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Abstract

We investigate the approval mechanism (AM) for a common pool resource (CPR) game with three players, underlining the role of unanimity and majority rules. The game involves two stages. In stage 1, players simultaneously and privately choose a proposed level of extraction from the CPR. In the second stage, they simultaneously decide whether to approve or disapprove others' choices. If the group approves, players' first stage proposed extractions are implemented. Otherwise, a uniform extraction level, called disapproval benchmark (DB), is implemented onto each group member. We combine two approval rules, majority and unanimity, with two DBs, the minimum extraction level (MIN DB) and the Nash extraction level (NASH DB). These combinations offer four different treatments for testing the approval mechanism (AM). Our experimental findings show that the AM reduces significantly over-extraction in each treatment, and that the unanimity rule is more effective than the majority rule to lower extractions. The MIN DB reduces more group extractions than the NASH DB. Finally, only the MIN DB with unanimity implements the Pareto-efficient extraction level.

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Key-words: Approval mechanism, lab experiment, common pool resource, majority/unanimity, difference in difference

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1 Introduction

In the absence of regulation, self-interested agents will over-extract common pool resources (CPR), (see e.g. Hardin (1968); Ostrom (1990); Walker et al. (1990)), a socially undesirable outcome which leads to the so-called CPR dilemma. The CPR dilemma belongs to the wider class of social dilemmas, i.e. a context in which private interests are conflicting with the collective interest.

The theoretical literature has proposed smart mechanisms designed to mitigate social dilemmas (e.g. Clarke (1971); Groves (1973); Groves and Ledyard (1977); Green and Laffont (1979); Varian (1994) or Falkinger (1996)). However, few of them are targeted towards CPR dilemmas, the compensation mechanism (Varian (1994)) being a notable exception. In this paper we consider the approval mechanism (AM thereafter) proposed by Masuda et al. (2014) and Saijo et al. (2015, 2018) as a potential candidate that could help mitigating CPR over-extraction and guarantee its sustainability. The AM was initially conceived as as solution for public good dilemmas. Its simplicity and parsimony are attractive properties allowing to consider its application to other types of dilemmas. In addition the AM can be carried out endogenously by the involved parties, i.e. it does not require a regulator for its implementation[1].

The AM is a two-stage mechanism that introduces a social approval stage before extraction decisions are implemented. For instance, in the case of voluntary contributions to a public good, the individual contributions of stage 1 are publicly revealed and submitted to collective approval in stage 2. In case of approval the first stage decisions are implemented, otherwise some pre-announced benchmark contribution is enforced onto each group member, the disapproval benchmark (DB thereafter). Masuda et al. (2014) and Saijo et al. (2015, 2018) established, theoretically and experimentally, that

[1]Of course, its enforcement requires an intervention by a third party, as any other mechanism.

the AM solves the social dilemma in the case of the prisoner's dilemma game and in the two-player linear public good game.

Yao et al. (2021) provided experimental evidence that the AM can also be effective in the case of a two-player CPR dilemma. The CPR game with the AM proceeds alike the public good game: in the approval stage players can reject the stage 1 extraction proposals in which case a uniform extraction level is imposed onto each player. Otherwise the stage 1 proposals are simply implemented.

So far, the evidence about the effectiveness of the AM is restricted to the case of two-player games. In this paper we propose an extension to the case of three players, theoretically and experimentally. The effectiveness of AM in CPR with three players has never been assessed. The three-player extension raises a non-trivial issue about the approval mechanism, as it allows for various approval rules, e.g. unanimity, majority, consensus or dictatorship. In particular, the distinction between majority and unanimity, which is irrelevant in the two player case, becomes meaningful in the three player case. Each rule determines a different set of equilibria for the extraction game. In addition, the possible equilibria depend also on the DB. In the case of voluntary contributions, the Nash contributions and the minimum contribution were both considered by Masuda et al. (2014). Other possibilities are the maximum, the mean or the median contribution. More generally, the DB is a function of the vector of proposals. In this paper we consider the same rules as in Masuda et al. (2014), i.e. the $NASH\ DB$ and the $MIN\ DB$[2].

We contribute to the literature in two ways. First, we study the effectiveness of the AM in the context of a CPR dilemma with a non-linear payoff function. The latter property implies that both the Nash extraction and the efficient extraction are in the interior of the players' strategy sets[3]. In contrast, in the linear public good game considered by Masuda et al. (2014), the Nash equilibrium is the null contribution and the efficient outcome is the full contribution (each player contributes her whole endowment at the social optimum). Second, we consider a three player game, which allows us

[2]Because of the quadratic form of the payoff function in the CPR game, one of the properties of the AM, "voluntariness" discussed by Masuda et al. (2014), cannot always be satisfied. This issue is extensively discussed in Yao et al. (2021)

[3]Saijo et al. (2017) showed that the non-linearity of the payoff function combined with a sufficient number of players ($n \geq 4$) can lead to fundamental instability of the Nash equilibrium and to a a worse outcome than the Nash extraction level.

to study two different approval rules: the majority rule and the unanimity rule. Because previous investigations of the AM considered only two players, such distinction was irrelevant.

In the experiment, participants were randomly assigned to a group of three players for the whole duration of a session. They received a uniform per period token endowment that they could use to extract units of resource from a CPR. The extraction game was repeated over 10 rounds. Each group played two sequences of 10 rounds. Sequence 1 corresponds to the baseline treatment without the AM: each round consisted of a single extraction stage. In sequence 2 the AM was introduced, i.e. each round had two stages: the proposal stage (stage 1) and the approval stage (stage 2). In the proposal stage subjects had to choose their level of extraction. In the approval stage they were asked to approve or disapprove the extraction vector. Four variants of the AM were considered as test treatments: the $NASH\ DB$ with unanimity, the $NASH\ DB$ with majority, the $MIN\ DB$ with unanimity and the $MIN\ DB$ with majority. Furthermore, in a fifth control treatment we simply repeated the baseline sequence twice. We distinguish the proposed extractions (stage 1 decision) from the realized extractions, i.e. the extractions implemented after the approval stage. Our empirical strategy relies on a difference in difference setting based on the contrast between the baseline treatment and the four test treatments, before and after the introduction of the AM.

Our main goal is to assess experimentally the effect of the majority and the unanimity rules on the effectiveness of the AM in reducing group extractions. From a theoretical point of view, the combination of the unanimity rule with the MIN DB achieves the optimum extraction level as an equilibrium of the game. However, reaching the optimum extraction under the majority rule is less likely because the two-thirds of the player approval rule allows for a larger set of equilibrium extraction vectors. Multiplicity of equilibria may eventually lead to lower effectiveness compared to the unanimity rule. Under the NASH DB with the unanimity rule, multiple equilibria are also predicted, but the set of equilibria is narrower than under the majority rule. Our experimental investigation should allow us to better understand the effectiveness of the two approval rules combined with each DB, and thereby identify the most efficient combination. We first investigate the extent to which the AM reduces the level of group extraction in a three player game. Second, we compare the effectiveness of the majority rule versus the unanimity rule. Finally, we analyze whether and how the disapproval benchmark affects the effectiveness of the reduction.

Overall, we find that the AM reduces the level of extractions in all test treatments. However, there are some sharp differences according to the approval rule and the DB. First, with respect to the approval rule we find that unanimity is more efficient to reduce extractions than majority. Second, we find that the $MIN\ DB$ reduces group extraction by a larger amount than the $NASH\ DB$. Third, the combinations of approval rules and DBs have very heterogeneous outcomes. The optimum extraction level is achieved only under the $MIN\ DB$ with the unanimity rule. The $MIN\ DB$ with unanimity is more effective than the $MIN\ DB$ with majority, which in turn is more effective than the $NASH\ DB$ with unanimity and the $NASH\ DB$ with majority. Finally, unanimity and majority lead to comparable extraction levels under the $NASH\ DB$. The $MIN\ DB$ is more effective than the $NASH\ DB$ because the implementation of the minimum promotes the sustainability of the CPR. Moreover, the unanimity rule is more effective than the majority rule because, under majority, some subjects are able to form successfully coalitions that over-exploit the CPR. Inequality aversion explains to some extent the difference between the mechanisms.

The rest of the paper is organized as follows. Section 2 derives the theoretical predictions. Section 3 describes the experimental design. Section 4 presents the experimental results. Section 5 discusses the results and section 6 concludes.

2 Theoretical predictions

We consider a symmetric n-player CPR game with $n > 2$. Each player i is endowed with $w > 0$, which he has to allocate between a private activity and a CPR extraction activity. We adopt the procedure used in previous experiments on CPR games (Walker et al., 1990; Keser and Gardner, 1999; Cardenas, 2004; Ostrom, 2006; Cárdenas et al., 2015), i.e. players decide about the fraction that they want to invest in the CPR extraction activity. The complementary fraction is automatically invested in their private activity. We equate player i's investment in the CPR with his extraction level. Let x_i denotes the extraction level of player i, with $x_i \in [0, w]$. The group extraction is given by: $X = \sum_{j=1}^{n} x_j = x_i + x_{-i}$, and $x \equiv (x_1, , ..., x_i, ..., x_n)$ is the vector of extractions.

The payoff of player i from the CPR extraction activity is given by :

$$R_i(x_i, x_{-i}) = \frac{x_i}{x_i + x_{-i}}[a(x_i + x_{-i}) - b(x_i + x_{-i})^2] \quad (1)$$

The expression in brackets corresponds to the group payoff from the CPR extraction activity. a and b are positive constants. $\frac{x_i}{x_i+x_{-i}}$ is the fraction of the group payoff that is captured by player i. The group payoff can also be written $R(X) = \sum_{i=1}^{n} R_i(x_i, x_{-i})$. $R(X)$ is a concave function with a unique maximum. Therefore, $R(X)$ is increasing when group extraction is low and decreasing when group extraction if high.

Player i's payoff from his private activity, $Z_i(x_i)$, depends only on his own investment in that activity. We assume a linear payoff function i.e.:

$$Z_i(x_i) = p(w - x_i), \quad (2)$$

where $p > 0$ is an opportunity cost. The total payoff generated by the combination of the two activities is given by $\pi_i(x_i, x_{-i}) = R_i(x_i, x_{-i}) + Z_i(x_i)$.

Let us denote $\pi \equiv (\pi_1, ..., \pi_i, ..., \pi_n)$ the payoff vector corresponding to the extraction vector of the group members.

We first state our two benchmark predictions (subsection 3.2.1): the unregulated, i.e. free access (FA), Nash extraction level, and the Pareto efficient level of extraction. Second (subsection 3.2.2), we state 5 propositions about the impact of variants of the approval mechanisms on the levels of extractions.

2.1 Free access and efficient extractions

Under FA a selfish rational player i chooses x_i to maximize his total payoff $\pi_i(x_i, x_{-i})$ given others' extractions x_{-i}. We consider only the symmetric case.

Proposition 1 (Nash equilibrium): *Under FA, the symmetric Nash Equilibrium is given by X^* and by the vectors x^{NE} and π^{NE}, such that: $x^* = \frac{1}{n+1}\frac{a-p}{b}$ is the common component of the vector x^{NE}, $\pi^* = \frac{(a-p)^2}{b(n+1)^2} + pw$ is the common component of π^{NE}, and group extraction is $X^* = n\mathrm{x}^*$.*

Proposition 2 (Social optimum): *The Efficient extraction, defined by $\hat{X}$ and the vectors x^E and π^E, is given by $\hat{x} = \frac{a-p}{2bn}$, $\hat{\pi} = \frac{(a-p)^2}{4bn} + pw$ and $\hat{X} = \frac{a-p}{2b}$.*

Proofs of propositions 1 and 2 are provided in the appendix. Note that the efficient individual extraction and the efficient individual payoff both decrease as the size of the group increases ($\frac{\partial \hat{x}}{\partial n} < 0$ and $\frac{\partial \hat{\pi}}{\partial n} < 0$) but $\hat{X}$ does not depend on the group size n .

We next introduce the approval mechanisms. The AM is characterized by a disapproval benchmark and an approval rule. We consider two benchmarks: the Nash extraction vector, x^{NE}, and the minimum extraction vector $x^{min} = (\underline{x}, ..., \underline{x}, ..., \underline{x})$, where $\underline{x}= min(x_1, ..., x_i, ..., x_n)$. We refer to these benchmarks as the NASH DB and the MIN DB, respectively. We also consider two approval rules: the *unanimity* rule and the *majority* rule. In the CPR extraction game, the AM introduces a second stage following the first stage extraction proposal, which involves an approval/disapproval decision. Player i approves in stage 2 if and only if $\pi_i(x_i, x_{-i}) \geq \pi^{DB}$, where π^{DB} is his disapproval benchmark payoff. Under the NASH DB, $\pi^{DB} = \pi^*$ and under the MIN DB, $\pi^{DB} = \pi^{min}$, where $\pi^{min} = \pi_i(\underline{x}, \underline{x})$. Note that there is an important difference between the two benchmarks: under the NASH DB players know ex ante the level of the imposed extraction in case of disapproval. In contrast, under the MIN DB this level is endogenous, and becomes only known ex post at the end of stage 1.

The inequality $\pi_i(x_i, x_{-i}) \geq \pi^{DB}$ is satisfied if and only if $x_i \in I =]\underline{x}_i, \bar{x}_i[$ where the upper and lower bounds, $\bar{x}_i$ and $\underline{x}_i$ depend on the type of disapproval benchmark (NASH DB or MIN DB) and the type of rule (unanimity or majority). The set of equilibria belong to I^n, the Cartesian product of I for the n players. We adopt the notation $I^n_{DB\_AR}$ to designate the set of equilibria for a disapproval benchmark $DB \in \{NASH, MIN\}$ and an approval rule $AR \in \{U, M\}$, where U stands for unanimity and M for majority.

2.2 Equilibrium extractions under MIN DB

Under the MIN DB the minimum of stage 1's proposed extractions is implemented in case of disapproval. Consider the levels of extraction in the set $S = [0, w]$. Note x_i, x_j and x_k the proposed extraction by player i, j and k, respectively. The corresponding payoffs are: $\pi_l(x_i, x_j, x_k) = ax_l - bx_l(x_i + x_j + x_k) + p(w - x_l)$, with $l \in \{i, j, k\}$. Assume that $x_i = min(x_i, x_j, x_k)$, such that $\pi^{min} = \pi(x_i, x_i, x_i) = ax_i - 3bx_i^2 + p(w - x_i)$. In stage 2 of the MIN DB, player l compares $\pi_l(x_i, x_j, x_k)$ to $\pi(x_i, x_i, x_i)$. Thus, player l approves if $\pi_l(x_i, x_j, x_k) \geq \pi(x_i, x_i, x_i)$[4] and disapproves if $\pi_l(x_i, x_j, x_k) < \pi(x_i, x_i, x_i)$. We first consider the MIN DB under unanimity and majority, before analyzing the NASH DB. All proofs are relegated to appendix 1.

2.2.1 MIN DB with unanimity

Under the unanimity rule, a single disapproval by one player is sufficient to achieve group disapproval. We rely on backward elimination of weakly dominated strategies (BEWDS) to determine the equilibrium strategies under the MIN DB.

Proposition 3: *The MIN DB with unanimity implements the symmetric Pareto-efficient outcome in backward elimination of weakly dominated strategies (BEWDS).*

The proof of proposition 3 is provided in appendix 1. It proceeds in two steps. In step 1 it shows that only symmetric extractions vectors are approved, because the player who proposes to extract the minimum is always better of if he disapproves. Step 2 consists in showing that the symmetric optimum vector weakly dominates any other symmetric vector.

[4] In case of indifference we assume that player i approves.

2.2.2 MIN DB with majority

Let us assume $x_1 \leq x_2 \leq x_3$, with at least one strict inequality, and let $X^{min} = 3x_1$ designate the outcome of the $MIN\ DB$.Proposition 4 below applies to any permutation of the extraction vector among the three players.

Proposition 4: *Under the MIN DB with majority, players following BEWDS reject any subgame if $X \geq \alpha$, and accept any subgame that satisfies $x_2 > x_1 \frac{\alpha - X^{min}}{\alpha - X}$ if $X < \alpha$.*

According to proposition 4, asymmetric proposal vectors may be approved by two players, and therefore constitute equilibria. Such equilibria are possible when the minimum winning coalition (MWC thereafter) is smaller than the number of players. This is the case in our three player game, where the MWC consists of two players. Consider the following example: player 1 proposes $\hat{x}$ while players 2 and 3 both propose larger extractions. Provided that the upwards deviation from the optimum extraction is not "too large" (i.e. above twice the optimum extraction level ($\frac{\alpha}{2}$)), players 2 and 3 will both make larger profits if they approve, i.e. $\pi_j(\hat{x}, x_2, x_3) > \hat{\pi}$ for $j \in \{2, 3\}$. However, player 1 disapproves because $\pi_1(\hat{x}, x_2, x_3) < \hat{\pi}$. The implication is that players 2 and 3 approve while player 1 disapproves.

Proof (see appendix 1)

According to proposition 3, the MIN DB with unanimity implements the socially optimum level of extraction. In contrast, the MIN DB with the majority rule is more permissive because it requires approval by only 2 players. When $MWC = n$, we cannot distinguish majority and unanimity, both give the same outcomes. However, when $MWC < n$, the majority rule can lead to additional extraction vectors that would be disapproved under unanimity. For example, under the MIN rule, the sub-game $(x, x+1, x+1)$ is disapproved under unanimity but approved under majority for $x < \frac{2}{5}(\hat{X} - 1)$. If $x < \frac{2}{5}(\hat{X} - 1)$, player 2 and player 3 (i.e. $\frac{2}{3}$ of the players) obtain a larger payoff by approving than by disapproving.

2.3 Equilibrium extractions under the NASH DB

Under the NASH DB the disapproval benchmark is given by the vectors x^{NE} and π^{NE}. In stage 2, player i approves if and only if $\pi_i(x_i, x_{-i}) > \pi^*$.

2.3.1 NASH DB with unanimity

Proposition 5: *Under the NASH DB with unanimity, players following BEWDS approve all sub-games in* I^n_{NASH-U} *with* $I_{NASH-U} =]\frac{1}{n}x^*, x^*[$.

The proof of proposition 5 is reported in appendix 1. Intuitively, each player has an incentive to propose to extract less than the Nash level x^*. Above the optimum extraction level, $\hat{x}$, a player who extracts less than x^* increases both his own and others' profit. By symmetry of the payoff function, above $\frac{x^*}{n}$ extracting more, increases also ones own and the others' profit. On the other hand, if one of the players' proposed extraction falls outside this range, a single disapproval guarantees the Nash payoff to each one.

2.3.2 NASH DB with majority

Proposition 6: Under the NASH DB with majority, players following $BEWDS$ approve all sub-games in I^n_{NASH-M} with $I_{NASH-M} =]\underline{x}_i, \bar{x}_i[$ such that $\bar{x}_i > x^*$ and $\underline{\mathrm{x}}_i < \frac{x^*}{n}$.

The proof of proposition 6 can be found in appendix 1. First note that any vector belonging to I_{NASH-U} is also approved when the majority rule prevails. As shown for the unanimity rule, these extraction vectors lead to higher payoffs for every player compared to the Nash payoff. In addition, there are some vectors whose components fall outside the I_{NASH-U} set that are approved by a MWC under the majority rule.

In the next section, we design the mechanisms in order to test propositions (3-6) and to assess the effectiveness of each AM.

3 Experimental design

The experiment involves 5 treatments which are summarized in table 1. Besides the baseline treatment, we test the impact of four variants of the AM for mitigating over-extraction: the NASH DB with unanimity, the NASH DB with majority, the MIN DB with unanimity and the MIN DB with majority. Our CPR game relies on the same calibration as in Walker et al. (1990). Given that $a = 23$, $b = 0.25$ and $p = 5$, we have $x^* = 6$ tokens, $\hat{x} = 4$ tokens, $X^* = 18$ tokens, $\hat{X} = 12$ Tokens, $\pi^* = 6$ ecus, $\hat{\pi} = 4$ ecus. Each period, each player was endowed with 10 tokens that he had to allocate between the CPR extraction and the private activity. Note that we reason in terms of token units rather than in terms of resource units. We made this choice of measurement units in order to simplify the presentation of the payoff table that was provided in the instructions. The following conversion rule applies: 1 token = 3 resource units. Walker et al. (1990)'s findings are robust to our change in units and group size. Our baseline treatment replicates their main result: groups' extraction efforts are above the Nash extraction level of 18 tokens.

In each test treatment, participants played the CPR game under FA in sequence 1, before playing the CPR game under the AM in sequence 2. In the baseline the FA was repeated in both sequences. Each sequence consisted of a repeated extraction game over 10 rounds. All extraction decisions were made simultaneously and independently without communication[5]. Each subject participated only in one treatment. Participants were randomly selected from a large pool of volunteers registered at the Laboratory of Experimental Economics of Montpellier (LEEM), with no prior participation in the CPR extraction game. Selected participants were randomly assigned to a session.

The sessions were conducted at the LEEM of the University of Montpellier and programmed with the z-Tree software (Fischbacher, 2007). 252 participants, split into 84 groups of 3 players, were involved in the experiment (see table 1). At the beginning of each session, subjects were randomly assigned to a group of three players. Once constituted, each group remained unchanged until the end. A session lasted on average one hour and forty-five minutes. Each participant received written instructions describing the game and the tasks to be performed. The instructions presented the

[5]Communication was forbidden in the experiment

extraction possibilities of each group member and his payoff according to his own extraction and the extraction of the two other group members. The payoff table displayed the total payoff, i.e. the sum of the payoffs of the extraction activity and of the private activity.[6] Several examples were provided as illustrations to facilitate subjects' understanding and reading of the payoff table. After a first reading, the experimenter performed a second reading aloud to implement common knowledge of the game. After that, subjects were requested to answer a short questionnaire to check their understanding of the instructions. At the end of sequence 1, subjects received new instructions. These instructions detailed the stage 2 decisions that were added to the description of the stage 1 decisions (except for the baseline). For each version of the AM, the instructions described the consequences of approval and disapproval, as well as the approval rule (unanimity or majority).

Table 1: Experimental design

	AM Treatments				Baseline
	NASH DB		MIN DB		
	Majority	Unanimity	Majority	Unanimity	
Sequence 1: Periods 1-10	FA	FA	FA	FA	FA
Sequence 2: Periods 11-20	AM	AM	AM	AM	FA
Number of groups and subjects	17 groups 51 subjects	18 groups 54 subjects	15 groups 45 subjects	19 groups 57 subjects	15 groups 45 subjects

In each period of the CPR game under FA, participants had to decide simultaneously about their extraction level. At the end of each round, the level of extraction and the corresponding total payoff of each group member was displayed on the screen of each member of the group. For the CPR game under AM, each period had 2 stages. In stage 1, each participant proposed an extraction level. In stage 2, each group member's extraction level and its associated payoff were displayed on the screen of every group member. They were reminded of the DB that would be implemented in case of disapproval: the minimum of all members' proposals (MIN DB) or the FA Nash contribution (NASH DB). After that, the computer asked each one to approve [yes] or to disapprove [no], others'

[6]In a preliminary pilot study of a two-player game experiment, Yao et al. (2021) observed that several subjects omitted to add the payoffs of the two activities, and therefore reasoned only on the payoff table that corresponded to the extraction activity.

proposals. Following this stage, each player in the group was informed about the issue of the approval stage, the final realized extractions and his total payoff. This information was publicly displayed.

4 Results

This section is organized as follows. In the first subsection we provide descriptive results, in the second one we introduce our empirical strategy, and in the third subsection we state our main results.

4.1 Summary statistics

Our main objective is to analyze the general relevance of the AM for reducing group extraction. We therefore concentrate on the two key dimensions of the AM: the approval rule, i.e. the aggregation of individual approval/disapproval decisions, and the benchmark disapproval outcome, i.e. the default extraction level in case of disapproval. We compare two approval rules, the *unanimity* rule and the *majority* rule, and two disapproval benchmarks, the NASH DB and the MIN DB (see table 1). By combining approval rules and disapproval benchmarks, we consider four variants of the AM.

For analyzing the relevance of the AM, we compare the level of group extraction with and without the AM. Let us remind that all treatments involve two sequences of 10 rounds. The AM is always introduced in the second sequence (rounds 11-20). We can therefore compare the group extractions in sequence 1 to those of sequence 2, and contrast the groups in which the AM was implemented to groups where FA continues to prevail in sequence 2. Furthermore, we analyze the impact of the approval rule, the disapproval benchmark and their interactions, on group extraction. The summary statistics presented in table 2 details the average levels of group extraction by sequence and by treatment. In sequence 1 the level of extraction is above the FA Nash extraction level (18 tokens) in all treatments and significantly larger (*rank-sum test*, $p = 0.000$). This corresponds to severe over-extraction according to Lindahl et al. (2016), i.e. a level of over-extraction with respect to the social optimum (i.e. 12 tokens) that is larger than the Nash extraction level (18 tokens), in accordance with Walker et al. (1990). Besides, the average extraction in the control group is stable in sequence

1 and in sequence 2.[7] After implementing the AM in sequence 2, we observe a sharp drop of the average extraction level in all treatments. On average, the implementation of the AM reduces the proposed extraction level by 1.85 and the realized extraction level by 3.87 tokens (*rank-sum test*, $p = 0.000$).

Table 2 also summarizes the data according to the aggregation rule and the type of DB. In fact, we can also see that the unanimity rule performs better than the majority rule and that the MIN DB leads to a sharper reduction than the $NASH$ DB.

Table 2: Average group extraction by sequence and the effect of the AM

		Sequence 1 Periods 1 – 10	Sequence 2 Periods 11 – 20		Within-group difference		
		(1)	(2) proposed	(3) realized	(4)	(5)	(6)
Baseline		19.22	19.92	19.92	+0.70	+0.70	0
AM		19.43	17.58	15.56	-1.85	-3.87	-2.02
AM with Approval Rule	**Unanimity**	19.26	16.59	14.93	-2.67	-4.33	-1.66
	Majority	19.63	18.58	16.3	-1.05	-3.33	-2.26
AM with Disapproval Benchmark	**MIN** *DB*	19.33	17.26	13.80	-2.07	-5.53	-3.46
	NASH *DB*	19.53	17.89	17.27	-1.64	-2.26	-0.62

Note : AM treatments are in bold. The first three columns show the average extractions by sequence. The last three columns display the effect of the AM on the reduction of group extraction. (4) = (2) − (1); (5) = (3) − (1) and (6) = (3) − (2). In sequence 2, the proposed and the realized extractions are distinguished except for the baseline.

We first observe a larger average reduction of the proposed extraction, under unanimity (2.67) than under majority (1.65). This difference persists for realized extractions: under unanimity the average reduction is 4.33 and under majority it is only 3.33. To sum up, both aggregation rules lead to significant reductions of extractions, but the effect is stronger for the unanimity rule than for the majority rule (rank-sum test, $p = 0.000$). [8] Second, we observe a similar reduction in the proposed extraction levels (rank-sum test, $p = 0.2265$) for the MIN DB and the $NASH$ DB (2.07 and 1.64,

[7] A small, insignificant (sign-rank test, $p = 0.153$), increase is however observed, probably generated by the combination of a restart effect and a learning effect .

[8] These results also highlight differences between proposed and realized extraction but we only focus on realized extraction in the following section. Nevertheless, proposed extraction is analyzed in the discussion section.

respectively). Concerning realized extractions, the reduction is larger (rank-sum test, $p = 0.001$) for the MIN DB than for the NASH DB (5.53 and 2.26 respectively).

Table 3 summarizes the data by combining the aggregation rule and the DB. With the MIN DB, the average reduction of the proposed extractions is 3.0 tokens under the unanimity rule and 0.89 tokens under the majority rule, respectively. With the NASH DB the corresponding average reduction is 2.32 tokens under unanimity and 0.92 tokens under majority. Turning to realized extraction, with the MIN DB the average reduction is 6.09 tokens under unanimity and 4.83 tokens under majority. The corresponding reductions with the NASH DB are 2.49 tokens and 2.02 tokens, respectively.

Table 3: The combined effect of the disapproval benchmark and the approval rule

	Sequence 1 Periods 1 – 10	Sequence 2 Periods 11 – 20		Within-group difference		
	(1)	(2) proposed	(3) realized	(4)	(5)	(6)
MIN DB with unanimity	18.80	15.80	12.71	-3.00	-6.09	-3.09
NASH DB with unanimity	19.75	17.43	17.26	-2.32	-2.49	-0.17
MIN DB with majority	20.01	19.12	15.18	-0.89	-4.83	-3.94
NASH DB with majority	19.30	18.38	17.28	-0.92	-2.02	-1.10

Note : The first three columns show the average extractions by sequence. The last three columns display the effect of the AM on the reduction of group extraction. (4) = (2) − (1); (5) = (3) − (1) and (6) = (3) − (2). In sequence 2, the proposed and the realized extractions are distinguished.

In the next section we will confirm these differences relying on the difference in differences estimation approach.

4.2 Empirical strategy

We rely on a difference in differences (DiD) specification to obtain an exact identification of the effect of the implementation of the AM on the level of extraction. The identification strategy is based on groups and over time variation. To mitigate endogeneity issues, and to infer the causal impact of the AM on group extraction, we use the implementation of the AM as an exogenous controlled change. We compare the level of group extraction, before and after the implementation period of the AM, in groups where the AM was implemented and in baseline groups (without the AM). We estimate the parameters of equation:

$$Y_{it} = \alpha_0 + \alpha_1(Seq \times AM)_{it} + \sigma_t + \omega_i + \epsilon_{it}. \tag{3}$$

Y_{it} is the extraction level of group i in period t, Seq is a dummy variable which is equal to 1 for $t > 10$ (sequence 2) and 0 otherwise and AM is a dummy variable that takes value 1 if the AM is implemented in the group and 0 otherwise. The coefficient of the interaction variable, α_1, is the DiD parameter, which captures the direct marginal effect of the implementation of the AM (in sequence 2 in treated groups). We control for temporal patterns by including period dummies as well as a sequence dummy variable in σ_t.[9] We also control for unobserved time-invariant characteristics at the group level, ω_i, acting as group fixed effect. ϵ_{it} corresponds to the error term.

Equation 4 allows to identify the additional effect on group extraction of the majority rule versus the unanimity rule with respect to the implementation of the AM. The coefficient γ_2 of the dummy variable $(Seq \times AM \times Maj)$ captures the additional effect in sequence 2 when the AM is implemented under the majority rule.

$$Y_{it} = \gamma_0 + \gamma_2(Seq \times AM \times Maj)_{it} + \gamma_1(Seq \times AM)_{it} + \sigma_t + \omega_i + \epsilon_{it} \tag{4}$$

Finally, Equation 5 captures the additional effect of the disapproval benchmark on the level of group extraction. This effect is measured by the parameter β_2 which corresponds to the interaction variable $(Seq \times AM \times MIN)$ in equation 5.[10] β_2 measures the additional marginal effect of the MIN DB with respect to the NASH DB, on top of the effect of the AM which is measured by β_1.

$$Y_{it} = \beta_0 + \beta_2(Seq \times AM \times MIN)_{it} + \beta_1(Seq \times AM)_{it} + \sigma_t + \omega_i + \epsilon_{it} \tag{5}$$

In the results section, we also measure the combined effect of the approval rule and the disapproval

[9] The period dummy corresponds to twice 10 periods in order to take into account the 10 periods timing of the game acting as temporal fixed effects.

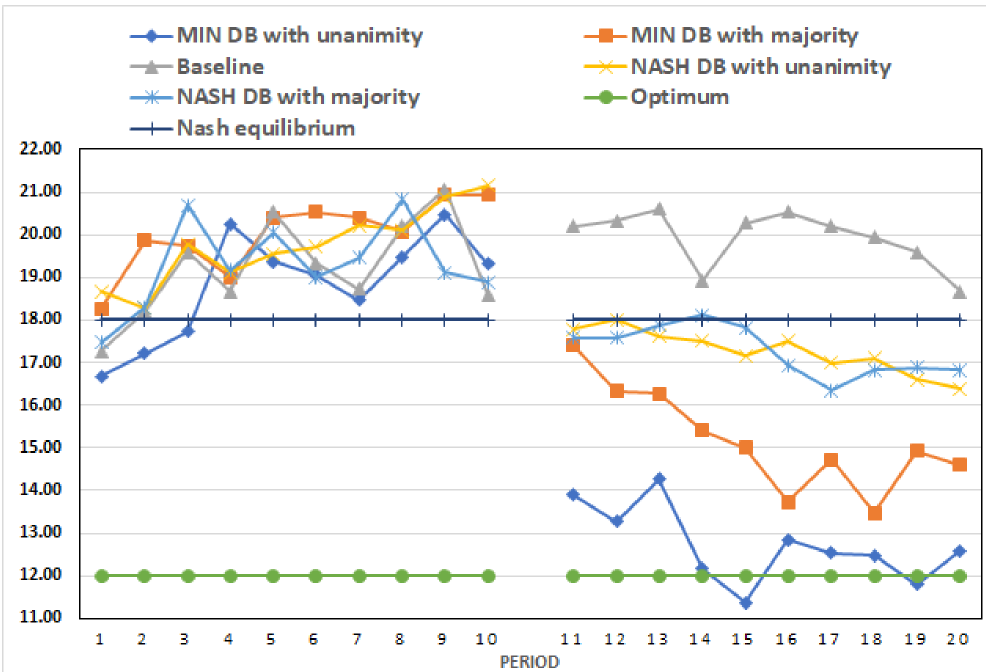
[10] All interactions variables are not displayed in equations 4 and 5 due to exact colinearity. For example, SEQ*MIN corresponds exactly to Seq*AM*MIN and Seq*MAJ corresponds exactly to Seq*AM*MAJ.)

benchmark. We do this by measuring the additional marginal effect of the majority rule with respect to unanimity rule, not only on top of the effect of the AM, but also on top of the combined effect of the AM with the MIN DB versus the NASH DB.

4.3 Estimation results

We start by examining the effect of different variants of the AM on the level of group extraction.

Figure 1: Average extraction by period



Analogous to table 2, figure 1 displays the evolution of the average group extraction for each treatment by period. As with any difference-in-difference design, the key underlying assumption for identification is that the control group serves as a valid counterfactual for the treatment group with parallel trends. Although we cannot explicitly verify this assumption, figure 1 provides some support by showing that in sequence 1 groups followed a similar pattern of extraction across treatments. In sequence 1, before the implementation of the AM, the average level of group extraction is similar across treatments. According to the Kruskal-Wallis test, the average level of group extractions between baseline and treatment groups do not significantly differ from zero ($p = 0.1537$). In sequence

2, however, there is a significantly lower group extraction (*rank-sum test*, $p = 0.000$) in treatments where a variant of the AM is implemented compared to the baseline condition.
We summarize this observation as result 1.

Result 1: *The implementation of the AM reduces significantly the level of group extraction.*

Support for result 1: Column 1 of table 4 summarizes the estimates of a difference-in-differences specification of equation 3. The direct impact of the introduction of the AM is a reduction of 4.78 units of the level of realized extraction.[11] This result is highly significant.

Table 4: Overall regression results for realized extractions

	Realized extractions			
Variables	(1)	(2)	(3)	(4)
$Seq \times AM$	-4.78***	-5.042***	-2.964***	-2.964***
	(0.363)	(0.384)	(0.376)	(0.376)
$Seq \times AM \times Maj$		1.001***		
		(0.332)		
$Seq \times AM \times MIN$			-3.275***	-3.832***
			(0.317)	(0.350)
$Seq \times AM \times MIN \times Maj$				1.263**
				(0.523)
$Constant$	19.27***	19.27***	19.27***	19.27***
	(0.248)	(0.241)	(0.247)	(0.241)
$Seq - FE$	yes	yes	yes	yes
$Group - FE$	yes	yes	yes	yes
$Period - FE$	yes	yes	yes	yes
$Observations$	1,680	1,680	1,680	1,680
$R - squared$	0.428	0.432	0.465	0.468
F	52.66	52.40	53.65	55.87

Note: Table 4 shows the effect of several variants of the AM on realized group extractions, using DiD estimation. We account for period fixed effects ($Period - FE$), group fixed effects ($Group - FE$) and sequence fixed effect ($Seq - FE$). All variables are binary. Robust standard errors are in parentheses. $*$ denotes significance at the 10-percent level, $**$ at the 5-percent level and $***$ at the 1-percent level.

The overall strong impact of the AM may hide differences across treatments. We therefore address

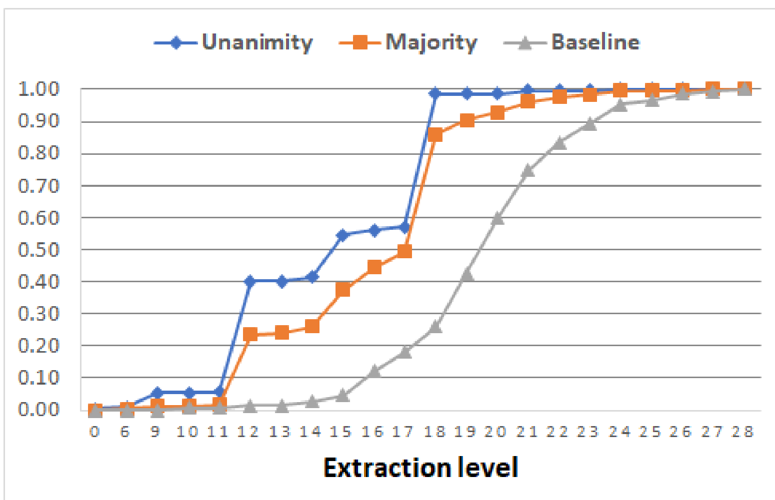
[11] It turns to 2.55 tokens when the outcome corresponds to the proposed extraction level as shown in table 7

the impact of the approval rule on extractions.

Result 2: *The reduction in the level of group extraction is lower under the majority rule than under the unanimity rule.*

Support for result 2: We observe that the reduction effect on group extractions is mitigated under the majority rule with respect to the unanimity rule (see figure 2 and column 2 of table 4). Column 2 of table 4 details the results of the double difference specification of equation 4. While the introduction of the AM reduces the level of extraction by 5 units on average, there is a 1 token attenuation effect under the majority rule. The latter result is once again reinforced by considering separately the disapproval benchmarks (see figure 2, (KS, p < 5%).

Figure 2: CDF for approval rules

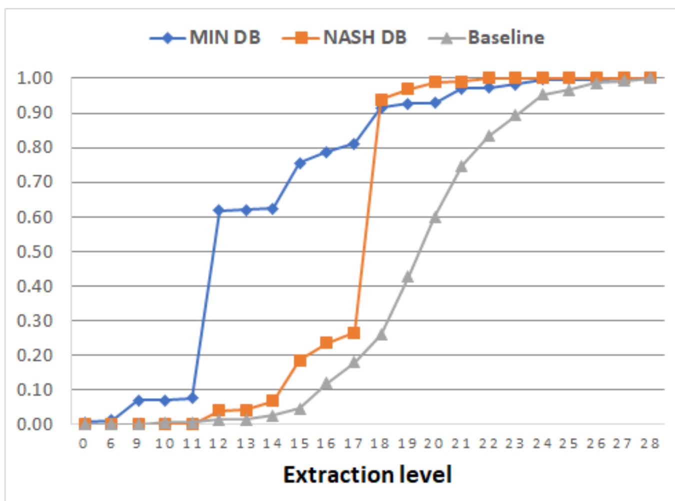


After comparing the effectiveness of the majority rule versus the unanimity rule, we analyze whether and how the disapproval benchmark affects the effectiveness of the reduction.

Result 3: *The MIN DB is more effective than the NASH DB in reducing the level of realized group extraction.*

Support for result 3: Figure 3 displays the cumulative distributions of extractions for the MIN DB and the NASH DB. It seems graphically that the MIN DB second order dominates the NASH DB. By analogy to figure 3 , column 3 of table 4 presents the results of the double difference specification of equation 5. The difference with column 1 is that we use additional information on disapproval benchmarks of a group, in addition to the general AM. While the introduction of the AM reduces the level of extraction by 2.96 units on average whatever the disapproval benchmark, there is an additional reduction of 3.27 units when the AM involves the MIN DB rather than the NASH DB[12]. The coefficient of $Seq \times AM \times MIN$ is negative and significant. It also emphasizes strong differences between the MIN DB and the NASH DB[13].

Figure 3: CDF for disapproval benchmarks



Up to now we considered separately the effectiveness of the AM, either with respect to the approval rule (unanimity versus majority) or with respect to the disapproval benchmark (NASH DB versus MIN DB). However, we do not know whether the effectiveness of a given approval rule is affected or not by the type of disapproval benchmark. As previously underlined, one can observe from figure

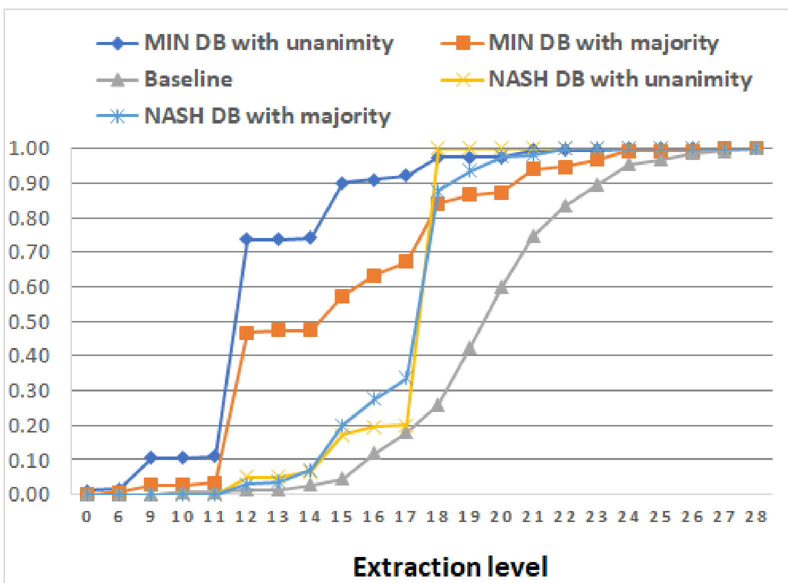
[12]The estimation shows that the outcome of the combination of the effects of AM (2.77) and $AM \times MIN$ (3.3) is not significant.

[13]This result is not significant under proposed extraction as shown in column 2 of table 7 (see appendix). The reduction in the group's level of proposed extraction does not differ for the MIN DB and the NASH DB

1 that the introduction of the AM in period 11 reduces the level of group extraction, but also that this reduction varies strongly across conditions. In addition, after the implementation of the AM, we observe a continuous decline of the level of extraction with the repetition of the CPR game, except for the MIN DB with unanimity where we observe a sharp drop in period 11 followed by an extraction path that converges towards the optimum extraction level.

Column 4 of table 4 shows the additional effect of Maj combined with $Seq \times AM \times MIN$ on the level of group extraction. While the introduction of the AM with the MIN DB reduces the level of extraction by 6.8 units on average (2.96 + 3.83), there is a one token attenuation effect when the AM with the MIN DB involves the majority rule rather than the unanimity rule. By analogy, figure 4 shows that whatever the approval rule, the cumulative distribution of extractions under the MIN DB first-order dominates the distribution of extractions under the NASH DB (KS, p $<$ 5%)

Figure 4: CDF for the AM treatments



We next analyze separately the effectiveness of the approval rules for each disapproval benchmark in table 5 in order to underline potential differences with sub-samples. In panel A (columns (1) and (2)) of table 5[14] we report test results for the majority and the unanimity rules under the NASH

[14]In the appendix, table 8 repeats the exercise for proposed extraction.

DB. Panel B (columns (3) and (4)) displays the test results for the two rules under the MIN DB. Note that column (1) and column (3) replicate the estimation of equation 3 for each sub-sample as a robustness test. Similarly, column (2) and column (4) replicate the estimation of equation 4 for each sub-sample.

Result 4: *Under the MIN DB, the majority rule mitigates the reduction of group extraction induced by the AM.*

Support for result 4: (see figure 4 and column 4 of table 5). Figure 4 shows that the cumulative distribution of extractions under the MIN DB with unanimity first-order dominates the distribution of extractions under the MIN DB with majority (KS, p $<$ 5%). Thus, Figure 4 shows lower extractions for the MIN DB with unanimity. The visual impression is confirmed by the regression of column 4 of table 5. It shows that the AM with majority attenuates the reduction in the level of group extraction under MIN DB. In fact the coefficient for $Seq \times AM \times Maj$ is positive and significant for the sub-sample where the MIN DB was implemented.

Result 5: *Under the $NASH$ DB, the approval rule does not affect the level of group extraction.*

Support for result 5: (see figure 4 and column 2 of table 5). The coefficient of $Seq \times AM \times Maj$ in column of table 5 is not significant. We see the same effect on figure 4 which shows that the cumulative distribution of extractions under the $NASH$ DB with unanimity does not first-order dominate the cumulative distribution of extractions under the $NASH$ DB with majority (KS, p $>$ 10%). We therefore conclude that the majority rule and the unanimity rule affect extractions equally under the $NASH$ DB.

5 Discussion

Our experimental results support the prediction that the approval mechanism can be effective at reducing extractions from a common pool resource (*Result 1*). However, we also found that the

Table 5: Impact of approval rules on realized extractions (by disapproval benchmark)

	Panel A : NASH DB (Unanimity vs Majority)		Panel B : MIN DB (Unanimity vs Majority)	
Variables	(1)	(2)	(3)	(4)
$Seq \times AM$	-2.964***	-3.190***	-6.239***	-6.796***
	(0.375)	(0.414)	(0.411)	(0.437)
$Seq \times AM \times Maj$		0.466		1.263**
		(0.386)		(0.524)
$Constant$	19.10***	19.10***	19.14***	19.14***
	(0.278)	(0.276)	(0.345)	(0.345)
$Seq - FE$	yes	yes	yes	yes
$Group - FE$	yes	yes	yes	yes
$Period - FE$	yes	yes	yes	yes
$Observations$	1,000	1,000	980	980
$R - squared$	0.306	0.307	0.507	0.510
F	14.34	13.49	45.99	48.86

Note: Table 5 shows the effect of the approval rules on the realized group extractions for each disapproval benchmark separately, using DiD estimation. The treatments, NASH DB with majority and NASH DB with unanimity, are pooled in Panel A, while the treatments, MIN DB with unanimity and MIN DB with majority, are pooled in Panel B. We account for period fixed effects ($Period - FE$), group fixed effects ($Group - FE$) and sequence fixed effect ($Seq - FE$). All variables are binary. Robust standard errors are in parentheses. $*$ denotes significance at the 10-percent level, $**$ at the 5-percent level and $***$ at the 1-percent level.

effectiveness of the approval mechanism depends on the type of approval rule (*Result 2*) and the type of disapproval benchmark (*Result 3*) that are implemented.

First, we found that the AM is more effective in achieving Pareto-improving levels of group extractions under the unanimity rule than under the majority rule. The regressions reported in table 4 show that when the majority dummy is interacted with the AM in sequence 2, there is a positive impact on extractions: while the AM lowers group extractions overall by 5 tokens on average, under the majority rule this effect is attenuated by 1 token on average. We therefore conclude that the majority rule is counterproductive for the effectiveness of the AM to solve CPR dilemmas. The main reason for such effectiveness is that the majority rule allows for winning coalitions that have an incentive to counteract the AM's target to reduce extractions. Another advantage of the unanimity rule is that it leads to fairer outcomes than the majority rule. We observe a lower average Gini index under unanimity ($Gini_{una} = 0.084$) than under majority ($Gini_{maj} = 0.111$), a significant difference (rank-sum, $p = 0.0228$)[15]. If we had to advise a policy designer, we would recommend that he preferably rely on the unanimity rule, although this rule entails also a drawback because of the veto power that is embodied in it. The latter drawback however, can be mostly circumvented by choosing appropriately the disapproval benchmark (DB). The disadvantage of the veto power seems therefore less prohibitive than the possibility, under the majority rule, of forming counterproductive coalitions.

Second, we found that the reduction of extractions is significantly larger under the $MIN\ DB$ than under the $NASH\ DB$. This result holds at the aggregate level, but also separately, for the majority and the unanimity treatments[16]. The larger effectiveness of the $MIN\ DB$ compared to the $NASH\ DB$ was observed by Masuda et al. (2014) in the context of a two-player voluntary contribution mechanism (VCM). They justify their result on theoretical grounds: the full contribution of both players under the $MIN\ DB$ is supported by five different equilibrium concepts or heuristics: (i) backward elimination of weakly dominated strategies ($BEWDS$, Masuda et al. (2013, 2014)), (ii) limit logit agent quantal response equilibrium (limit LAQRE; McKelvey and Palfrey (1995, 1998)), (iii) sub-game perfect minimax regret equilibrium (SPMRE; Renou and Schlag (2011)), (iv) level-k thinking (Costa-Gomes and Crawford (2006)), and (v) diagonalization heuristics (see *proposition 3* in Masuda et al. (2014)). In contrast, except for the prisoner's dilemma game, the $NASH\ DB$ does not lead to full contributions according to the same five equilibrium concepts or heuristics. Interestingly however, our results agree with those of Masuda et al. (2014) despite the many distinctive features of our CPR game compared to their voluntary contribution game. Our CPR game involves three players and allows for two different approval rules: majority and unanimity. Furthermore it has a non-linear payoff function which implies that both the Nash extraction and the optimum extraction vectors are interior. In contrast, the linear public good game studied in Masuda et al. (2014), involves two players and admits corner outcomes: zero group contribution at the Nash equi-

[15] The difference is mainly due to the $MIN\ DB$ for which we observe that $Gini_{una} = 0.079$ and $Gini_{maj} = 0.121$, a significant difference (rank-sum, $p = 0.0122$), whereas for the $NASH\ DB$ we have $Gini_{una} = 0.084$ and $Gini_{maj} = 0.101$, respectively, an insignificant difference (rank-sum, p = 0.2296).

[16] The reduction of extractions is largest under the $MIN\ DB$ with unanimity, followed by the $MIN\ DB$ with majority, the $NASH\ DB$ with unanimity and majority (under the $NASH\ DB$ unanimity and majority reduce equally the level of extractions).

librium and full group contribution at the Pareto optimum.

A possible reason for result 3 is that the $MIN\ DB$ provides stronger incentives to reduce extractions. If it were the case, it would imply that subjects make lower extraction proposals in stage 1 of the game under the $MIN\ DB$. However, according to the estimates reported in table 8 (see appendix), the effect size for the reduction of proposed extractions is comparable for the $MIN\ DB$ and the $NASH\ DB$. This observation suggests that the $MIN\ DB$ and the $NASH\ DB$ provide similar incentives to reduce proposed extractions in stage 1. We need therefore to explain the higher effectiveness, as measured by the realized extractions, by relying on the success of the approval stage. Does approval success depend on the approval rule? Let us consider first the unanimity rule: on average, only 20% of the proposals were positively approved, both under the $NASH\ DB$ and the $MIN\ DB$. Although the rates of approval success are equal under both benchmarks, the consequences of a disapproval are quite different. By definition $MIN\ DB$ favors lower extractions. Therefore, given that the disapproval rates are equal for the two benchmarks, the $MIN\ DB$ mechanically leads to lower realized extraction levels. A similar interpretation applies to the majority rule. Disapproval is more frequent under the $MIN\ DB$ (66%) than under the $NASH\ DB$ (50%), a fact that also mechanically leads to lower realized extractions under the $MIN\ DB$. Support for this interpretation is provided by table 6 which shows that the interaction variable $Seq \times AM \times Success$ has a clear negative impact on realized extractions under the $NASH\ DB$ and a positive impact under the $MIN\ DB$. This is not observed with proposed extraction where the reduction of the (stage 1) proposed extractions do not differ between the $MIN\ DB$ and the $NASH\ DB$ as underlined in Table 9 of the annex due to the mechanical effect of the $MIN\ DB$ in case of disapproval. Since the variable $Seq \times AM \times Success$ is equal to 1 if the group approves the proposed extraction vector, this result is true whatever the approval rule. Our main result seems therefore driven by a differential outcome of disapproval. The realized reduction in group extraction is larger under the $MIN\ DB$ when the group disapproves the extraction vector than when it approves it. Note also that whenever success is obtained under the majority rule, the reduction of group extraction is attenuated for both disapproval benchmarks (see columns (2) and (5) of table 6 for the impact of $Seq \times AM \times Success \times Maj$).

Table 6: Effect of group approval on the realized extraction (by disapproval benchmark)

	Panel A : NASH DB (Unanimity vs Majority)			Panel B : MIN DB (Unanimity vs Majority)		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Seq \times AM$	-2.814***	-2.647***	-2.644***	-7.397***	-7.092***	-7.092***
	(0.411)	(0.415)	(0.415)	(0.446)	(0.450)	(0.450)
$Seq \times AM \times Maj$	1.030***	0.614	0.629	0.843*	0.0288	0.0218
	(0.372)	(0.383)	(0.382)	(0.508)	(0.573)	(0.574)
$Seq \times AM \times Success$	-1.881***	-2.715***	-2.728***	3.002***	1.478***	1.478***
	(0.272)	(0.430)	(0.430)	(0.448)	(0.567)	(0.567)
$Seq \times AM \times Success \times Maj$		1.333**	0.362		3.021***	3.368***
		(0.555)	(0.580)		(0.919)	(1.147)
$Seq \times AM \times Success \times MWC$			1.717***			-0.575
			(0.522)			(1.031)
$Constant$	19.16***	19.19***	19.18***	19.17***	19.15***	19.15***
	(0.266)	(0.266)	(0.264)	(0.338)	(0.337)	(0.337)
$Seq - FE$	yes	yes	yes	yes	yes	yes
$Group - FE$	yes	yes	yes	yes	yes	yes
$Period - FE$	yes	yes	yes	yes	yes	yes
$Observations$	1,000	1,000	1,000	980	980	980
$R - squared$	0.329	0.332	0.338	0.536	0.542	0.543
F	15.13	15.02	15.91	50.29	47.42	44.27

Note: Robust standard errors are in parentheses. $*$ denotes significance at the 10-percent level, $**$ at the 5-percent level and $***$ at the 1-percent level. We account for period fixed effects ($Period - FE$), group fixed effects ($Group - FE$) and sequence fixed effect ($Seq - FE$). The first column shows the variables names. All variables are binary. Treatments MIN DB with majority and MIN DB with unanimity are pooled in AM of Panel A while treatments NASH DB with unanimity and NASH DB with majority are pooled in AM of Panel B. The variable Seq equals 1 for sequence 2 and 0 for sequence 1. $Seq \times AM$ is the interaction between the variables Seq and AM. $Seq \times AM$ is 1 for the CPR game with AM in sequence 2 and 0 otherwise. $Seq \times AM \times Success$ is the interaction variable between $Seq \times AM$ and $Success$, where $Success$ is 1 when the group approved unanimously (for unanimity rule) or mostly (for majority rule) in the current period and 0 otherwise. $Seq \times AM \times Success \times Maj$ is the interaction variable between $Success$ and Maj. Finally, $Seq \times AM \times Success \times Maj \times MWC$ is the interaction variable between $Seq \times AM \times Success \times Maj$ and MWC. MWC equals 1 for 2/3 approval under majority rule and 0 otherwise. We perform DiD regression using proposed extractions.

6 Conclusion

We analyzed the outcomes of a common pool resource extraction game regulated by the approval mechanism (AM) with three-player allowing us to compare two approval rules, the unanimity rule and the majority rule. We further aim to assess the effectiveness of the two approval rules combined with two approval or disapproval benchmarks, the NASH DB or the MIN DB. Hence we specifically studied four variants of the AM: the $MIN\ DB$ under unanimity, the $MIN\ DB$ under majority, the $NASH\ DB$ under unanimity and the $NASH\ DB$ under majority. Theoretically the efficient level of extraction is implemented only under the $MIN\ DB$ with unanimity in $BEWDS$. The other AM implement multiple equilibria in $BEWDS$.

We also tested experimentally the effectiveness of the AM in groups of 3 participants. First, we observed that the implementation of the AM always reduces the level of group over-extraction. We also emphasize that the unanimity rule is more effective than the majority rule while the $MIN\ DB$ is more effective at reducing extractions than the $NASH\ DB$ whatever the approval rule.

We confirm experimentally that the optimum extraction level is achieved only if the $MIN\ DB$ is combined with the unanimity rule. This result is driven by a narrower set of equilibria with the unanimity rule that lead to higher effectiveness compared to the majority rule as it leads to fairer payoff and prevents coalitions.

While this paper argues the AM can be a powerful mechanism that can help mitigating CPR over-extraction, we acknowledge several limitations of our experiment: first, we considered a single parametric setting (the one proposed by Walker et al. (1990)): allowing a sharper or weaker curvature of the payoff function could affect the effectiveness of the AM. Second, our sequences contained only 10 periods and we observed high variability across rounds in all treatments: this could indicate a lack of convergence due to a small number of periods. Longer sequences could lead to the stabilization of extractions over time and allow for a more robust comparison of treatments.

Besides, several extensions are of particular interest. First,does the AM remain effective in large populations, e.g. 10 or more players? Second, some alternative disapproval rules would be worth investigating, such as the median extraction or dictatorship (i.e. one player is randomly selected to decide for the group in case of disapproval). Finally, the external validity of the AM is not warranted. It would therefore be wise to test it in a field setting, with subjects that are involved in a real CPR exploitation dilemma. Demonstrating that the AM can be implemented in practice and that it curbs downwards extractions in a real situation, would open the door to the design of new policies for CPR regulation.

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7 Appendix 1: proofs

Proof of proposition 1. Under the assumption of selfish rational agents, each player i chooses x_i to maximize his total payoff. The FOC for an interior solution is given by $\frac{\partial \pi_i(x_i;x_{-i})}{\partial x_i} = 0$, which leads to $a - p - b(x_i + x_{-i}) - bx_i = 0$. Assuming symmetric extractions, i.e. $x_i^* = x_j^*$, for all i, j, $X^* = x_i + x_{-i} = nx^*$ and $x^* = \frac{1}{n+1}\frac{a-p}{b}$. It is easy to see that $\frac{\partial \pi_i(x_i;x_{-i})}{\partial n} < 0$, $\frac{\partial x^*}{\partial n} < 0$ and $\frac{\partial X^*}{\partial n} > 0$.

Proof of proposition 2. The social optimum level of extraction is reached if each player maximizes the group payoff. Let $\Pi(X) = \sum_{i=1}^{n} \pi_i(x_i; x_{-i}) = -bX^2 + (a-p)X + p\sum_{i=1}^{n} w$. The FOC is such as $\frac{\partial \Pi(X)}{\partial X} = 0$, which is equivalent to $a - p - 2bX = 0$. The optimum extraction level is therefore $\hat{X} = \frac{a-p}{2b}$ and each player extracts $\hat{x} = \frac{\hat{X}}{n} = \frac{a-p}{2nb}$.

Proof of proposition 3: The proof is divided into 2 parts.

- Firstly, we show that only symmetric sub-games survive to $BEWDS$ in stage 2. Consider the following subgame for which $x_i = min(x_i, x_j, x_k)$. Thus, $\pi(x_i, x_i, x_i) - \pi_i(x_i, x_j, x_k) = bx_i(x_j + x_k - 2x_i) \geq 0$. Therefore player i who proposed the minimum (x_i) always disapproves asymmetrical proposals. For this reason, proposed extractions (x_i, x_j, x_j) such that $x_i = min(x_i, x_j, x_k)$ lead to the same payoff for each player than the symmetric proposal vector (x_i, x_i, x_i). Consequently, only the sub-games for which the three players propose the same extraction level survive to $BEWDS$ in stage 2.

- Second, following Masuda et al. (2014, p. 76), we show that strategy $\hat{x}$ weakly dominates any strategy x_1 such that $x_1 \in [0, \hat{x}) \cup (\hat{x}, \bar{x}]$.

  a) Define $\underline{x} = \min(x_2, x_3)$ and suppose $\underline{x} = x_3$ (i.e. $x_3 \leq x_2$). Consider the case $\underline{x} \in [0, x_1]$ and $x_1 < \hat{x}$. Thus, we have $\pi_1(x_1, x_2, x_3) = \pi_1(\underline{x}, \underline{x}, \underline{x}) < \pi_1(x_1, x_1, x_1)$. Consider now the case $\underline{x} \in (x_1, \hat{x}]$. Thus, $\pi_1(x_1, x_2, x_3) = \pi_1(x_1, x_1, x_1) < \pi_1(\underline{x}, \underline{x}, \underline{x}) = \pi_1(\hat{x}, x_2, x_3) < \pi_1(\hat{x}, \hat{x}, \hat{x})$. It proves that $\hat{x}$ weakly dominates all strategies $x_1 \in [0, \hat{x})$.
  b) Consider $x_1 > x_2 > x_3 > \hat{x}$. Thus, $\pi_1(x_1, x_1, x_1) < \pi_1(x_1, x_2, x_3) = \pi_1(x_3, x_3, x_3)$. Moreover, consider that $\underline{x} \in (\hat{x}, x_1]$, $\pi_1(x_1, x_2, x_3) = \pi_1(\underline{x}, \underline{x}, \underline{x}) < \pi_1(\hat{x}, x_2, x_3) = \pi_1(\hat{x}, \hat{x}, \hat{x})$. Therefore, $\hat{x}$ weakly dominates all strategies $\underline{x} \in (\hat{x}, \bar{x}]$, where $\bar{x}$ is the highest extraction level.

Proof of proposition 4:

Consider the first case, i.e. $X \geqslant \alpha$. We show that $\pi_j < \pi^{\min}$ for each player $j \in \{1, 2, 3\}$. The case of player 1 has already been discussed, he always rejects. It is sufficient therefore to show that player 2 also rejects. Let us determine the sign of $\pi_2 - \pi^{\min}$. $\pi_2 - \pi^{\min} = \alpha\,(x_2 - x_1) - (x_2 X - 3x_1^2) = x_1(X^{\min} - \alpha) - x_2(X - \alpha) < 0$ because $x_1 < x_2$ and $X > X^{\min}$. Therefore player 2 always rejects. The same argument applies to player 3. We conclude that all players reject any subgame for which $X \geqslant \alpha$.

Consider now the case: $X < \alpha$. First, note that $\pi_3 > \pi_2$ if $x_3 > x_2$. Indeed, $\pi_3 - \pi_2 = (a - p)\,(x_3 - x_2) - bX(x_3 - x_2)$. Dividing by $b\,(x_3 - x_2)$ leads to $\alpha - X > 0$ which is satisfied by assumption. Since player 1 always disapproves, it suffices to consider player 2's decision. Player 2 approves if $\pi_2 - \pi^{\min} > 0$. $\pi_2 - \pi^{\min} = x_1(X^{\min} - \alpha) - x_2(X - \alpha) > 0 \Leftrightarrow x_2(\alpha - X) > x_1(\alpha - X^{\min})$.

Proof of proposition 5. Under the NASH DB, the disapproval benchmark is given by the vectors x^{NE} and π^{NE}. In stage 2, player i approves if and only if $\pi_i(x_i, x_{-i}) > \pi^*$. If any player j disapproves, the FA Nash payoff vector π^{NE} is implemented. Each player has therefore an incentive to choose x_i^a such that $\pi_i(x_i^a, x_{-i}^a) > \pi^*$. Since for any x_{-i}^a, choosing $x_i^a < x^*$ is Pareto-improving and is non-binding, each player i chooses his/her extraction level accordingly. Therefore, x^* is the upper-bound of the set of Pareto-improving extraction level. By symmetry of the payoff function, $x^{**} = \frac{x^*}{n}$,is the lower bound of the set of Pareto-improving extractions. It implies $x^{**} < x_i^a < x^*$, for all i.

Proof of proposition 6. Approval under the majority rule arises if a MWC approves. If the MWC contains all players, approval under the majority rule is consistent with approval under the unanimity rule. In both cases all members of the group receive a higher payoff than the $NASH$ DB payoff. Therefore, the predictions under the unanimity rule are exactly the same as under the majority rule when all players approve. However, under majority, additional sub-games are approved by a MWC that is smaller than n. Consider the interval $[\ x^*,\ \bar{x}_i)$ (a symmetric reasoning applies to the interval $(\underline{x}_i,\ x^*/n])$. Assume that there are two types of players, i and j, who propose to extract $x_i = \hat{x}$ and $x_j = x^*$, respectively. In other words, the j-types play Nash while the i-types choose optimum extraction. If the j-types belong to the MWC they approve the extraction vector while the i-types disapprove. This extraction vector is therefore an equilibrium under majority according to BEWDS. We conclude that under the NASH DB, the set of approved sub-games with unanimity is included in the set of approved sub-games under majority.

8 Appendix 2: Instructions

Welcome

We thank you for agreeing to participate in this decision-making experiment. This experiment will be paid. Your earnings will depend on your decisions as well as those of the other participants in this experiment. Your identity and decisions will be kept anonymous. You will have to indicate your choices on the computer in front of which you are seated, and the computer will notify your earnings (in points) as the experiment progresses.

From now until the end of the experiment we ask you to stop all communication. If you have any questions, please raise your hand, an instructor will answer you privately.

General procedure

At the beginning of the experiment you will be randomly assigned to a group of three players. The composition of your group remains unchanged until the end of the experiment. Each member of your group (including you) will have an ID 1 or 2 or 3.

The experiment is divided into 2 parts. Each part consists of a series of ten periods. The rest of the instructions concern only part 1. At the end of part 1, you will receive new specific instructions for part 2. At the end of the experiment, one of the 20 periods will be drawn and your earnings (in points) for that period will be converted into euros according to a rule defined at the end of the instructions.

Once all participants have read the instructions, an experimenter will read them out loud again. After reading the instructions, you will be asked to complete a questionnaire to verify your understanding of the experiment. When all participants have completed this questionnaire, the experiment will begin.

Types of investments

In each period, each player of your group has 10 tokens, which he has to split between two activities: activity A and activity B. Activity A is common to all the three players in your group. Activity B is specific to each player. Each token must be invested, either in activity A or in activity B. Earnings associated with your investment in each activity and the total earnings are described as follows.

Earnings activity A

Your earnings from activity A depend on your investment in activity A and the investment in the activity A of the other players in your group.

Earnings from the investment in activity B

Your earnings from activity B depend solely on your own investment in that activity. Each token invested in activity B earns you 15 points. Similarly, each token that the other player invests in his activity B earns him 15 points.

Total earnings

Your total earnings in each period are equal to your earnings from activity A + your earnings from activity B.
We present the different possibilities of total earnings. They are described in the earnings table (see sheet "Table of total earnings")(see figure **??**). The first column corresponds to your investment in

activity A (between 0 and 10). The other columns correspond to the sum of the investments of the other players in your group in activity A (between 0 and 20). Both your earnings and those of the other players are measured in points. Your own total earnings in points are displayed in each cell of the table. These values also apply to the other players in your group. For example, you are Player 1 and the other two players are Player 2 and Player 3. You decide to invest 8 tokens in activity A and therefore 2 tokens in your activity B. Player 2 decides to invest 6 tokens in activity A and therefore 4 tokens in his activity B. Player 3 decides to invest 7 tokens in activity A and therefore 3 tokens in his activity B. For player 1: His investment in activity A is 8 tokens and the sum of the investments of players 2 and 3 is 13. For player 2: His investment in activity A is 6 tokens and the sum of the investments of players 1 and 3 is 15. For player 3: His investment in activity A is 7 tokens and the sum of the investments of players 1 and 2 are 14 tokens. Your (Player 1) total earnings for the period are therefore 204 points. The total earnings for player 2 in your group are 190.5 points and the total earnings for player 3 in your group are 197.25 points.

Part 1

In each period, you must split your 10 tokens between your investment in activity A and your investment in your activity B. You are free to choose how you want to allocate your 10 tokens. For example, you can decide whether to allocate all your tokens in activity A or all your tokens in activity B.

In practice, the computer will ask you to indicate the number of tokens you want to invest in activity A. The rest of your 10 tokens will automatically be invested in your activity B. The sum of these two investments is exactly equal to your 10 tokens for this period. As a result, you cannot transfer a part or all of your tokens from one period to another.

You and the other players make your decisions simultaneously. Once the investment decisions have been made, the computer calculates your total earnings, as well as the earnings of the other players for the current period. It will tell you how many tokens you have invested in each of the two activities and your total earnings in points. The same information about the other the two other players will also be displayed on your screen. The next period can then begin. Before each new period, you will be informed about your total earnings from each of the previous periods. When the 10^{th} period will be over, the computer will summarize the amount of your earnings for each of the 10 periods.

Part 2 [AM treatments]

As in part 1, there are 10 periods in part 2 in which you will interact with the same persons as in part 1. You and the other players in your group must decide how much you will invest in activity A. The earnings in activity A and activity B are exactly the same as in part 1, so you will use the same "table of total earnings" as in part 1.

In part 2, each period consists of two stages: Stage 1 and Stage 2. Stage 1 corresponds to the investment decision: you and the other two players will each have to decide how much to invest in activity A. Stage 1 corresponds exactly to the same investment decision as in part 1. Stage 2 is new. Once the three members of your group have chosen their amount to invest in activity A, these decisions and their associated total earnings are published on the screens of all members (including yourself) and submitted for approval.

- [**unanimity rule:**] If all members of your group approve the proposed investment decisions, they will be applied and everyone will earn the corresponding earnings.
- [**majority rule**] If at least two of the three members in your group approve the proposed investment decisions, then these will apply and everyone will earn the corresponding returns.

In this case, the proposed investments are applied and everyone receives the corresponding total earnings. If at least one player [**unanimity rule**] or at least two of the three players [**majority rule**] in your group disapprove, the computer will apply an identical investment level as explained in the following instructions.

In practice, in stage 1, the computer will ask you to indicate the amount of your investment in activity A. In stage 2, the computer will tell you how many tokens you proposed for both activities and how many tokens the other players proposed in the current period. It will also tell you your total earning as well as the total earning of each other player. In addition, the computer will inform you about the minimum [**under the MIN DB**] of the proposed investments in activity A or 6 tokens [**under the NASH DB**] and the total associated earnings. Then, the computer will ask you whether you approve or reject the proposals from the other members of your group. You will click YES if you agree with the proposals, or NO if you disagree with the proposals. At the same time, the other players also have to approve or reject the proposals for the current period. As aforementioned, if they approve, the computer implements the proposals. Otherwise, it imposes a uniform level of investment in activity A :

- the minimum of proposals [**under MIN** DB]
- always 6 tokens [**under NASH** DB]

and the rest of the 10 tokens is invested in activity B. Then the computer will display the investments (tokens in activities A and B respectively) and the total earnings.

At the end of stage 2, the computer displays the final total earnings of each group member for that period. The next period can then start. Before each new period you will know your earnings for each of the previous periods. When the 10^{th} period is over, the computer will summarize the amount of your total earnings for each of the 10 periods.

The exchange rate is 1 euro for 15 points. One of the 20 periods will be randomly chosen to be paid out for real.

Part 2 [Baseline treatment]

As in part 1, there are 10 periods in part 2 in which you will interact with the same persons as in part 1. You and the other players in your group must decide how much you will invest in activity A. The earnings in activity A and activity B are exactly the same as in part 1, so you will use the same "table of total earnings" as in part 1.

You and the other players make your investment decisions simultaneously. Once the investment decisions have been made, the computer calculates your total earnings, as well as the earnings of the other players in your group for the current period. It will show you how many tokens you invested in each of the two activities and your total earnings in points. The same information about the other players will also be displayed on your screen. The next period can then begin. Before each new period, you know your total earnings from each of the previous periods. When the 10^{th} period is over, the computer will summarize the amount of your winnings for each of the 10 periods

The exchange rate is 1 euro for 15 points. One of the 20 periods is randomly drawn to be remunerated.

9 Appendix 3: Analysis of proposed extractions

Table 7: Overall regression results using proposed extractions

	Proposed extractions			
Variables	(1)	(2)	(3)	(4)
$Seq \times AM$	-2.556***	-2.777***	-3.377***	-2.341***
	(0.364)	(0.400)	(0.391)	(0.402)
$Seq \times AM \times MIN$		-0.436		-1.371***
		(0.335)		(0.376)
$Seq \times AM \times Maj$			1.770***	
			(0.334)	
$Seq \times AM \times MIN \times Maj$				2.119***
				(0.475)
$Constant$	19.37***	19.37***	19.37***	19.37***
	(0.254)	(0.254)	(0.250)	(0.253)
Seq	yes	yes	yes	yes
$Group - FE$	yes	yes	yes	yes
$Period - FE$	yes	yes	yes	yes
$Observations$	1,680	1,680	1,680	1,680
$R - squared$	0.313	0.314	0.326	0.323
F	13.15	12.31	15.11	13.97

Note: Robust standard errors are in parentheses. * denotes significance at the 10-percent level, ** at the 5-percent level and *** at the 1-percent level. The regressions contain Period fixed effect, groups fixed effect and effect of sequences (Seq). The first column shows the variables names. All variables are binary. Treatments MIN DB and Nash DB are pooled in AM. The variable Seq equals 1 for sequence 2 and 0 for sequence 1. $Seq \times AM$ is the interaction between the variables Seq and AM. $Seq \times AM$ is 1 for the CPR game with AM in sequence 2 and 0 otherwise. $Seq \times AM \times MIN$ is the interaction variable between $Seq \times AM$ and MIN, where MIN is 1 for groups submitted to the MIN DB and 0 otherwise. $Seq \times AM \times MIN$ exhibits the additional effect of the MIN DB on the approval mechanism ($Seq \times AM$) in the reduction of extraction. $Seq \times AM \times Maj$ is the interaction between $Seq \times AM$ and Maj, where Maj equals 1 when groups played under the NASH DB and the MIN DB with majority and 0 otherwise. $Seq \times AM \times Maj$ exhibits the additional effect of majority on the approval mechanism ($Seq \times AM$) in the reduction of extraction. We perform DiD regression using realized extractions.

Table 8: Impact of approval rules on proposed extractions (by disapproval benchmark)

Variables	Panel A : NASH DB (Unanimity vs Majority) (1)	(2)	Panel B : MIN DB (Unanimity vs Majority) (3)	(4)
$Seq \times AM$	-2.341***	-3.023***	-2.777***	-3.712***
	(0.402)	(0.464)	(0.400)	(0.435)
$Seq \times AM \times Maj$		1.405***		2.119***
		(0.475)		(0.476)
$Constant$	19.24***	19.24***	19.17***	19.17***
	(0.313)	(0.307)	(0.341)	(0.340)
Seq	yes	yes	yes	yes
$Group - FE$	yes	yes	yes	yes
$Period - FE$	yes	yes	yes	yes
$Observations$	1,000	1,000	980	980
$R - squared$	0.282	0.289	0.333	0.348
F	5.637	5.893	9.296	11.23

Note: Robust standard errors are in parentheses. $*$ denotes significance at the 10-percent level, $**$ at the 5-percent level and $***$ at the 1-percent level. The regressions contain Period fixed effect, groups fixed effect and effect of sequences (*Seq*). The first column shows the variables names. All variables are binary. Treatments NASH DB with majority and NASH DB with unanimity are pooled in AM of Panel A while treatments MIN DB with unanimity and MIN DB with majority are pooled in AM of Panel B. The variable *Seq* equals 1 for sequence 2 and 0 for sequence 1. $Seq \times AM$ is the interaction between the variables Seq and AM. $Seq \times AM$ is 1 for the CPR game with AM in sequence 2 and 0 otherwise. $Seq \times AM \times Maj$ is the interaction variable between $Seq \times AM$ and Maj, where Maj is 1 for groups submitted to the majority rule (NASH DB with majority for Panel A and MIN DB with unanimity for Panel B) and 0 otherwise. We perform DiD regression using proposed extractions.

Table 9: Effect of group approval on proposed extractions (by disapproval benchmark))

	Panel A : NASH DB (Unanimity vs Majority)			Panel B : MIN DB (Unanimity vs Majority)		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$Seq \times AM$	-2.917***	-2.875***	-2.876***	-3.840***	-3.577***	-3.579***
	(0.498)	(0.516)	(0.516)	(0.465)	(0.471)	(0.471)
$Seq \times AM \times Maj$	1.717***	1.609***	1.625***	2.311***	1.612***	1.621***
	(0.509)	(0.596)	(0.596)	(0.509)	(0.569)	(0.569)
$Seq \times AM \times Success_1$	-0.789**	-1.025*	-1.019*	0.0307	-1.251**	-1.242**
	(0.388)	(0.591)	(0.591)	(0.431)	(0.598)	(0.598)
$Seq \times AM \times Success_1 \times Maj$		0.367	0.668		2.562***	2.920***
		(0.784)	(0.813)		(0.890)	(0.944)
$Seq \times AM \times Success_1 \times MWC$			-0.925			-1.188
			(0.658)			(0.847)
$Constant$	19.38***	19.39***	19.40***	19.31***	19.35***	19.34***
	(0.306)	(0.306)	(0.306)	(0.341)	(0.337)	(0.338)
Seq	yes	yes	yes	yes	yes	yes
$Group-FE$	yes	yes	yes	yes	yes	yes
$Period-FE$	yes	yes	yes	yes	yes	yes
$Observations$	900	900	900	882	882	882
$R-squared$	0.310	0.310	0.311	0.364	0.371	0.372
F	7.026	6.904	6.602	11.87	11.54	10.85

Note: Robust standard errors are in parentheses. * denotes significance at the 10-percent level, ** at the 5-percent level and *** at the 1-percent level. The regressions contain Period fixed effect, groups fixed effect and effect of sequences (*Seq*). The first column shows the variables names. All variables are binary. Treatments NASH DB with majority and NASH DB with unanimity are pooled in AM of Panel A while treatments MIN DB with unanimity and MIN DB with majority are pooled in AM of Panel B. The variable Seq equals 1 for sequence 2 and 0 for sequence 1. $Seq \times AM$ is the interaction between the variables Seq and AM. $Seq \times AM$ is 1 for the CPR game with AM in sequence 2 and 0 otherwise. $Seq \times AM \times Success_1$ is the interaction variable between $Seq \times AM$ and $Success_1$, where $Success_1$ is 1 when the group approved unanimously (for unanimity rule) or mostly (for majority rule) in the previous period and 0 otherwise. $Seq \times AM \times Success_1 \times Maj$ is the interaction variable between $Success_1$ and Maj. Finally, $Seq \times AM \times Success_1 \times Maj \times MWC$ is the interaction variable between $Seq \times AM \times Success_1 \times Maj$ and MWC, where MWC equals 1 for 2/3 approval under majority rule and 0 otherwise. We perform DiD regression using proposed extractions.

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