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DISCUSSION PAPER

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**Abstract.** International climate negotiations have so far failed to produce ambitious climate cooperation. We combine laboratory experiments with simulations to investigate the performance of two negotiation design features to address this failure: The Paris Agreement's ratchet-up mechanism, which requires countries to gradually increase their ambition, and a new policy proposal to negotiate more frequently. We find that more frequent interactions allow subjects to build trust and cooperation more safely over time. Conversely, subjects in a ratchet-up design tend to become more cautious to protect themselves from free riders. Thus, more frequent revisions of commitments promote cooperation, but the ratchet-up design fails to achieve the same result.

**Keywords.** Climate change, climate negotiations, cooperation, laboratory experiments, simulations

**JEL.** C72, C91, C92, D02, H41, Q54

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## 1. Introduction

The initial commitments of the Paris Agreement on climate change fell substantially short of achieving the agreement's climate objective to limit global warming to well below 2°C (Lui and Raftery, 2021; Climate Action Tracker, 2023). To address this challenge, the Paris Agreement includes a number of mechanisms to increase ambition. One important example is the ratchet-up mechanism that requires countries to submit Nationally Determined Contributions (NDCs) every five years, with each new NDC being more ambitious than the previous one (UNFCCC, 2015, Article 4). However, in line with results in cooperation and behavioral research (Barrett and Dannenberg, 2016; MacKay et al., 2015; Schmidt and Ockenfels, 2021), the gap between the NDCs and the emissions reductions needed to meet the long-term goals remains substantial, so other proposals are being made to adapt and supplement the agreement. One recent proposal is to increase the frequency of interactions in climate negotiations (Carattini and Löschel, 2021; Reuters, 2021). However, little is known about the effectiveness of such climate negotiation design features. While they appear plausible at first glance, they may actually backfire, for instance if a ratchet-up mechanism leads countries to be more reluctant to commit to climate policies in the first place. Unfortunately, controlled evidence on counterfactual institutional changes in international climate policy is lacking. Therefore, in this study, we investigate the effectiveness of these two important negotiation design features in the context of the Paris Agreement by combining a simulation approach with causal evidence from a highly controlled laboratory setting.

Specifically, we investigate how the ratchet-up mechanism interacts with more frequent decisions in a canonical repeated cooperation game (Isaak and Walker, 1988; Ledyard, 1995). To test these two important design features, both independently and in interaction, we use a full factorial design that varies in two dimensions: Whether contributions must ratchet-up and the frequency with which contributions must be made. The ratcheting condition requires that each contribution to the public good must be at least as large as the contribution in the previous round. The frequency of interactions concerns whether participants with a given endowment contribute to the public good either in one or multiple decisions per round. As point of departure for hypotheses building, we use simulations that examine the interaction between the negotiation design features and robust behavioral patterns previously observed in empirical cooperation research – in particular, the willingness of some participants to conditionally cooperate (Fischbacher et al., 2011). This allows us to gain insight into potential behavioral responses to the negotiation design features and to derive testable predictions.

Our study contributes to an experimental literature that examines the impact of behavioral complexities and the institutional context on the level of cooperation in climate negotiations, such as the role of equity preferences (Dannenberg et al., 2010), probabilistic and ambiguous thresholds (Dannenberg et al., 2015), inequality and communication (Tavoni et al., 2014), and different negotiation foci (Schmidt and Ockenfels, 2021). We go beyond this literature by examining the role of incremental and irreversible contributions in the context of the climate dilemma. Schelling (1960) hypothesized that small, sequential, and contingent commitments can foster cooperation in negotiations. A subsequent theoretical literature on Schelling's hypothesis shows that more frequent interactions can indeed increase the provision of public goods, especially when incremental contributions are irreversible (Admati and Perry, 1991; Choi et al., 2008; Gale, 2001; Lockwood and Thomas, 2002; Marx and Matthews, 2000; Simon and Stinchcombe, 1989). Previous experimental studies have tended to confirm this prediction (Dorsey, 1992; Duffy et al., 2007; Kurzban et al., 2001). Also, two recent studies have shown that a ratchet-up mechanism may fail to increase cooperation in certain settings (Alt et al., 2023; Gallier and Sturm, 2021). Our simulations and laboratory data bring these different lines of research together, providing robust evidence for the benefits of more frequent commitments in laboratory climate bargaining settings with and without ratcheting, and allowing us to ground the very different interactions of institutional design and behavior in our treatments in the robust conditional cooperation pattern that is ubiquitous in cooperation games.

More specifically, our laboratory experiments show that while the ratchet-up mechanism is ineffective in promoting cooperation, more frequent commitments always lead to substantially higher cooperation. The simulations suggest an explanation, which the data confirm: With ratcheting, participants become more cautious, in order to protect themselves from becoming more vulnerable to exploitation in the future. More frequent interactions, on the other hand, reduce the vulnerability to exploitation, allowing participants to build trust and cooperation more safely over time.

## 2. Experimental design and procedure

Our laboratory experiment builds on a standard repeated public goods game. At the beginning of the experiment, participants are matched to groups of four, that stayed constant for all five rounds. In each round $t \in \{1, \ldots, 5\}$, we endow participant $i \in \{1, \ldots, 4\}$ with 100 ECUs ($w = 100$; 60 ECU = 1 Euro). Participants make $d \in \{1, \ldots, D\}$ contribution decisions per round. Each decision requires participants to decide how much of their endowment they want to contribute to the public good ($g_{i,t,d}$). Each member of the group receives a benefit of 0.5 ECU for each ECU contributed to the public good. At the end of each round, $i$'s cumulative contribution to the public good is given by $g_{i,t} = \sum_{d=1}^{D} g_{i,t,d}$ and the public good provision level amounts to $G_t = \sum_{j=1}^{4} g_{j,t}$. The payoff of participant $i$ is given by

$$\pi_{i,t} = w - g_{i,t} + 0.5 * G_t$$

For completely rational and purely self-interested participants, this is a social dilemma. Individual payoff maximization predicts $g_{i,t}^{*} = 0$ while the maximization of the group's payoff demands $g_{i,t}^{opt} = w$.

We implement four treatments in a 2x2 factorial design. We compare between two settings: A repeated public goods game in which participants make one contribution decision per round and a public goods game in which they make five contribution decisions per round. We implement both settings in two different contribution mechanisms, one standard voluntary contribution mechanism and one in which contributions cannot decrease over time.

In our baseline treatment (BASE 5x1), participants play the public goods game for five rounds ($t = 5$) with only one contribution decision ($d = 1$) per round. In each round, participants decide how much they want to contribute to the public good. Their contribution can range from zero to their initial endowment, i.e., $0 \leq g_{i,t} \leq w$. We have three more treatments. In BASE 5x5, participants play $t = 5$ rounds with $d = 5$ decisions per round. In each decision, participants decide upon their contribution to the public good. In the first decision ($d = 1$), their contribution can range from zero to their initial endowment, i.e., $0 \leq g_{i,t,1} \leq w$. From the second decision onwards ($d > 1$), participants' contribution can range between zero and their disposable endowment, i.e., $0 \leq g_{i,t,d} \leq w - \sum_{d=1}^{d-1} g_{i,t,d}$. In RAT 5x1, participants play $t = 5$ rounds with only $d = 1$ decision per round. Unlike in BASE 5x1, the ratchet-up mechanism applies. Each contribution per round must be at least as high as in the previous round, i.e., $0 \leq g_{i,t} \leq w$ in round $t = 1$ and $g_{i,t-1} \leq g_{i,t} \leq w$ for $t > 1$. In RAT 5x5, participants play $t = 5$ rounds with $d = 5$ decisions per round under the ratchet-up mechanism. In the first round ($t = 1$), the same conditions apply as in BASE 5x5, i.e., $0 \leq g_{i,t,1} \leq w$ for $d = 1$ and $0 \leq g_{i,t,d} \leq w - \sum_{d=1}^{d-1} g_{i,t,d}$ for $d > 1$. From the second round onwards ($t > 1$), participants' contribution in the first decision ($d = 1$) must be at least as high as the cumulative contribution in the previous round ($g_{i,t-1} \leq g_{i,t,1} \leq w$). From the second decision onwards ($d > 1$), contributions can range between zero and the disposable endowment, i.e., $0 \leq g_{i,t,d} \leq w - \sum_{d=1}^{d-1} g_{i,t,d}$.

The experiment was approved by the Institutional Review Board of the Faculty of Management, Economics and Social Science at the University of Cologne. We conducted 20 sessions, including a pilot, online via the Cologne Laboratory of Economic Research (CLER). We recruited students from CLER via ORSEE (Greiner, 2015) and programmed the experiment in oTree (Chen et al., 2016). We followed the protocol by Buso et al. (2021) to conduct our online visually monitored sessions and used a widely used web conferencing platform to moderate and monitor the sessions. The protocol guaranteed that the experimenter could talk publicly to all participants. While participants could communicate privately with the experimenter, they could not see or communicate with each other. At the beginning of each session, we informed participants about the general procedure. Participants then read on-screen instructions that explained the rules of the game.[1] If participants had questions, they could use a chat function implemented in the web conferencing platform. Sessions lasted around 60 minutes and we paid participants afterwards via bank transfer. The cumulative earnings ranged from 5.25 Euro to 18.60 Euro, with an average of 13.10 Euro. This included a show-up fee of 1 Euro.

A total of 368 participants took part in our experiment, all gave informed consent. By having 22 groups of four participants each for BASE 5x1 and RAT 5x1 and 24 groups each for BASE 5x5 and RAT 5x5, we reached a total of 92 independent observations. This allows us to detect frequency effects comparable to our prior at a conventional level of statistical significance (5%) at a very high level of statistical power (more than 87%, see Appendix A).

## 3. Simulation studies to derive predictions

We use a simulation approach to generate valid predictions about how the ratchet-up mechanism and more frequent interactions affect the provision of a public good. We apply simulations because the predictive and explanatory power of the standard theoretical model is limited in this context. While by the standard backwards induction arguments, rationality and selfish preferences imply no contributions to the public good in any round and in any of our treatments, it is, however well-established in the literature that cooperation can emerge, based on robust patterns of (conditional) cooperation observed in the laboratory (Chaudhuri, 2011; Fischbacher et al., 2001; Fischbacher and Gächter, 2010; Ledyard, 1995) and the field (Diederich and Göschl, 2018; List, 2011). In the literature, there are generally three robust behavioral patterns in cooperation games: (i) some agents selfishly defect, (ii) others are conditionally cooperative, i.e., willing to cooperate but only as long as others do, and (iii) initial cooperation is very heterogeneous (the heterogeneity can be interpreted as some agents are willing to lead by example and contribute more to the public good than others, especially initially; Eisenkopf and Kölpin, 2023; Gächter et al., 2012). Our simulation approach allows us

[1] Instructions are available from the authors upon request.

to study and predict how these patterns potentially interact with ratcheting and more frequent interactions in a public goods game.[2]

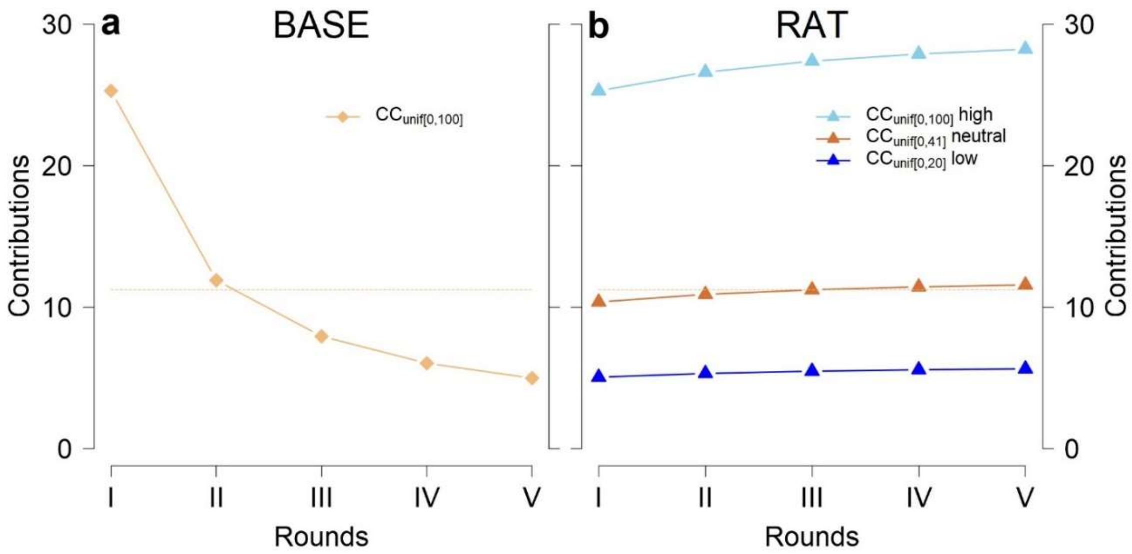
For our simulations, we randomly sample (with replacement) 1,000 groups of size $n = 4$ from a large population of artificial agents. The population consists of an equal number of agents who selfishly defect (DFs) and conditional cooperators (CCs). The simulations are based on a two-step procedure. In the first step, agents determine their contribution in the first interaction of the game. DFs do not contribute to the public good. CCs' initial contributions are uniformly distributed on the interval between 0 and an exogenously determined upper bound. In the second step, agents decide on their contributions as the game progresses. DFs continue to contribute nothing. CCs' contributions are based on the contributions of their group members in the previous interaction. They respond differently depending on whether they have been free ridden by their group members or have been free riding on their group members' contributions. Agents who contributed more than their group members reduce their contributions by a larger amount than agents who contributed less than their group members increase their contributions (Blanco et al., 2011; Nunnari and Pozzi, 2022).[3]

Based on these behavioral patterns, the simulation in Fig. 1a predicts a negative trend in cooperation levels in BASE 5x1, as indeed has been typically observed and previously predicted in such dilemma games (Fischbacher and Gächter, 2010). CCs reciprocate the behavior of other agents in the previous interaction, and they respond more strongly when being exploited than when being more selfish than others. Over time, this process compresses individual contributions and thus reduces the negative trend.

Fig. 1b summarizes the results of three different scenarios for the ratchet-up mechanism in the 5x1-setting with low, neutral, and high initial contributions. By design, in contrast to BASE, contributions in RAT cannot decrease over time, and they in fact tend to increase, driven by CCs with contributions below their other group members' contributions. The increase in contributions diminishes over time and eventually reaches a ceiling, because CCs' contributions are increasingly compressed over time and limited due to DFs' defections.

[2] Our approach follows several papers at the intersection between economic experiments and simulation studies. See, for example, Carpenter (2007), Duffy (2006), Fischbacher and Gächter (2010), Miller and Andreoni (1991), and Sethi and Somanathan (2003). For a general discussion of the complementarities between these two methods, see, e.g., Contini et al. (2006).
[3] See Appendix B for further details.

**Fig. 1. Predicting contributions in BASE 5x1 and RAT 5x1**



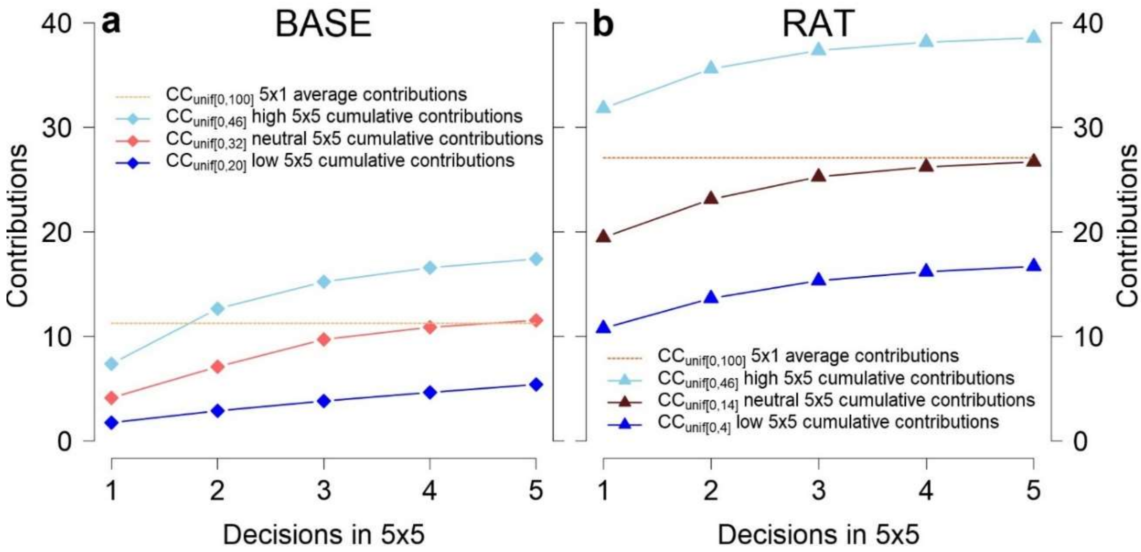

*Note*: Simulation results show predicted contributions per scenario in BASE (**a**) and RAT (**b**). $CC_{unif[0,\{100,41,20\}]}$: 50% defective types (DFs) and 50% conditionally cooperative types (CCs). DFs contribute zero. CCs' contributions in Round I are drawn from a uniform distribution in [0,{100,41,20}] ECU. The corresponding predicted contributions in Round I are equal to 0.5*0.5*{100,41,20} = {25,10.25,5} ECU. The horizontal dotted lines indicate the average of the predicted contributions for $CC_{unif[0,100]}$ in BASE 5x1 and $CC_{unif[0,41]}$ in RAT 5x1, respectively. See Appendix B for further details.

Whether ratcheting increases cooperation depends on initial cooperation rates in Round I, as illustrated by the three different scenarios in Fig. 1b. The neutral scenario is chosen such that it yields exactly the same total cooperation as BASE. This is the case when CCs in Round I cooperate approximately slightly less than half of their initial BASE cooperation. However, because ratcheting removes CCs' option to reciprocally decrease their contributions if others free-ride, the same total level of cooperation comes with greater vulnerability against exploitation. This is why we hypothesize that players initially tend to be more cautious and initially cooperate much less with ratcheting. So, while the precise level of the initial contributions is unknown and ratcheting may lead to more or less cooperation (as illustrated by the high or low scenario), our hypothesis is that the limited flexibility to respond to exploitation offsets the desired ratchet effect, or may even backfire.[4]

Next, we use our simulations to show how the possibility to make more frequent contributions can promote cooperation. Fig. 2a shows the predicted cumulative contributions for an average round (consisting of five decisions) in BASE 5x5. It is natural to expect that contributions in

[4] Only if the initial contributions in RAT 5x1 exceed the initial contributions in the neutral scenario (10.25 ECU), our simulations predict higher overall contributions in RAT 5x1 than in BASE 5x1 (11.2 ECU). Fig. 1b also shows that lower initial contributions in Round I lead to a smaller increase in contributions over rounds, because less initial variation limits the scope for increasing contributions by CCs.

**Fig. 2. Predicting contributions in BASE 5x5 and RAT 5x5**




*Note*: Simulation results show predicted contributions per scenario in BASE (**a**) and RAT (**b**). $CC_{unif[0,100]}$ 5x1 average of the predicted contributions in 5x1-settings (see Fig. 1). $CC_{unif[0,\{46,32,20,14,4\}]}$ 5x5 predicted cumulative contributions per decision across rounds for CCs' initial contribution in [0,{46,32,20,14,4}] ECU. See Appendix B for further details.

the 5x5-setting start below those in the first round of the 5x1-setting (Schelling, 1960). We propose three different scenarios, with low, neutral, and high initial contributions. The neutral scenario is chosen such that CCs' initial contributions in BASE 5x5 lead to the same total contributions as in BASE 5x1. More frequent commitments have a positive effect on total contributions, if the initial cooperation per decision in BASE 5x5 is higher than in neutral scenario, e.g., if the initial cooperation per decision is one fifth of the Round-I-level in BASE 5x1 (high scenario). We hypothesize that this is plausible in this treatment, because more frequent interactions allow players to more closely build trust and cooperation over time, thus reducing the vulnerability against exploitation.[5]

Fig. 2b shows the predicted average cumulative contributions per decision in RAT 5x5. Again, we use three different scenarios (low, neutral, high) for different initial contributions. If the initial cooperation is relatively low, below the neutral scenario, cumulative contributions in RAT 5x5 do not reach the average contributions in RAT 5x1.[6] If, however, the initial

[5] Only if the initial contributions per decision in BASE 5x5 are higher than those in the neutral scenario (4.1 ECU), our simulations predict that the cumulative contributions in BASE 5x5 exceed the average contributions in BASE 5x1 (11.2 ECU). In all scenarios, the average cumulative contributions increase, but the increase depends on the initial contributions. The lower the level and thus the variation of the initial contribution, the lower the increase in cumulative contributions.

[6] Only if the initial contributions per decision in RAT 5x5 are higher than those in the neutral scenario (19.5 ECU), our simulations predict that the cumulative contributions in RAT 5x5 exceed the average contributions in RAT

contributions per decision in Round I are relatively large, above the neutral scenario, cumulative contributions in RAT 5x5 exceed the average contributions in RAT 5x1, for instance, in the high scenario where the initial contributions per decision in Round I are one fifth of the initial RAT 5x1 cooperation. Again, the latter effect appears to be more plausible as more frequent interactions reduce the vulnerability against exploitation. Similar to the 5x1-setting, the downward momentum of the contributions per decision in BASE 5x5 and the upward momentum of the cumulative contributions per decision in RAT 5x5 tend to decrease over time.

To summarize, our simulations show that the initial contribution levels determine the relative performance of the 5x5-settings. Since the initial contributions are ex-ante unknown, it remains an empirical question how the possibility to make more frequent commitments will affect public good provision levels. That said, we hypothesize that ratcheting is less powerful, or even backfires, when promoting cooperation than more frequent interactions. The reason is that analogous behavior to BASE increases the scope of being exploited with ratcheting, but reduces this scope with more frequent interactions.

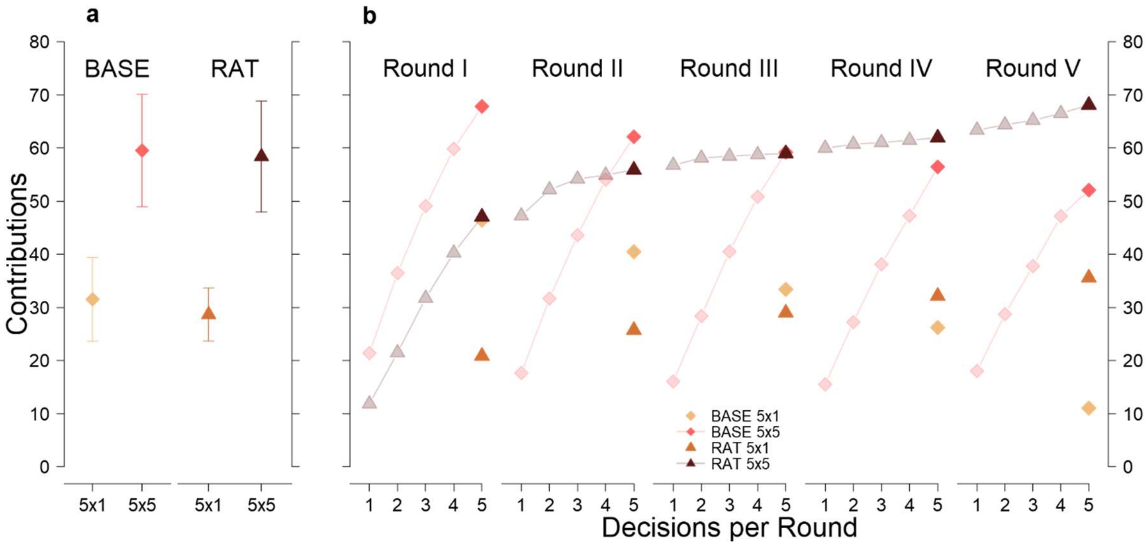
## 4. Laboratory results

To estimate the overall effects of our treatment interventions, we aggregate observations across all five rounds of the experiment. Fig. 3a shows, in line with our prediction, that overall public good provision levels are significantly higher when there are more frequent interactions, both in BASE and RAT. In BASE, contributions to the public good in the 5x5-setting (59.5) are almost twice as high as in the 5x1-setting (31.5; $P < 0.001$; Appendix C, Table C1). Similarly, with ratcheting, contributions to the public good increase from 28.7 in the 5x1-setting to 58.4 in the 5x5-setting ($P < 0.001$; Appendix C, Table C1). The ratchet-up mechanism, in contrast, does not promote cooperation. The difference between BASE and RAT is not statistically significantly different from zero, neither in the 5x1-setting (31.5 vs. 28.7, $P = 0.535$; Appendix C, Table C1) nor in the 5x5-setting (59.5 vs. 58.4, $P = 0.877$; Appendix C, Table C1).

Next, we extend the analysis by investigating the trends in contributions to the public good over the course of the experiment. Fig. 3b displays groups' average contributions to the public good per treatment, round, and decision. Contributions in BASE 5x1 are very similar to previous results in voluntary contribution experiments (Ledyard, 1995; Fischbacher and Gächter, 2010;

5x1 (27.1 ECU). As in the 5x1-setting, a lower contribution in the first decision of Round I is equivalent to less initial variation and leads to a smaller increase in cumulative contributions over decisions.

**Fig. 3. Overall contributions to the public good**



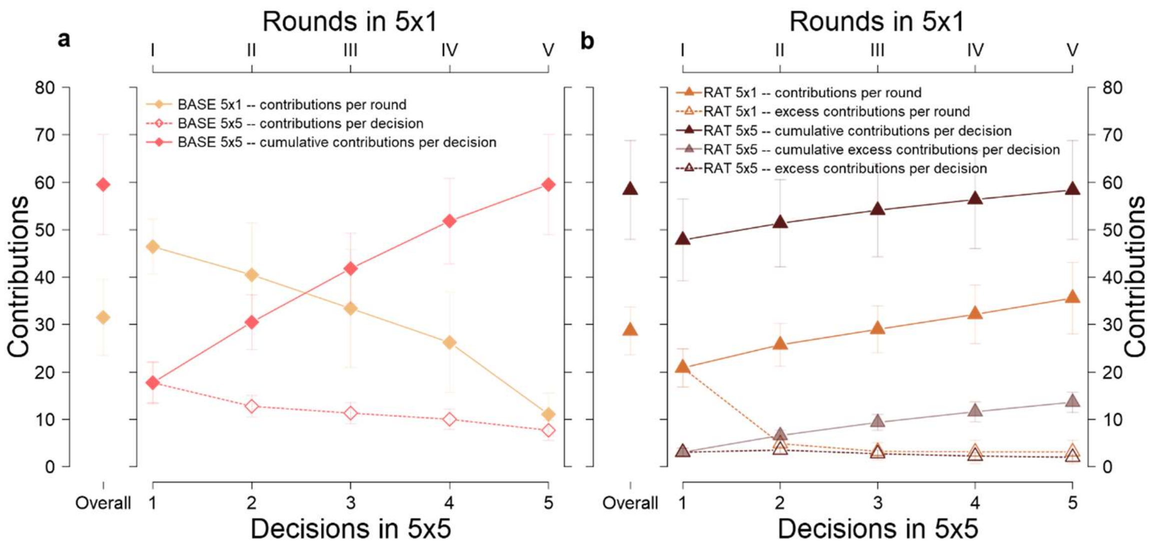

*Note*: All results are based on $n = 368$ subjects participating in groups of four and randomly assigned to treatments: $n_{BASE\ 5x1} = 88$, $n_{BASE\ 5x5} = 96$, $n_{RAT\ 5x1} = 88$, and $n_{RAT\ 5x5} = 96$. We use groups' average contribution to the public good as unit of observation. **a**, overall contributions by contribution mechanism (BASE vs. RAT) and setting (5x1 vs. 5x5), measured by the average of groups' contributions from all five rounds of the experiment. We report 90% confidence intervals based on robust estimates for the standard errors (Appendix C, Table C1). **b**, in 5x1-settings, groups' contributions per round by contribution mechanism. In 5x5-settings, groups' cumulative contributions per decision and round by contribution mechanism. We report 90% confidence intervals based on robust estimates for the standard errors (Appendix C, Table C2 – Model 1 and 2).

Chaudhuri, 2011), both in terms of the average level of the public good provision and the pattern across rounds. On average, participants contribute 31.5 to the public good. Furthermore, contributions decrease from 46.4 in Round I to 11.1 in Round V (P < 0.001; Appendix C, Table C2 – Model 1).

Contributions to the public good in Round I of RAT 5x1 are significantly lower than those in BASE 5x1 (20.9 vs. 46.4, P < 0.001; Appendix C, Table C2 – Model 1). Even though contributions in RAT 5x1 increase from round to round and are significantly higher than those in BASE 5x1 in Round V (11.1 vs. 35.6, P < 0.001; Appendix C, Table C2 – Model 1), the opposing trends are not strong enough to compensate for the initial loss of cooperation due to more cautious initial contributions.

Contributions in the 5x5-settings show very similar patterns, but at a much higher level. In BASE 5x5, cumulative contributions decrease from 67.8 in Round I to 52.1 in Round V (P = 0.031; Appendix C, Table C2 – Model 2). Again, as predicted, with ratcheting, the contributions in Round I of RAT 5x5 are significantly lower than those in BASE 5x5 (47.1 vs. 67.8, P = 0.003; Appendix C, Table C2 – Model 2). Even though the cumulative contributions in RAT 5x5 increase to 68.1 in Round V, which clearly exceed the provision level

**Fig. 4. Contributions to the public good per round and decision**




*Note*: **a**, we use groups' contributions per round and decision as unit of observation in BASE 5x1 and BASE 5x5, respectively. In BASE 5x1, we use groups' contributions per round. In BASE 5x5, we use the average of groups' contributions in a given decision from all five rounds of the experiment. Moreover, we differentiate between the actual and the cumulative contributions per decision. We report 90% confidence intervals based on robust estimates for the standard errors (Appendix C, Table C3 – Model 1). **b**, we use groups' contributions per round as unit of observation in RAT 5x1. In addition, we show the excess contributions, i.e., groups' contributions above the required minimum. In RAT 5x5, we use the average of groups' cumulative contributions in a given decision from all five rounds as unit of observation. We also disentangle the cumulative contributions into the excess contributions and the cumulative excess contributions per decision. We report 90% confidence intervals based on robust estimates for the standard errors (Appendix C, Table C3 – Model 2).

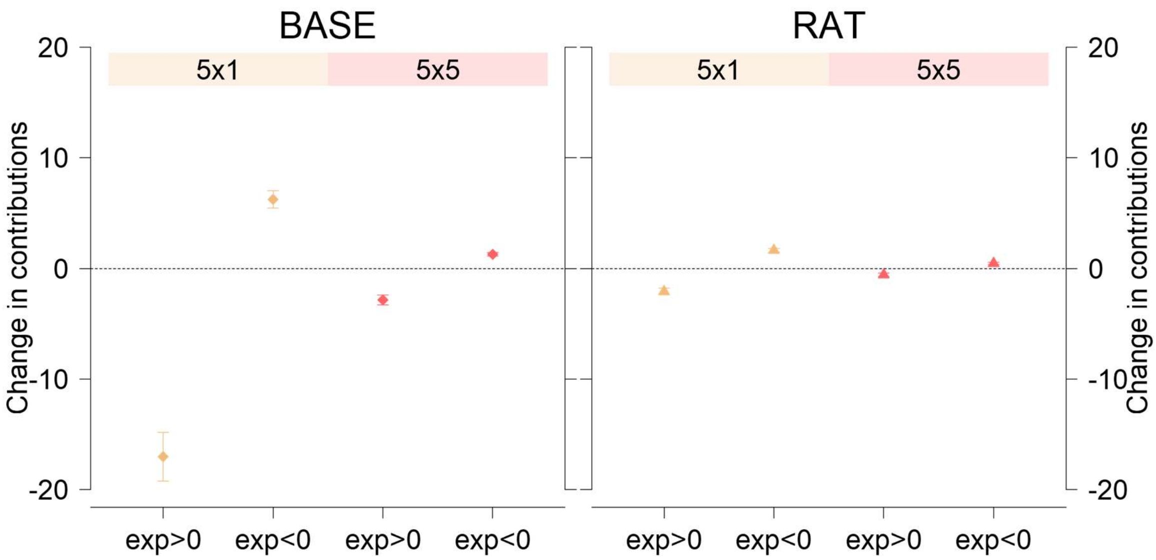
of 52.1 in BASE 5x5 (P = 0.037; Appendix C, Table C2 – Model 2), the difference in average cumulative contributions between BASE 5x5 and RAT 5x5 is not statistically significantly different from zero (59.5 vs. 58.4, P = 0.877; Appendix C, Table C1).

Participants cooperate more when they can make many small contribution decisions, rather than a few large ones. Fig. 4a shows that contributions to the public good start relatively low in the first decision of BASE 5x5. Compared to the contributions in the first round in BASE 5x1, participants contribute significantly less in the first decision of an average round in BASE 5x5 (46.4 vs. 17.7, P < 0.001; Appendix C, Table C3 – Model 1). However, the decline in contributions across decisions in the 5x5-setting is much less pronounced than the decline in contributions across rounds in the 5x1-setting (P < 0.001; Appendix C, Table C3 – Model 2). While contributions in BASE 5x1 decrease from 46.4 in Round I to 11.1 in Round V, contributions in BASE 5x5 decrease from 17.7 in Decision 1 to 7.7 in Decision 5. As a result, the cumulative contributions in the last decision of an average round in BASE 5x5 clearly exceed the average contributions per round in BASE 5x1 (59.5 vs. 31.5, P < 0.001; Appendix C, Table C1).

To ease interpretation of the results under the ratchet-up mechanism, we decompose the contributions in our ratcheting treatments into the required minimum contributions, which are equal to the contributions in the previous interaction, and the excess contributions, i.e., the contributions that exceed the minimum contributions. Fig. 4b shows that the excess contributions in the first decision of an average round in RAT 5x5 are substantially lower than the excess contributions in the first round of RAT 5x1 (3.1 vs. 20.9, $P < 0.001$; Appendix C, Table C3 – Model 3). While the excess contributions decline sharply over rounds in RAT 5x1, they decline significantly less over decisions in RAT 5x5 ($P < 0.001$; Appendix C, Table C3 – Model 4). Consequently, the cumulative excess contributions in Decision 5 of an average round in RAT 5x5 are significantly higher than the average excess contributions in RAT 5x1 (13.6 vs. 7.1, $P < 0.001$; Appendix C, Table C3 – Model 6). This explains that the cumulative contributions at the end of an average round in RAT 5x5 are significantly higher than the average contributions in RAT 5x1 (59.5 vs. 28.7, $P < 0.001$; Appendix C, Table C1).

The reason why the level of contributions to the public good in the 5x5-setting exceeds that in the 5x1-setting, both in BASE and RAT, is shown in Fig. 4: Contributions start relatively low in the first decision of the 5x5-settings, but they hardly decline from decision to decision. Thus, the cumulative contributions at the end of an average round in the 5x5-settings are higher than the average contributions in the corresponding 5x1-settings. This confirms the notion that more frequent interactions allow subjects to build trust more successfully when they have more opportunities to do so. Indeed, one measure of successful trust is the degree of exploitation, measured as the difference between participants' contributions to the public good and the average of the other group members' contributions. While a level of exploitation greater than zero implies that the participant has been free ridden by her group members, a level of exploitation less than zero means that she was free riding on her group members' contributions. Appendix D, Fig. D1 shows that in the 5x1-settings participants have more reason to be concerned about exploitation than in the 5x5-settings. The level of exploitation in the 5x1-settings is much greater than in the 5x5-settings. In BASE, the interquartile range is 35 in the 5x1-setting and 5.83 in the 5x5-setting. In RAT, the range between the 3rd and the 1st quantile is 30.33 and 3.58 in the 5x1- and 5x5-setting, respectively. In this sense, it is safer to cooperate in 5x5-settings. One further result, summarized in Fig. 5, reveals important heterogeneities in the effect of exploitation: We find that the drop in contributions after being exploited clearly exceeds the lift in contributions after exploiting the other group members. To estimate the total effect of exploitation, we combine the level of exploitation with the marginal effect of

**Fig. 5. Total effect of exploitation by mechanism and setting**




*Note*: **a**, shows the total effect of exploitation on participants' contributions to the public good in BASE 5x1 and BASE 5x5. **b**, shows the total effect of exploitation on participants' excess contributions in RAT 5x1 and RAT 5x5. The total effect of exploitation is given by the product of the level of exploitation (see Appendix D, Fig. D1) and the marginal effect of exploitation (see Appendix C, Table C4). Across the contribution mechanisms and settings, we separately report the effects for participants who have been free ridden by their group members (exp>0) and those who have been free riding on their group members' contributions (exp<0).

exploitation. In this way, we create a uniform measure that combines the average level of exploitation with the marginal effect of exploitation. Consistent with the empirical evidence that many subjects are conditional cooperators who are willing to cooperate if others cooperate as well (Fischbacher et al., 2001; Fischbacher and Gächter, 2010), we find that participants' contributions in a given interaction depend on their group members' contributions in the previous interaction of the experiment. More precisely, participants who have been free ridden by their other group members in a given interaction reduce their contributions to the public good in the subsequent interaction. In contrast, those participants who have been free riding on their group members' contributions, follow their group members and contribute more in the subsequent interaction. Most importantly Fig. 5 shows two important heterogeneities: First, we find that the drop in contributions after being exploited clearly exceeds the lift in contributions after exploiting the other group members. For example, in BASE 5x1, participants who have been free ridden by their group members reduce their contributions in the subsequent round by 17.2. In contrast, those participants who have been free riding on their group members' contributions, increase their contributions by on average 6.2. This is in line with the literature showing that participants suffer more from disadvantageous than advantageous inequality (Blanco et al., 2011; Nunnari and Pozzi, 2022). Second, the effects are more pronounced in BASE than in RAT.

## 5. Conclusions

Addressing climate change is a collective challenge that hinges on cooperation. Trust is the key to such cooperation, and it largely relies on reciprocity (Fehr and Gächter, 2000; MacKay et al., 2015). Thus, embedding reciprocity within climate negotiations is critical. In this context, we investigate two mechanisms underpinning the Paris Agreement—ratcheting and increased frequency of commitments. Our question cannot be answered by field studies. Instead, we employ simulations anchored in established patterns of (conditional) cooperative behavior to guide our thinking and to produce predictions, and corroborate these with laboratory experiments.

Our findings reveal that ratchet-up mechanisms, perhaps contrary to expectations, do not promote cooperation in our setting. Instead, they heighten the risk of exploitation, deterring trust and cooperation. Conversely, increasing the frequency of commitments promotes cooperation. This design feature diminishes the fear of exploitation, allowing trust to emerge. The fundamental reason is that, as hypothesized by Elinor Ostrom and her colleagues in Poteete et al. (2010, p. 227), "[…] *trust and reciprocity are mutually reinforcing.* […] *a decrease in either can generate a downward cascade leading to little or no cooperation* […]". More frequent interactions allow trust to evolve more safely, which in turn, escalate ambition and cooperation. Our analysis thus suggests that the recent intended policy shift towards more frequent interactions in the context of the Paris climate agreement is a strategic advance.

Further research should explore additional behavioral mechanisms that could reinforce trust and reciprocity. Changing the framing of climate negotiations from a distributive carbon budget to a cooperation framework could mitigate the adversarial dynamics of zero-sum scenarios. Moreover, the empirical literature suggests that reciprocal cooperation is unlikely to robustly arise within large, heterogeneous groups. A phased strategy, perhaps initiating with a "climate club" (Nordhaus, 2015) or strategic bilateral partnerships, may be an effective complement in fostering an environment of safe trust and reciprocity, not much unlike a strategy of more frequent interactions can foster such an environment. Reciprocity may also be strengthened by a shared understanding of mutual expectations. While such an understanding may not be necessary in symmetric laboratory dilemma games, where norms of fairness occur naturally, explicit agreements on contributions in asymmetric environments may be useful to crystallize these expectations, guiding complex negotiations towards a common goal. We leave such questions to further research.

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## Appendix

**Appendix A** explains the details of our sample size calculation in Section 2 of the main body of the text.

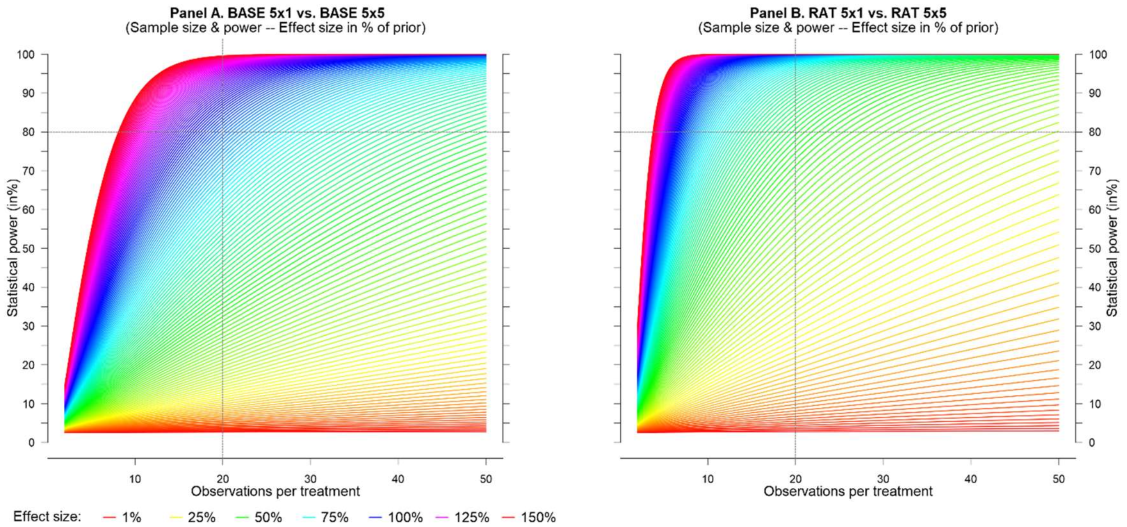
**Appendix B** describes the technical details of our simulation approach in Section 3 of the main body of the text.

**Appendix C** contains the details of the statistical analysis in Section 4 of the main body of the text.

**Appendix D** contains additional figures that complement the analysis in Section 4 of the main body of the text.

## Appendix A: Sample Size Calculations

### Fig. A1. Power analyses 5x1- vs. 5x5-settings




*Note*: Panel **A** (**B**) shows the power curves in BASE (RAT). For each contribution mechanism we simulate a variety of different potential frequency effects ranging from 1% to 150% of our prior.

In order to determine the sample size, we conducted a series of power analyses performed in R (R Core Team, 2018[7]) using the pwr package (Champely, 2018[8]). We base all our power calculations on two-sided t-tests of means per treatment with independent samples. To derive a clear prior for the true effect sizes, we use the data from the first two sessions per treatment. Based on this, we simulated a variety of potential effects sizes for the frequency effect ranging from 1% to 150% of our prior – the difference between participants' contributions in BASE 5x1 vs. BASE 5x5 (**Fig. A1 – Panel A**) and RAT 5x1 vs. RAT 5x5 (**Fig. A1 – Panel B**). The power analyses reveal a required minimum of 20 independent observations per treatment to detect frequency effects between BASE 5x1 and BASE 5x5 as well as RAT 5x1 and RAT 5x5 comparable to our priors at conventional levels of statistical significance (5%) and high levels of statistical power of more than 87% and 99%, respectively. In addition, our power calculations reveal that our priors for the true effect sizes for the differences between BASE and RAT are so small that it is highly unlikely to detect a positive effect of the ratchet-up mechanism at conventional levels of statistical inference, both in the 5x1- and 5x5-settings. This is in line

[7] R Core Team, 2018. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/. Accessed 8 August 2024.
[8] Champely, S., 2018. pwr: Basic Functions for Power Analysis. R package version 1.2-2. https://CRAN.R-project.org/package=pwr. Accessed 8 August 2024.

with previous experiments that find that the mechanism fails to promote cooperation (Alt et al., 2023[9]; Gallier and Sturm, 2021[10]).

**Appendix B: Simulation Studies**

**Sampling.** We randomly sample (with replacement) 1,000 groups of size $n = 4$ from a large population of artificial agents. The population consists of 50% defectors (DFs) and 50% conditional cooperative agents (CCs).

**5x1-settings.** In a first step, agent $i$ determines her contribution in the first round of the game (Round I): $g_{i,I}$. DFs contribute zero. CCs' initial contributions are drawn from a uniform distribution in $[0, k * 100]$ ECU where $0 < k \leq 1$. $k$ scales CCs' initial contributions in different scenarios. In a second step, agent $i$ decides on her contributions from the second round (Round II) onwards. DFs continue to contribute zero. CCs' contributions depend on their group members' contributions in the previous round where $g_{i,II} = \beta \bar{g}_{-i,I} + (1 - \beta) g_{i,I}$ with $\beta = 0.5$ if $g_{i,I} \leq \bar{g}_{-i,I}$, $\beta = 1$ if $g_{i,I} > \bar{g}_{-i,I}$, and $\bar{g}_{-i,I}$ is the average contribution of the other group members in Round I. On the one hand, this implies that agents who contributed more than their group members in Round I, reduce their contributions in Round II. On the other hand, agents who contributed less than their group members, increase their contributions. Moreover, agents who have contributed more than their group members reduce their contributions by a greater amount than agents who have contributed less than their group members increase their contributions. In RAT 5x1, an additional restriction applies. Here each contribution must be at least as high as in the previous round, i.e., $g_{i,II} \geq g_{i,I}$. This sequential process continues from round to round until the end of the game at the end of Round V.

**5x5-settings.** In a first step, agent $i$ determines her contribution in the first interaction of the game (Decision 1 in Round I): $g_{i,I,1}$. DFs contribute zero. CCs' initial contributions are drawn from a uniform distribution in $[0, k * 100]$ ECU where $0 < k \leq 1$. $k$ scales CCs' initial contributions in different scenarios and links contributions from round to round. In a second step, agent $i$ decides on her contributions from the second decision (Decision 2) in Round I onwards. DFs continue to contribute zero. CCs' contributions in Decision 2 of Round I are given by $g_{i,I,2} = \beta \bar{g}_{-i,I,1} + (1 - \beta) g_{i,I,1}$ where $\beta = 0.5$ if $g_{i,I,1} \leq \bar{g}_{-i,I,1}$, $\beta = 1$ if $g_{i,I,1} > \bar{g}_{-i,I,1}$ and $\bar{g}_{-i,I,1}$ is the others' average contribution in Decision 1 in Round I. This sequential

[9] Alt, M., Gallier, C., Kesternich, M., Sturm, B., 2023. Collective Minimum Contributions to Counteract the Ratchet Effect in the Voluntary Provision of Public Goods. J. Environ. Econ. and Manag. 122, 102895.

[10] Gallier, C., Sturm, B., 2021. The Ratchet Effect in Social Dilemmas. J. Econ. Behav. Organ. 186, 251–268.

process continues from decision to decision until the end of the fifth decision of Round I. Then agents determine their contributions in the first decision of Round II. DFs continue to contribute zero. CCs base their contributions on the cumulative contribution in Round I where $g_{i,I} = \sum_{t=1}^{5} g_{i,I,t}$ is agent $i$'s cumulative contribution in Round I. For CCs, the sequential process implies a benchmark for the cumulative contributions in Round II of $g_{i,II\ benc} = \beta\bar{g}_{-i,I} + (1-\beta)g_{i,I}$ where $\bar{g}_{-i,I}$ is the others' average cumulative contribution in Round I. CCs' contributions in the first interaction of Round II (Decision 1 in Round II) are then $g_{i,II,1} = kg_{i,II\ bench}$. In RAT 5x5, also the ratchet-up mechanism applies such that each contribution in the first decision of a given round must be at least as high as the cumulative contribution in the previous round, i.e., $g_{i,II,1} \geq g_{i,I}$ holds. This sequential process continues from round to round until the end of the game at the end of Round V.

**Scenarios.** For the high scenario in RAT 5x1 ($CC_{unif[0,100]}$, $k = 1$), the initial contribution in Round I in RAT 5x1 is the same as in BASE 5x1. For the neutral scenario in RAT 5x1 ($CC_{unif[0,41]}$, $k = 0.41$), the initial contribution in Round I is equal to the average of the contributions across all five rounds in BASE 5x1. For the low scenario in RAT 5x1 ($CC_{unif[0,20]}$, $k = 0.2$), the initial contribution in Round I is equal to the contribution in Round V in BASE 5x1. For the high scenarios in the 5x5-settings ($CC_{unif[0,46]}$ for BASE 5x5 and RAT 5x5, $k = 0.46$), the cumulative contribution in Round I is equal to the contribution in Round I in the corresponding 5x1-setting. Thereby, this cumulative contribution is allocated across all five decisions such that on average per decision one fifth of the Round I contribution in the 5x1-setting is realized. For the neutral scenarios in the 5x5-settings ($CC_{unif[0,32]}$ for BASE 5x5 and $CC_{unif[0,14]}$ for RAT 5x5, $k = 0.32$ and $k = 0.14$), the initial contribution in Round I guarantees that the cumulative contributions in the 5x5-settings reach exactly the average contributions in BASE 5x1 and the high scenario in RAT 5x1, respectively. For the low scenarios in the 5x5-settings ($CC_{unif[0,20]}$ for BASE 5x5 and $CC_{unif[0,4]}$ for RAT 5x5, $k = 0.2$ and $k = 0.04$), the initial contribution in Round I is chosen such that the cumulative contributions in the 5x5-settings are below the average contributions in BASE 5x1 and the high scenario in RAT 5x1, respectively.

## Appendix C: Statistical analysis

In **Table C1**, we estimate the overall effects of our treatment interventions by aggregating observations across all five rounds of the experiment. At this most aggregate level, we have one independent observation for each of the 92 groups in the experiment. In the 5x1-settings, we use the average of groups' contributions from all five rounds as dependent variable. In the 5x5-settings, we use the average of groups' cumulative contributions from the fifth decision of each of the five rounds as dependent variable.

**Table C1. Overall treatment effects**

| | Dependent variable: Contributions |
|---|---|
| BASE 5x5 | 28.013*** |
| | (6.494) |
| RAT 5x1 | -2.857 |
| | (4.588) |
| RAT 5x5 | 26.872*** |
| | (6.441) |
| Constant | 31.516*** |
| | (3.873) |
| Observations | 92 |
| $R^2$ | 0.319 |
| Adjusted $R^2$ | 0.296 |

*Note*: OLS regression. Robust standard errors in parentheses. As explanatory variables, we use the following indicator variables for the different treatments. BASE 5x5: indicator for the BASE 5x5 treatment; RAT 5x1: indicator for the RAT 5x1 treatment; RAT 5x5: indicator for the RAT 5x5 treatment. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

In **Table C2**, we extend the analysis in **Table C1** by investigating the trends in public good contributions over the course of the experiment. To explore trends, we use groups' average contributions per round as dependent variable. Thus, we have five observations for each of the 92 groups in our experiment and 460 observations in total. We split the analyses and study groups in the 5x1-settings (Model 1 with 220 observations) and the 5x5-settings (Model 2 with 240 observations) separately. In Model 1, we use groups' contributions per round as dependent variable. The dependent variable in Model 2 captures groups' cumulative contributions in the fifth decision of each of the five rounds. In both models, we use indicator variables for the ratchet-up mechanism and the different rounds of the experiment as explanatory variables. To capture potentially different trends in the different contribution mechanisms, we also include the interaction between our treatment variable and the different rounds of the experiment.

**Table C2. Contributions over time**

| | Dependent Variable: Contributions | |
|---|---|---|
| | 5x1 | 5x5 |
| | (1) | (2) |
| RAT | -25.580*** | -20.771*** |
| | (3.469) | (6.897) |
| Round II | -5.955 | -5.708 |
| | (6.117) | (7.839) |
| Round III | -13.034* | -8.635 |
| | (6.760) | (7.709) |
| Round IV | -20.216*** | -11.375 |
| | (5.935) | (7.907) |
| Round V | -35.375*** | -15.750** |
| | (3.611) | (7.244) |
| RAT x Round II | 10.830 | 14.542 |
| | (6.805) | (10.871) |
| RAT x Round III | 21.170*** | 20.552* |
| | (7.451) | (10.728) |
| RAT x Round IV | 31.511*** | 26.260** |
| | (6.959) | (10.806) |
| RAT x Round V | 50.102*** | 36.792*** |
| | (5.544) | (10.292) |
| Constant | 46.432*** | 67.823*** |
| | (2.851) | (4.682) |
| Observations | 220 | 240 |
| $R^2$ | 0.221 | 0.049 |
| Adjusted $R^2$ | 0.187 | 0.012 |

*Note*: OLS regressions. Robust standard errors in parentheses. We analyze groups in the 5x1-settings (Model 1) and the 5x5-settings (Model 2) separately. As explanatory variables, we use the following indicator variables for the different contribution mechanisms and rounds of the experiment: RAT: indicator for RAT 5x1 and RAT 5x5 treatment; Round I to V: indicator for Round I to V. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

In **Table C3**, we explore the differences in public good contributions between the 5x1- and 5x5-settings in more detail. We compare contributions per round in the 5x1-settings to the cumulative contributions per decision in the 5x5-settings. As in **Table C2**, we separately analyze the data for groups in the voluntary contribution mechanism (BASE 5x1 and BASE 5x5; Model 1-2) and the ratchet-up mechanism (RAT 5x1 and RAT 5x5; Model 3-6). In Model 1-2, we use groups' contributions per round as dependent variable for groups in BASE 5x1. For groups in BASE 5x5, we use groups' cumulative contributions per decision as dependent variable. To derive the cumulative contributions per decision, we calculate the average of groups' cumulative contributions in a given decision from all five rounds of the experiment. We have 230 independent observations each for groups in the voluntary contribution mechanism and the ratchet-up mechanism. To ease the interpretation of the results under the ratchet-up mechanism, we decompose groups' contributions to the public good into the required minimum contributions, which are equal to the contributions in the previous round, and the excess contributions, i.e., the difference between the actual contributions and the required minimum contributions. In Model 3-4, we use groups' excess contributions as dependent variable. In RAT 5x1, we use groups' excess contributions per round as dependent variable. In RAT 5x5, we use the average of the cumulative excess contributions in a given decision from all five rounds as dependent variable. In Model 5, we focus on groups' cumulative excess contributions. For groups in RAT 5x1, we continue to use groups' excess contributions per round as dependent variable. For groups in RAT 5x5, we use the cumulative excess contributions as dependent variable. This variable captures the average of the sum of the excess contributions up to a given decision from all five rounds of the experiment. In Model 6, we aggregate the observations across all five rounds of the experiment. Here, we have in total 46 independent observations, one observation for each group in RAT 5x1 and RAT 5x5. As explanatory variables, we use an indicator variable for the 5x5-settings in all models. Furthermore, we use a set of indicator variables to capture the number of interactions in the experiment. In the 5x1-settings, this refers to one indicator for each of the five rounds of the experiment. In the 5x5-settings, this captures the five decisions per round. To measure the trends in contribution mechanisms across interactions, we also include a continuous measurement. Finally, we interact the contribution mechanisms with the number of interactions, to identify potentially different trends.

**Table C3. Contributions in the 5x1- vs. 5x5-settings**

| | BASE | | RAT | | | |
|---|---|---|---|---|---|---|
| | Dependent variable: | | Dependent variable: | | | |
| | Contributions | | Excess contributions | | Cumulative excess contributions | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 5x5 | -28.698*** | -38.269*** | -17.784*** | -14.340*** | -17.784*** | 6.503*** |
| | (3.564) | (4.344) | (2.022) | (2.212) | (2.022) | (1.290) |
| Interactions | | -8.501*** | | -3.656*** | | |
| | | (1.058) | | (0.597) | | |
| Interaction 2 | -5.955 | | -15.977*** | | -15.977*** | |
| | (6.117) | | (2.167) | | (2.167) | |
| Interaction 3 | -13.034* | | -17.591*** | | -17.591*** | |
| | (6.760) | | (2.174) | | (2.174) | |
| Interaction 4 | -20.216*** | | -17.693*** | | -17.693*** | |
| | (5.935) | | (2.321) | | (2.321) | |
| Interaction 5 | -35.375*** | | -17.420*** | | -17.420*** | |
| | (3.611) | | (2.341) | | (2.341) | |
| 5x5 x Interactions | | 6.220*** | | 3.316*** | | |
| | | (1.173) | | (0.608) | | |
| 5x5 x Interaction 2 | 0.982 | | 16.440*** | | 19.509*** | |
| | (6.579) | | (2.243) | | (2.275) | |
| 5x5 x Interaction 3 | 6.620 | | 17.276*** | | 23.876*** | |
| | (7.175) | | (2.245) | | (2.364) | |
| 5x5 x Interaction 4 | 12.503* | | 16.883*** | | 26.237*** | |
| | (6.396) | | (2.386) | | (2.579) | |
| 5x5 x Interaction 5 | 25.337*** | | 16.358*** | | 27.970*** | |
| | (4.331) | | (2.396) | | (2.603) | |
| Constant | 46.432*** | 57.019*** | 20.852*** | 18.083*** | 20.852*** | 7.116*** |
| | (2.851) | (3.913) | (1.977) | (2.172) | (1.977) | (0.743) |
| Observations | 230 | 230 | 230 | 230 | 230 | 46 |
| $R^2$ | 0.412 | 0.404 | 0.585 | 0.374 | 0.537 | 0.348 |
| Adjusted $R^2$ | 0.388 | 0.396 | 0.568 | 0.365 | 0.519 | 0.334 |

*Note*: OLS regressions. Robust standard errors in parentheses. We analyze groups in the voluntary contribution mechanism (Model 1-2) and the ratchet-up mechanism (Model 3-6) separately. As explanatory variables, we use the following variables: 5x5: indicator variable for 5x5-settings; Interaction 2 to 5: indicator variables for round (decision) one to five in 5x1-settings (5x5-settings); Interactions: continuous variable for round (decision) one to five in 5x1-settings (5x5-settings). * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

In **Table C4**, we study the marginal effect of exploitation on participants' contributions to the public good. In contrast to the previous analysis, we analyze the data at the participant level. We regress participants' contributions in a given interaction of the experiment on the level of exploitation in the previous interaction. Again, we separately analyze the data for participants in the voluntary contribution mechanism (BASE 5x1 and BASE 5x5; Model 1) and the ratchet-up mechanism (RAT 5x1 and RAT 5x5; Model 2). Since we regress participants' contributions on the level of exploitation in the previous interaction, we use only data from the second interaction onwards, i.e., Round II to V in the 5x1-settings and Decision 2 to 5 in the 5x5-

settings. In Model 1, we use participants' contributions to the public good as dependent variable for participants in BASE 5x1. For participants in BASE 5x5, we use participants' cumulative contributions per decision as dependent variable. In total, we have 736 observations in Model 1. That is the data from 184 participants in BASE 5x1 and BASE 5x5 for four rounds each. In Model 2, we use participants' excess contributions as dependent variable for participants in RAT 5x1. For participants in RAT 5x5, we use participants' cumulative excess contributions per decision as dependent variable. With four interactions for the 184 participants in RAT 5x1 and RAT 5x5, we have in total 736 observations in Model 2. We use participants' level of exploitation in the previous interaction as primary explanatory variable (see Appendix D, **Fig. D1**). In addition, we use an indicator variable to capture whether a participant has been free ridden in the previous interaction and interact it with the level of exploitation. This allows us to differentiate the effect of being free ridden by the other group members from that of free riding on the other group members' contributions. Finally, we control for participants' contributions in the previous interaction in the voluntary contribution mechanism or participants' excess contributions in the previous interaction in the ratchet-up mechanism.

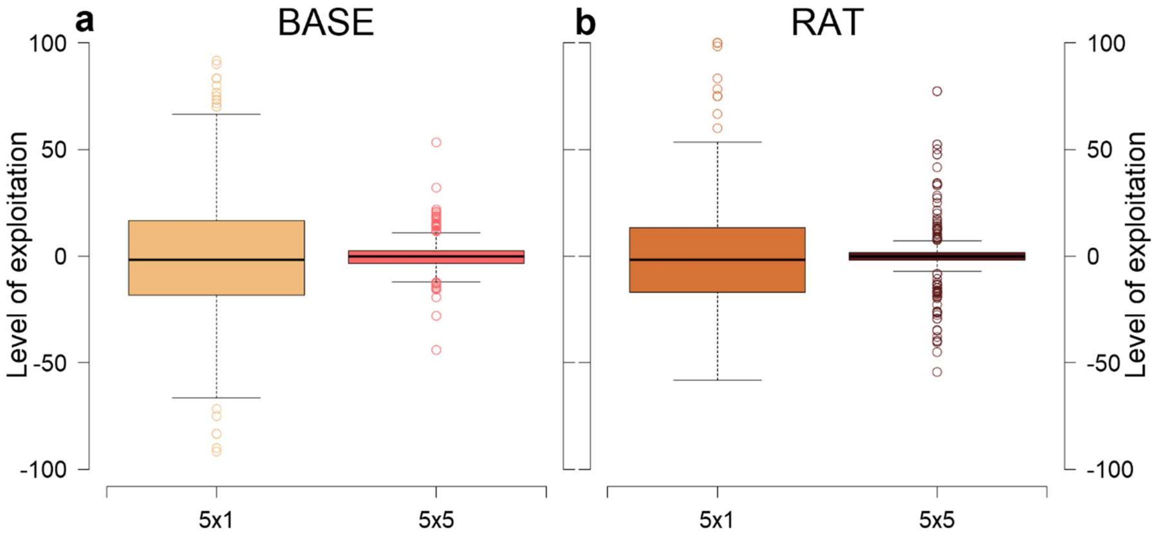
## Table C4. Marginal effect of exploitation

| | BASE | RAT |
|---|---|---|
| | Dependent variable: Contributions | Dependent variable: Excess contributions |
| | (1) | (2) |
| exp | -0.273*** | -0.087 |
| | (0.057) | (0.058) |
| exp > 0 | -0.440 | 0.903 |
| | (1.441) | (0.649) |
| exp x exp > 0 | -0.293** | -0.005 |
| | (0.135) | (0.065) |
| cont_prev | 0.838*** | 0.050*** |
| | (0.059) | (0.013) |
| Constant | 0.652 | 1.762*** |
| | (0.975) | (0.470) |
| Observations | 736 | 736 |
| $R^2$ | 0.475 | 0.033 |
| Adjusted $R^2$ | 0.472 | 0.028 |

*Note*: OLS regressions. Robust standard errors in parentheses. We analyze groups in the voluntary contribution mechanism (Model 1) and the ratchet-up mechanism (Model 3) separately. As explanatory variables, we use the following variables: exp: level of exploitation in the previous interaction; exp > 0: Indicator variable for positive level of exploitation in the previous interaction; cont_prev: participants' (excess) contributions in the previous interaction in the voluntary contribution mechanism (ratchet-up mechanism). * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

## Appendix D: Supplementary Figures

### Fig. D1. Level of exploitation by mechanism and setting




*Note*: **a**, boxplots of the level of exploitation in BASE 5x1 and BASE 5x5. **b**, boxplots of the level of exploitation in RAT 5x1 and RAT 5x5. We measure the level of exploitation by taking the difference between participants' contributions to the public good and the average of the other group members' contributions per interaction of the experiment, i.e., $exp_{i,t} = q_{i,t} - \bar{q}_{-i,t}$ where $q_{i,t}$ is participant $i$'s contribution and $\bar{q}_{-i,t}$ is the average of the other group members' contributions in interaction $t$. Thus, if the level of exploitation is greater than zero, the participant has been free ridden by her group members. In contrast, if the level of exploitation is less than zero, she was free riding on the contributions of her group members.

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