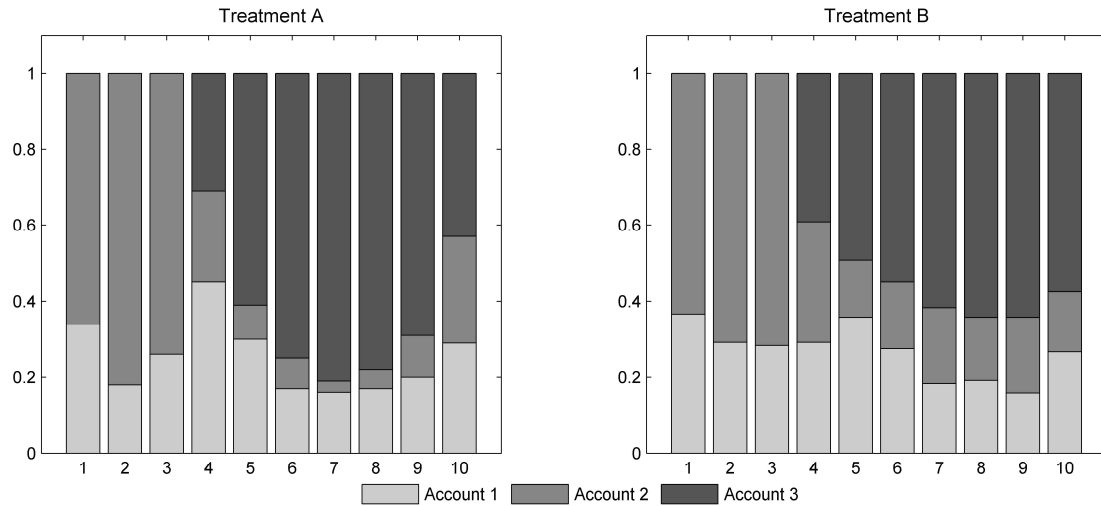
Figure 2. Mean Proportion of Account Users

Table 5. P-values of Non-Parametric Two-Way ANOVA Test of the Treatments' Proportion of Account Use Comparison

	Periods									
Accounts	1	2	3	4	5	6	7	8	9	10
1	0,7429	0,0492** (B)	0,6787	0,2255	0,1571	0,0041*** (B)	0,2407	0,2673	0,9533	0,8184
2	0,7429	0,0492** (A)	0,6787	0,2043	0,3903	0,0663* (B)	0,0023*** (B)	0,0072*** (B)	0,0144** (B)	0,1736
3	1	1	1	0,7012	0,0400** (A)	0,0026*** (A)	0,0007*** (A)	0,0153** (A)	0,1458	0,0932* (B)

Notes: *** indicates p-values < 0.01, ** indicates p-values < 0.05, and * indicates p-values < 0.1. Treatment with the higher proportion is shown in parentheses (see Figure 2).

differences are significant for periods 6 through 9. Moreover, the proportion of users of account 3 in treatment A is significantly higher (for every period after period 4, except for period 10).

While the myopic benchmark provides a reasonable description of the observed pattern of account use in treatment A, account use in treatment B is hardly classifiable. Figure 2 indicates that adding static externalities to the exploitation of accounts 2 and 3 encourages subjects to avoid using the same account their rivals do. The pattern of account use takes a particular shape with players splitting among the available accounts; this reveals some kind of preference for autonomy. A possible explanation is that with a static externality, agents' actions are no longer substitutes but become complements, reinforcing each others' actions. Since such reinforcement has a negative impact on payoffs, agents try to avoid the static externality by choosing different resources.

In the next subsection we analyze the genesis of the observed pattern of account use. In particular we aim to answer the following questions: Are the observed chosen accounts the outcome of stable and symmetric account choice decisions, or does the account use pattern result from a particular combination of asymmetric and high frequency switches between accounts? If the latter is the case, what is the logic behind the switching process?

Transitions Between Accounts

If we consider the different accounts as elements of a set of states, there are six different transition types depending on the initial and final states. Figure 3 plots for both treatments the proportion of account changes in each period, distinguishing the transition types. Table 6 shows the p-values of the Friedman's test comparing the mean transition proportions between treatments.

OBSERVATION 5. The observed pattern of account use results from unstable and asymmetric account choice decisions.

Theoretical benchmarks predict transitions in periods 4, 5, 9, and 10. The data reveal transitions in every period. Transitions are less frequent in treatment B than in treatment A, for all periods except periods 7 and 8. However, these differences are not always significant (except for periods 7, 8, and 10) (see Table 6).

Figure 3 shows the time distribution of transitions. In treatment A, we observe peaks in periods 4, 5, and 10, which is compatible with the myopic benchmark. In period 4 the main transition types are: 2→1 (a switch from account 2 to account 1), as predicted by the myopic benchmark, and 2→3, as predicted by the rational and optimum benchmark. In period 5, the most important observed transition type is 1→3, as in the myopic benchmark; the remaining transitions in this period do not correspond to any theoretical benchmark. In period 10 the main transition types are: 3→1, as in the myopic benchmark, and 3→2, which does not correspond to any benchmark (this is the type of transition predicted by the rational benchmark in period 9).

In both treatments we observe many out-of-equilibrium transitions. In treatment B the proportions of transitions are different from zero in every period, with a peak in period 4. In this period, the main transition type is 2→3, which is compatible with the rational and optimum benchmarks. But we do not observe, as the rational benchmark also predicts, transition types 3→2 and 2→1 in periods 9 and 10, respectively.

Because of the large number of out-of-equilibrium decisions, we further analyze the observed account choices, aiming at identifying the underlying logic of switching decisions. Allowing appropriators to make errors in choosing their ac-

count implies that, in every period, each account has a positive probability to be chosen. The probability of choosing an account depends on the decision history. On the one hand, the decision tree's information set in which appropriators will be in each period depends on their past account choices. On the other hand, given past account choices, unit orders in previous periods determine the current accumulated wealth and the expected future profit of each account. For example, if appropriator i has never chosen account 2 but has always ordered from account 1, the probability of choosing account 2 may increase or decrease over time. In order to take into account such path-dependent choices, we rely on a survival data model—the "competing-risk set model" (Lancaster 1990)—to estimate the probability of choosing a given account. We summarize our main results as observation 6:

OBSERVATION 6. The probability of switching between accounts:

  (i)   is lower in treatment B,

 (ii)   is not affected by the repetition of the game,

(iii)   responds positively to the relative abundance of units in account 2 and 3,

 (iv)   is reduced as profits in the previous period become higher.

Table 7 provides details about the regression: the estimated coefficients for the final model, the specification test performed to evaluate the proportional hazard assumption, and the definition of the explanatory variables. We excluded the repetition dummies from the final regression, because they were not significant (no "experience effect" detected). The presence of static externalities (in addition to dynamic externalities) in accounts 2 and 3 reduces by 63 percent the switching probability at the beginning of each period (variable *Treatment* = 1 if treatment B, and 0 otherwise). Hence, Observation 6 confirms our previous analysis of Figure 3, indicating that the proportion of transitions is smaller in treatment B than in treatment A. We therefore conclude that the pattern of account use is more stable in treatment B than in treatment A.

Subjects may rely on experience (backward-looking evaluation) and/or on some prospective evaluation of accounts' future profitability (for-
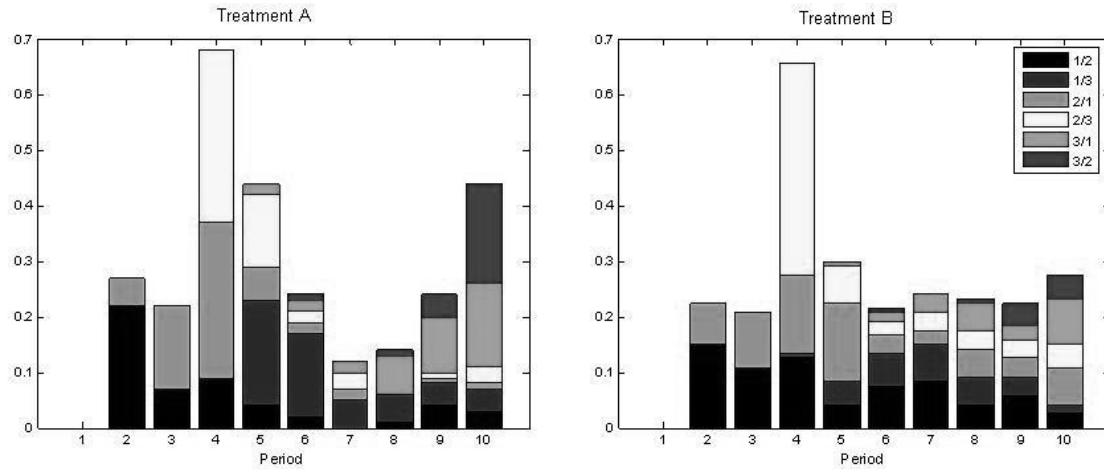
Figure 3. Mean Proportion of Account Changes in Each Period, by Type of Switch

Table 6. P-values of Non-Parametric Two-Way ANOVA Test of the Treatments' Proportion of Transitions Comparison

Transition Type	Period								
	2	3	4	5	6	7	8	9	10
Total Proportions of Transitions	0.5673	0.9544	0.4993	0.4481	1	0.0545* (B)	0.0634* (B)	0.8577	0.0512* (A)
1→2	0.5593	0.1870	0.4699	1	0.0515* (B)	0.0023*** (B)	0.1699	0.3051	1
1→3	1	1	0.3173	0.0389** (A)	0.1125	0.3838	0.7290	0.6394	0.3961
2→1	0.1748	0.8959	0.1457	0.0247** (B)	0.3865	0.6473	0.0079*** (B)	0.3035	0.0181** (B)
2→3	1	0.3173	0.7420	0.2736	1	0.6219	0.0396** (B)	1	0.2775
3→1	1	1	0.3173	0.1573	1	0.3865	0.4322	0.1647	0.1474
3→2	1	1	1	1	1	1	1	0.4879	0.0139** (A)

Notes: *** indicates p-values < 0.01, ** indicates p-values < 0.05, and * indicates p-values < 0.1. Treatment with the higher proportion is shown in parentheses (see Figure 3).

ward-looking evaluation) when choosing an account. Item (iii) of Observation 6 is related to the "forward-looking" part of account evaluation.

The coefficient of the ratio of available units in account 2 with respect to account 3 (the variable *Stock Ratio*) is highly significant. The probability of switching accounts is multiplied by 4.3 when the ratio of available units in account 2 and account 3 is incremented by one point (holding other covariates constant). However, due to the

convex relation between *Stock Ratio* and time, the impact of the relative abundance of units in account 2 depends on the period considered. For example, in period 1, a one-point increment of *Stock Ratio* (*ceteris paribus*) increases hazard by 359 percent, while in period 10 it increases hazard by just 1 percent. The intuition is straightforward: the higher the ratio, the higher the difference in available stock between accounts 2 and 3, which implies a sharper difference in the attain-

Table 7. Estimated Coefficients and Proportional Hazard Assumption Test

	Model		Proportional Hazard Assumption Test
Variables	Coef. (Robust Std. Err.)	Z (P>|z|)	Rho chi2 Pr > Chi2
Treatment	-0,6283936 (0,0690813)	-9,1 (0.000)	0,00352 0,00 0,9608
Lagged profit	-0,0282101 (0,0037692)	-7,48 (0.000)	-0,0154 0,05 0,818
Lagged wealth	0,0018821 (0,0022794)	0.83 (0.41)	0,03344 0,21 0,6459
Lagged wealth × period	0,0004744 (0,0006123)	0,77 (0.44)	0,01239 0,02 0,8855
Lagged wealth × period^2	-0,0000888 (0,0000416)	-2,13 (0.03)	-0,02613 0,08 0,7737
Stock ratio	4,304288 (0,5053008)	8,52 (0.000)	-0,07906 1,73 0,1879
Stock ratio × period	-0,7365922 (0,1125204)	-6,55 (0.000)	0,09128 2,07 0,1504
Stock ratio × period^2	0,0307634 (0,0063289)	4,86 (0.000)	-0,09225 1,79 0,1813
Wald test	Chi2(8) = 767,09 Prob> Chi2 = 0,000		Global test Chi2(8) = 15,51 Prob> Chi2 = 0,05

Notes: Treatment equals 1 if Treatment B, and 0 otherwise. Lagged profit is profit of previous period. Lagged wealth is accumulated wealth at the beginning of previous period (current wealth = lagged profit + lagged wealth). Lagged wealth multiplied by period is lagged wealth multiplied by the current period. Lagged wealth multiplied by period^2 is lagged wealth multiplied by the square of the current period. Stock ratio is available units in account 2 at the beginning of period *t* relative to the available units in account 3. Stock ratio multiplied by period is the *Stock Ratio* variable multiplied by the current period. Stock ratio multiplied by period^2 is the *Stock Ratio* variable multiplied by the square of the current period.

able profits for each account, encouraging switching. Conversely, as the ratio increases, switching between accounts is discouraged in final periods. Actually, the ratio is a relative measure of available units that ignores the size of attainable profits. Recall that the stock size increases the profit by extracted unit in accounts 2 and 3. Then, since in final periods the stock size becomes smaller than in initial periods, because of the accumulated overexploitation, profit differences between accounts become negligible. The probability of

switching is lower indeed. It must be noted that in this case the convex relation between the ratio and time reflects, rather, a correlation between the ratio and the stock sizes.

Item (iv) in Observation 6 emphasizes the weight of experience in the previous period on the account choice decision. There are two effects of the accumulated wealth on the switching probability: one depending on the lagged profit, and one depending on the lagged wealth. While the latter does not have a significant impact, a one-

point increase of the lagged profit reduces the switching probability by 2.8 percent. This indicates some inertia in account choices, which is supported by the economic intuition that switching becomes less likely when the used account has paid.

Conclusion and Policy Implications

The experimental results presented in this paper were motivated by an empirical question: how do static and dynamic externalities interact in the exploitation of coastal area aquifers? Overexploitation of coastal aquifers can lead to irreversible damage to water quality as a consequence of seawater intrusion, engendering a major challenge for sustainable development of these regions. Moreover, the dynamics of the seawater intrusion process may imply that the negative economic consequences (i.e., a dynamic negative externality) would not be perceptible until after many years of accumulated overexploitation. The presence of static externalities may enhance the agents' awareness about the link that ties them together. The behavioral responses to such perception can mitigate the short-run effects of the dynamic externality, by a more careful exploitation of the resource. In order to evaluate this hypothesis, we compared the exploitation efficiency of a set of CPRs under two treatments having the same theoretical predictions. In treatment A, exploitation of the CPRs generates only a dynamic externality, while in treatment B it generates both a static and a dynamic externality.

In our finite-horizon dynamic game, individuals had two decisions to make per period: (i) which resource to extract from three imperfectly substitutable resources, and (ii) the quantity to extract from the chosen resource. We took as benchmarks the predictions derived from three different behavioral assumptions: joint payoff maximization (the optimum), rational behavior (subgame perfect equilibrium), and myopic behavior.

In order to validate our hypothesis about the effect of static externalities, decisions in treatment B should be closer to the optimum benchmark than in treatment A. The optimum benchmark offers the best protection strategy against static externalities, provided that subjects cooperate.

Observations made from the experiment do show that individual extraction trajectories fit the myopic and the rational strategies better in both treatments. This is probably the reason why we do not find a different extraction pattern for treatment B compared to treatment A. Rational and myopic players do not care enough about the available stock of resource for future uses. Nevertheless, the presence of static externalities does induce some kind of payoff reassurance strategies in the resource choice decisions, but these strategies do not correspond to the optimum benchmark. In particular, in treatment B we observe a marked trend to secure payoff by choosing the resources in order to minimize the interaction with the other agents. This kind of behavior is found in a rather standard way when users have a choice between several resources: households and farmers prefer to withdraw from "their" own well in order to be autonomous with respect to others since a collective water resource involves constraints (payment, and also sometimes water turns) and uncertainties. Our econometric analysis confirms that the hypothesized preference for autonomy results from decisions following a clear economic intuition: (i) the probability of switching between accounts 2 and 3 responds positively to the relative abundance of available units in these accounts, and (ii) the switching probability is affected by profits earned in the previous period from these accounts. Hence, account choices are expected to respond to financial incentives.

Decisions are far from the optimum benchmark in both treatments. Moreover, the presence of static externalities increases asymmetries in the resource choices, deteriorating the efficiency of decisions. This militates for an intervention of public authorities.

Roughly speaking, public authorities can implement demand and supply-side policies for managing groundwater. The former refers to every measure taken to reduce or limit withdrawals (i.e., financial incentives and regulations), while the latter aims to prevent water resource degradation without restricting water consumption.

A widely used supply policy consists in investing in substitutes for groundwater: surface water can be made available by river dams or aqueducts; other water substitutes may be seawater desalinization and wastewater reuse. Our results about the exploitation of substitute CPR indicate that such a policy can be particularly effective in the short run. Users will look forward to use the substitutable resources with the aim of minimizing the interaction with the others users, which in

turn alleviates the anthropogenic pressure on each resource. However, the resource choice process demands that users coordinate on which resource to use, by whom, and when. Coordination is expected to fail in a laissez-faire situation. In the long run, the new water substitutes are unlikely to totally eliminate the groundwater resource overexploitation. Rather, the individual optimum would be different from the collective optimum even when there are substitutable resources (as is the case in our experiment). Our results show that substitute availability loosens the pressure on each resource because subjects' resource choices were aimed to minimize interaction with the other subjects. However, the observed individual extraction strategies are away from the social optimum. As the number of users of each resource is expected to grow, in the long run resource stock will continue to be threatened. In such cases, supply-side policies must be combined with demand-side ones.

Public intervention can take various forms: communication, to help water users to choose and consume water resources in a socially optimal way; incentives (through taxes or levies on individual or collective withdrawals), to induce water users to take into account externalities; or regulation, to constrain water users to follow the socially optimal path. Public authorities can act at the two levels of decision: the investment decision and the quantity to withdraw. As presented in this article, extracting water requires having a well or a borehole. Public authorities can then regulate groundwater access by putting legal constraints (license or declaration to drill) on future water users or on drillers, or by increasing investment cost (through taxes or through technical constraints put on well construction). Public authorities can also regulate water withdrawals, by setting quantitative restrictions or incentives on individual or collective withdrawals. Most of these manners are observed in real cases: North America and Australia have strong regulations on borehole construction; European countries generally prefer taxes on individual withdrawals, but tax rates are not always calibrated to curb extractions toward the socially optimal level; that is why, in some countries, regulations are added to the water tax system. In France, for instance, in case of structural water scarcity, available water quantity is allocated to groups of water users rather than directly to individuals to induce collective behav-

ior. This allows public authorities to reach the optimal path of extraction without imposing a predefined rule of water allocation.

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Appendix. Equilibrium Derivation

This appendix describes how myopic, rational, and optimum outcomes are derived.

Myopic Outcome

In the myopic behavior case, the optimization horizon is just one period. Assuming that everybody behaves myopically, the myopic appropriator calculates a subgame perfect equilibrium at each period. Hence, first the profit-maximizing extraction for each resource, $y_{i,j}^{t*}$ ($j = 1, 2, 3$), must be determined, and second, the myopic appropriator chooses the most paying available resource, j_i^{t*}, under budget constraint. For each $t = 1 , ..., T$,

(A1) $j_i^{t*} = \sup\left\{U(y_{i,j}^{t*})\,\middle|\,j=1,2,3\right\}$ u.c. $c_j \leq W_i^t$,

where

(A2)

$$y_{i,j}^{t*} = \max_{y_{i,1}^t} U_i(y_{i,j}^t) = \frac{a - p_j + f \cdot S_j^t}{2b + (n+1)z}, \quad j = 2, 3$$

and

(A3) $y_{i,1}^{t*} = \max_{y_{i,1}^t} U_i(y_{i,1}^t) = \frac{a - p_1}{2b}$.

Rational Outcome

In order to choose between substitutable resources, appropriators compare flows of future net returns generated by exploitation of each of them. Rationally behaving appropriators internalize the impact of their current extractions on their own future returns. Then, they must know exactly in which periods they will use that resource. These periods may not be consecutive, because appropriators can change the resource in each period. The optimization problem consists of identifying the decision tree's branch that maximizes the individual discounted profit. For the sake of simplicity, we will derive just the symmetric solution of the game.

Let be:

$[1, T]$ the whole optimization horizon (finite);

$$V_{i,j}^{t0,tf} = \sum_{\tau=t0}^{tf} U_{i,j}^{\tau*},$$

the sum from period t_0 to t_f, of the individual i's net return obtained by the optimal exploitation of the jth resource, taking as the optimization horizon, for the resources 2 and 3 cases, the time interval from t_0 to t_f;

$U_{i,j}^{t^*}(t_0,t_f)$, where $t \in (t_0,t_f]$, the individual i's net return in period t, obtained by the optimal exploitation of the jth resource ($j = 2, 3$), taking as the optimization horizon the time interval from t_0 to t_f;

$U_{i,1}^{t^*}$, the individual i's net return in period t, obtained by the optimal exploitation of the resource 1 (which is independent of time);

$\tilde{t}$, the first period for which the condition $U_{i,j}^{t_f^*}(t_0,t_f) \le U_{i,1}^{t_f^*}$ is satisfied;

$\hat{t}$, the first period for which the condition $W_i^{\hat{i}} \ge c_3$ is satisfied (the budget constraint allows investing in accessing resource 3).

At each final node of the tree, the appropriator must calculate his or her optimal extraction path, taking the extraction path of other appropriators as given.

The first step is as follows:

Taking the optimization horizon $[t_0, t_f]$ as given, each appropriator calculates an optimal feedback for resources 2 and 3, supposing that there are $n-1$ other appropriators who behave identically. Individual optimal extraction at each period $t \in [t_0, t_f]$ is given by equation (A4):

(A4)
$$y_j^t(S_j^t) = C_j^t \times \left[A_j^t \times E_j^t + (f \times r_j - d) \times (G_j^t + F_j^t) \right],$$

where

(A5) $A_j^t = a - p_j + f \times S_j^t,$

(A6)
$$C_j^t = 1 \Big/ \left\{ D - fn \sum_{\tau=t+1}^{T} \rho^{\tau-t} \left[fE_j^{\tau} C_j^{\tau} \left[1 + \sum_{s=t+1}^{\tau-1} \prod_{q=s}^{\tau-1} \left(-fnE_j^q C_j^q \right) \right] f \left[2 \left(1 - fn \sum_{s=t+1}^{\tau-1} E_j^s C_j^s \right) \right. \right. \right.$$

$$\left. \left[1 + \sum_{e=t+1}^{\tau-2} \prod_{q=e}^{\tau-2} \left(-fnE_j^q C_j^q \right) \right] \right] - 2(b+zn)E_j^{\tau}$$

$$\left. \left. C_j^{\tau} \left[1 + \sum_{s=t+1}^{\tau-1} \prod_{q=s}^{\tau-1} \left(-fnE_j^q C_j^q \right) \right] \right] \right] \right\},$$

(A7) $D = 2b + (n+1)z,$

(A8) $E_j^t = 1 + \left(\frac{1}{C_j^t} - D \right) \frac{1}{f \times n},$

(A9) $G_j^t = (E_j^t - 1) - \rho \times f \times C_j^{t+1}(E_j^{t+1} + F_j^{t+1} - 1)$
$$\times \left[E_j^{t+1} \times C_j^{t+1} \times 2(b+zn) - 1 \right],$$

(A10) $F_j^t = \sum_{\tau=t+2}^{T} \rho^{\tau-t} \left\{ fE_j^{\tau} C_j^{\tau} \left[1 + \sum_{s=t+1}^{\tau-1} \prod_{q=s}^{\tau-1} \left(-fn \right. \right. \right.$

$$E_j^q C_j^q \right) \right] \times \left[1 - 2(b+zn) \left[\left(E_j^{\tau} - 1 \right) C_j^{\tau} \right. \right.$$

$$+ \sum_{e=1}^{\tau-2} E_j^{\tau} C_j^{\tau} \left[1 + \sum_{s=e+1}^{\tau-1} \prod_{q=s}^{\tau-1} \left(-fnE_j^q C_j^q \right) \right]$$

$$\left. \left[1 + fnC_j^{s-1} \left(F_j^{s-1} + G_j^{s-1} \right) \right] \right] \right]$$

$$+ f \left(1 - fn \sum_{h=t+1}^{\tau-1} E_j^h C_j^h \left[1 + \sum_{k=t+1}^{h-1} \prod_{q=k}^{h-1} \left(-fnE_j^q \right. \right. \right.$$

$$C_j^q \right) \right] \right) \times \left[\left(E_j^{\tau} - 1 \right) C_j^{\tau} + \sum_{e=1}^{\tau-2} \left(E^{\tau} C^{\tau} \left[1 + \right. \right. \right.$$

$$\sum_{s=e+1}^{\tau-1} \prod_{q=s}^{\tau-1} \left(-fnE^q C^q \right) \right] \cdot \left[1 + fnC^{s-1} \right.$$

$$\left. \left. \left. \left(F^{s-1} + G^{s-1} \right) \right] \right) \right] \right\}.$$

The second step is as follows:

Each appropriator chooses transition periods, taking transition periods of her or his rivals as given, and supposing that extraction behavior of everybody is in accordance with the feedback strategy calculated in the first step.

Optimum Outcome

The optimum outcome results from maximizing the sum of all appropriators' net returns for the whole temporal horizon. The procedure to find transition periods is similar to that reported for

the rational outcome case. The unique difference is the calculation of extraction trajectories for resources 2 and 3. The collective optimum individual extraction at each period $t \in [t_0, t_f]$ is given by equation (A11):

(A11) $y_j^{t*} = C_j^t \left\{ E_j^t (a - p_j)(1 - fnE_j^{t-1}C_j^{t-1} \right.$

$$\left[1 + \sum_{s=1}^{t-2}\prod_{q=s}^{t-2} -fnE_j^q C_j^q \right] \right) + E_j^t S_j^0 f \times$$

$$\left[1 - fnE_j^{t-1}C_j^{t-1}\left[1 + \sum_{s=1}^{t-2}\prod_{q=s}^{t-2}\left(-fnE_j^q C_j^q\right)\right]\right] +$$

$$+fr\left[E_j^t + G_j^t + F_j^t + \sum_{s=1}^{t-1}\left(E_j^s + G_j^s + F_j^s\right)\times \right.$$

$$\left.\prod_{e=s}^{t-1} -E_j^{e+1} fnC_j^e \right]\right\}.$$

For the calculation of the optimum outcome's trajectories, equations A_j^t, E_j^t, F_j^t, and G_j^t are given, as in the rational benchmark, by equations (A5), (A8), (A10), and (A9), respectively. But C_j^t and D_j^t are replaced by:

(A12) $$D = 2b + 2nz$$

(A13)

$$C_j^t = 1 \bigg/ \left\{ D - fn \sum_{\tau=t+1}^{T}\rho^{\tau-t}\left[fnE_j^\tau C_j^\tau \times \right.\right.$$

$$\left[1 + \sum_{s=t+1}^{\tau-1}\prod_{q=s}^{\tau-1}\left(-fnE_j^q C_j^q\right)\right] fn\left[(1 - 2b - zn)\right.$$

$$\left(1 - fn\sum_{s=t+1}^{\tau-1} E_j^s C_j^s\left[1 + \sum_{e=t+1}^{\tau-2}\prod_{q=e}^{\tau-2}\left(-fnE_j^q C_j^q\right)\right]\right)$$

$$-2(b + zn)E_j^\tau C_j^\tau \times$$

$$\left.\left.\left[1 + \sum_{s=t+1}^{\tau-1}\prod_{q=s}^{\tau-1}\left(-fn \cdot E_j^q \cdot C_j^q\right)\right]\right]\right\}.$$